A Training Simulation System with Realistic Autonomous Ship Control

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Abstract

In this paper we present a computational approach to developing effective training systems for virtual simulation environments. In particular, we focus on a Naval simulation system, used for training of conning officers. The currently existing training solutions require multiple expert personnel to control each vessel in a training scenario, or are cumbersome to use by a single instructor. The inability of current technology to provide an automated mechanism for competitive realistic boat behaviors thus compromises the goal of flexible, anytime, anywhere training. In this paper we propose an approach that reduces the time and effort required for training of conning officers, by integrating novel approaches to autonomous control within a simulation environment. Our solution is to develop *intelligent, autonomous controllers* that drive the behavior of each boat. To increase the system's efficiency we provide a mechanism for creating such controllers, from the demonstration of a navigation expert, using a simple programming interface. In addition, our approach deals with two significant and related challenges: the *realism of behavior* exhibited by the automated boats and their *real-time response to changes* in the environment. In this paper, we describe the control architecture we developed that enables the real-time response of boats and the repertoire of realistic behaviors we designed for this application. We also present our approach for facilitating the automatic authoring of training scenarios and we demonstrate the capabilities of our system with experimental results.

I. Introduction

Virtual simulation environments provide a good application area both for entertainment and for serious simulations such as those used in training. In this paper, we focus on an application for training conning officers and we describe our approach to creating a robust and effective training system. The goal of this training is to teach conning officers how to drive big ships in the context of high-traffic, potentially dangerous situations. Developing an appropriate training system poses significant challenges, which will be addressed in this paper.

A significant problem with current training solutions is the *reduced efficiency* of the systems, in terms of the personnel required for running them, and thus their cost. Currently, a typical training scenario follows scripted procedures, with pre-planned events, and are performed in low-density environments. The latter constraint is due to the fact that each boat has to be manually controlled by a subject mater expert (SME) in ship navigation. This results in two types of training strategies: i) multiple SMEs play the part of each of the traffic boats in the scenario (Figure 1), and ii) a single SME controls between 10-20 ships simultaneously, using a system such as the one shown in Figure 2. These approaches are both expensive, due to the number of SME involved, and tedious, due to the complexity of the boat control that the SMEs have to deal with. In this paper, we propose an approach to reducing the time and effort required for this training, by automating the behavior of the boats in the simulation (other than the ship driven by the student officer). The new approach allows for flexible training scenarios, with varied decision points, and with heavy density environments.

a) Multiple SMEs control traffic boats b) Trainee officer with head mounted display

Fig. 1. Current, expensive approach to training.

Fig. 2. Current, complex approach to training.

Taking inspiration from the field of autonomous robotics, we developed a *Controller Authoring Tool* (CAT) that enables the development of intelligent, autonomous controllers. Each controller drives the behavior of a single boat, which through automation allows for scenarios with significantly larger number of boats. For this work, we assume that a set of primitive behaviors (e.g., *avoidance*, *maintaining station*, etc.) are available as basic navigation capabilities, and the authoring tool allows the construction of controllers for complex tasks from these underlying behaviors. With CAT, a trainer expert can create new training scenarios, which could be run with minimal support, due to the fact that all the boats in the scenario are now under autonomous control (Figure 3). Thus, our system eliminates the necessity of having large number of personnel for a single student's training, significantly reducing the costs involved.

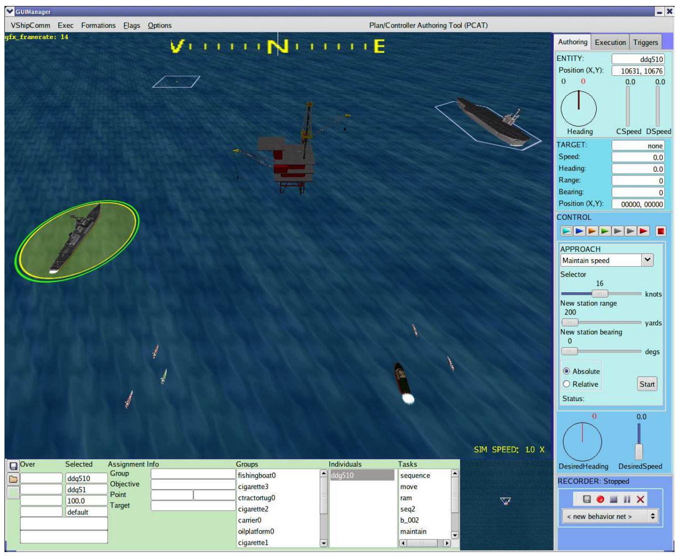


Fig. 3. Proposed solution to training: autonomous boat control and simple interface.

Developing the basis navigation behaviors for CAT poses two main challenges. A first challenge is the *readiness of response* of the automated boats when facing changing situations as a result of a trainee's or other boats' actions. This requires that the autonomous boat controllers be able to act in real-time, while continuing the execution of the assigned tasks. To achieve this goal we use Behavior-Based Control (BBC) (Arkin 1998), a paradigm that has been successfully used in robotics. BBC is an effective approach to robot and autonomous agent control due to its modularity and robust real-time properties. While BBC constitutes an excellent basis for our chosen domain, developing behavior-based systems requires significant effort on the part of the designer. Thus, automating the process of controller design becomes of key importance. In our work, the instructor uses the authoring tool to create challenging training scenarios for the student conning officers, for a fast and efficient transfer of knowledge from the expert to the automated control system.

A second challenge is the *realism of the behavior* exhibited by the autonomous boats involved in the simulation. This is due to the fact that any behavior that departs from standard boat navigation techniques would have a detrimental impact on the students' training experience. This requirement imposes new constraints on how the boats' underlying behaviors are implemented, in contrast with typical behavior-based systems in which the modality of achieving the desired goals is not necessarily important. To implement realistic navigation capabilities we acquired expert knowledge of ship navigation (John V. Noel 1988), which we encoded within a behavior-based framework.

The implementation of the game engine and the graphics display are also main components of the entire system, but they are outside the scope of this paper. The work presented here, a part of a larger scale project, focuses on the aspects related to autonomous boat control.

The remainder of the paper is structured as follows: Section II describes related approaches to our work and Section III describes our simulation environment. Section IV presents our behavior and controller representation and Section V presents our behavior repertoire. Section VI describes the concept of controller triggers and Section VII describes the details of our authoring approach. We present our experimental results in Section VIII and conclude with a summary of the proposed approach in Section IX.

II. Related Work

Simulation systems for training have received significant interest in recent years. Representative examples include flight simulators (Tambe, Johnson, Jones, Koss, Laird, Rosenbloom & Schwamb 1995, van Lent & Laird 1999, Pearson, Huffman, Willis, Laird & Jones 1993) and battlefield simulators (Calder, Smith, Courtemarche, Mar & Ceranowicz 1993, Phongsak Prasithsangaree & Lewis 2004). In contrast with the above approaches, the system we propose in this paper provides an authoring mechanism to facilitate the development of autonomous controllers for the agents involved in the simulation. Our approach is inspired by the *programming by demonstration* or *learning from apprenticeship* paradigm, in which systems learn from observing human expert behavior. This method has been employed in a wide range of domains, such as intelligent software systems (Lieberman 2001*a*, Lieberman 2001*b*, Lieberman & Shearin 2001), VLSI design (Mitchel, Mahadevan & Steinberg 2005), physics (Shavlik 1985), agent-based architectures (Angros 2000), and robotics (Schaal 1997, Dautenhahn & Nehaniv 2002, Abbeel & Ng 2005).

In the mobile robotics domain, which provided the inspiration for our system, successful approaches that rely on learning from demonstration have shown learning of reactive policies (Hayes & Demiris 1994), trajectories (Gaussier, Moga, Banquet & Quoy 1998), or high-level representations of sequential tasks (Nicolescu & Matarić 2003). These approaches employ a *teacher following* strategy, in which the robot learner follows a human or a robot teacher. Our work is similar to that of (Aleotti, Caselli & Reggiani 2004, Onda, Suehiro & Kitagaki 2002, Ogata & Takahashi 1994), who perform the demonstration in a simulated, virtual environment. Furthermore, our work relates to teleoperation, a very direct approach for teaching by demonstration. Teleoperation can be performed using data gloves (Voyles & Khosla 2001) or multiple DOFs trackballs (Kaiser & Dillmann 1996). These techniques enable robots to learn motion trajectories (Delson & West 1996) or manipulation tasks (e.g., (Yang, Xu & Chen 1993)). Using such "lead-through" teaching approaches (Todd 1986) requires that the demonstration be performed by a skilled teacher, as the performance of the teacher in demonstrating the task has a great influence on the learned capabilities. Another difficulty that may arise in teleoperation is that the training may be performed through instruments that are different than what the human operator would use in accomplishing the task. In addition, the actual manipulation of the robot may influence the accuracy of the demonstration. Within the scope of this work, we propose the use of an interface as a tool for learning new training scenarios from an expert's demonstration.

This interface is significantly optimized from that currently used by the navy experts during their training exercises and allows the transfer of expert knowledge through standard computer input devices.

III. Simulation Environment

For this work, we developed a 3D simulation environment, called *Lagoon* (Figure 3), which allows for simulating a wide range of boats, from small cigarette boats to medium ships, such as sailboats, to large ships, such as destroyers and aircraft carriers. All boats have realistic physics, which the controllers take into account when autonomously driving the ships. Within this architecture, each boat can be controlled via the *Authoring* or the *Execution* panel (Figure 3, right side of screen). When an entity is selected, the panel and its associated behaviors refer to that entity. Whenever a new entity is selected, the behavior information for that new entity is displayed. The boats are equipped with 7 primitive behaviors, each of which has an associated control panel (Section V): *approach*, *maintain station*, *ram*, *move to*, *avoid entity*, *avoid land* and *fire*. The top level of the *Authoring* panel displays information about the selected entity: name, current speed and course, desired speed and course, and position. The lower section displays information about the target ship (when applicable - Section V): name, speed, heading, position, range and bearing to target. The bottom section of the *Authoring* panel provides manual controls for actuating the selected entity, as an alternative to behaviors.

IV. Behavior-Based Control Architecture

Behavior-based control (BBC) (Arkin 1998) has become one of the most popular approaches to embedded system control both in research and in practical applications. Behavior-based systems (BBS) employ a collection of concurrently executing processes, which take input from the sensors or other behaviors, and send commands to the actuators. These processes, called *behaviors*, represent time-extended actions that aim to achieve or maintain certain goals, and are the key building blocks for intelligent, more complex behavior. In this paper we use a *schema-based representation of behaviors*, similar to that described in (Arkin 1987). This choice is essential for the purpose of our work, since it provides a continuous encoding of behavioral responses and a uniform output in the form of vectors generated using a potential fields approach.

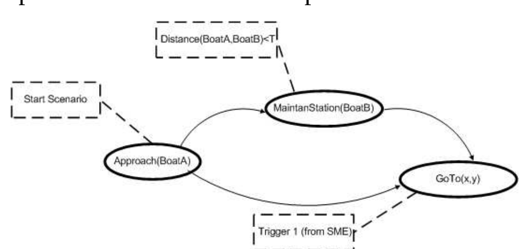


Fig. 4. Example of a behavior network. Behaviors are represented as ovals, triggers as rectangles.

For the *controller representation* we use an extension of the standard Behavior-Based Systems we developed, which provides a simple and natural way of representing complex tasks and sequences of behaviors in the form of networks of behaviors. In a behavior network, the links between behaviors represent precondition-postcondition dependencies, which allow for encoding and execution of sequenced tasks. The sequencing of behaviors can be encoded using three different types of precondition-postcondition links: *permanent*, *enabling* and *ordering* (Nicolescu & Matarić 2002).

Each link type corresponds to a different time interval during which a predecessor behavior's goals should be achieved, with respect to activating the successor behavior. In addition, the activation of a behavior can also be regulated by conditions that are independent of the behaviors' goals. These conditions are encoded as *triggers*, and can be dynamically created during authoring of new controllers (Section VI). Figure 4 shows an example of a behavior network, which describes the following activity: upon firing the *Start scenario* trigger, the controlled boat approaches *BoatA*; as soon as the distance between the controlled boat and *BoatB* is smaller than a threshold (as monitored by the *Distance* trigger), the boat moves into maintaining station with respect to *BoatB*; when *Trigger1* is set by the instructor, the boat moves to a specific location in the world.

In our architecture, the behaviors embed representations of a behavior's goals in the form of abstracted environmental states, which are continuously computed from the sensory data. The status of these goals is communicated through the postcondition – precondition links between behaviors. To decide weather it should run, each behavior checks the status of the goals from all predecessor behaviors and the status of its associated triggers. If all these conditions are met, the behavior starts its execution. With this representation, a task sequence is completely specified by the directed acyclic graph task network.

In our system, a controller could potentially have multiple concurrently running behaviors. For such situations, we use the following action selection mechanism. Each behavior, including the avoid entity and avoid land behaviors, computes a speed and a heading for the actuators. If more than one non-avoidance behavior is active at one time, the speed and heading returned by each active behavior, represented as a vectors, are added by vector addition. The resulting speed and heading are passed to the actuators. However, if one of the avoidance behaviors is active along with other non-avoidance behaviors, the vector from the avoidance behavior is not fused with the other behaviors' output. In such a case, the other behaviors' vectors are summed and sent to the avoidance behavior as a *"suggestion"*. If the avoidance behavior finds that the suggested heading and speed do not create a risk of collision, then the behavior will simply pass the suggested values directly to the actuators. If, on the other hand, the avoidance behavior finds that the suggested heading and speed will cause a collision, the avoid behavior will find an alternative heading and speed that is as close to the suggested values as possible without causing a collision. These alternative values will then be passed directly to the actuators (Section V-C).

If both avoidance behaviors are active at the same time as other behaviors, then each avoidance behavior (land and entities) will find an appropriate set of alternative values based on the same set of suggested values from the other behaviors. However, instead of passing these values directly to the actuators, the outputs of the two avoid behaviors will be fused as described above. The result will then be passed to the actuators.

V. Behavior Repertoire for Realistic Navigation

A. Description

The most important skill necessary for our behavior repertoire relates to vessel navigation, particularly where realistic navigation is concerned. In the agents/robotics domain, what is most important is to design behaviors or skills that achieve certain desired goals for the task, with little regard on the modality in which those goals are reached. For ship handling and navigation, following the *"rules of the road"'* (John V. Noel 1988) is of utmost importance and imposes signifi cant constraints on how the ship's basic capabilities are designed. An additional constraint is that the level of granularity for these skills has to be appropriate to allow for the types of tasks that the boats would need to perform.

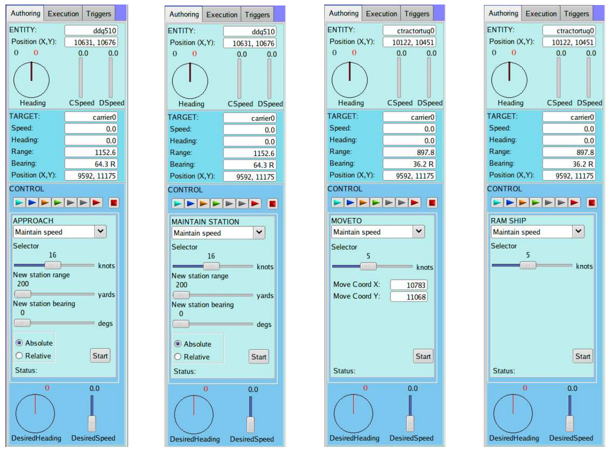


Fig. 5. Behavior Panels: Approach, Maintain Station, Move To, Ram

Based on the above requirements, we identifi ed a set of core behaviors, which can cover the entire spectrum of required navigation tasks (the control panels for four of the behaviors are shown in Figure 5):

- **Maintain Station:** This behavior encapsulates a typical navigation maneuver, in which a *maneuvering ship* (such as a destroyer) maintains a certain station (distance and bearing) with respect to a *reference ship* (such as an aircraft carrier). This behavior takes fi ve parameters: 1) the reference ship, 2) the way in which the maneuver is to be performed: constant speed, constant course or in a given amount of time, 3) the value for the maneuver (i.e., speed, course or time), 4) the desired stationing position in terms of distance and bearing, and 5) if the position is relative or absolute. When executing this behavior, the *maneuvering ship* gets into the required station, after which it continues to track the *reference ship's* course and speed. If the *reference ship* changes course or speed, the behavior re-computes the necessary control commands for the *maneuvering ship*, in order to maintain the desired station.
- **Approach:** This behavior is similar to the *Maintain Station* behavior and has the same input parameters. The difference is that the goal of this behavior is simply to get a *maneuvering ship* to reach a certain station (distance and bearing) with respect to a *reference ship*, without maintaining that station afterward.
- **Move To:** The goal of this behavior is to get a *maneuvering ship* to a specifi c location in the world, in (X, Y) coordinates. This behavior takes three main parameters: 1) the way in which the maneuver is to be performed: with a constant speed or in a given amount of time; 2) the value for the maneuver (i.e., speed or time), and 3) the desired (X, Y) position.
- **Ram:** The goal of this behavior is to have a *maneuvering ship* hit a *target ship*. This behavior takes three main parameters: 1) the target ship, 2) the way in which the maneuver is to be performed: constant speed, constant course

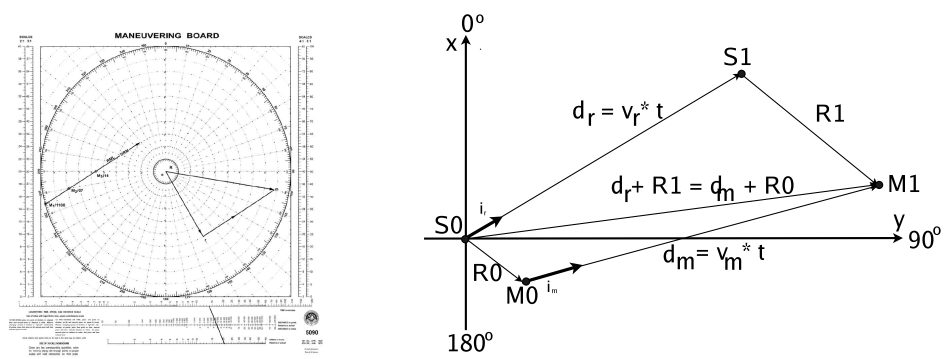
or in a given amount of time, and 3) the value for the maneuver (i.e., speed, course or time). This behavior uses the same procedure as maintain station, with the distance to target parameter set to zero.

- **Fire:** The goal of this behavior is to direct the weapon fire from a *maneuvering ship* to a *target ship*. The sole parameter of this behavior is the ship toward which to direct the fire.
- **Avoid Entity:** The goal of this behavior is to navigate a boat such that all collisions with other boats are avoided, in a manner consistent with the standard navigation rules (Section V-C).
- **Avoid Land:** The goal of this behavior is to avoid collisions with land, in a manner consistent with the standard navigation rules (Section V-D).

As previously mentioned, simply achieving the goals of these behaviors is insufficient if the boats do not obey the ship navigation rules. In addition, the large number of rules in the navigation domain makes very challenging the task of implementing these rules in a simple, modular manner. The following subsections describe our approach to implementing the main navigation rules into our behavior-based system.

B. *Navigation*

On an actual ship, the desired course and speed of a ship is computed using a *maneuvering board*, or *moboard* (Figure 6a)). This allows the crew to obtain the course and/or speed that the ship should take to get into the desired position with respect to another boat.



a) Standard maneuvering board b) Maneuvering board in Cartesian coordinates

Fig. 6. Maneuvering Board Representations

When using the moboard, the *maneuvering ship* is placed at the center of the board, and the location, course and speed of the *reference ship* are plotted with respect to the center. With this diagram, the three modes of maneuvering can be performed: 1) constant speed (course and time to completion are computed), 2) constant course (speed and time to completion are computed) and 3) given time (course and speed are computed). This representation is very useful for manual computation, such as that performed by a human operator. For our purpose, we represent the problem as the relative motion of two objects in Cartesian coordinates, assuming that both ships maintain their speed and course during the maneuver, as shown in Figure 6 b), where:

- S_0, S_1 - position of the *reference ship* at the beginning and end of the maneuver
- M_0, M_1 - position of the *maneuvering ship* at the beginning and end of the maneuver
- R_0, R_1 - displacement between the two ships at the beginning and end of the maneuver
- d_r - displacement of the *reference ship* over the course of the maneuver
- d_m - displacement of the *maneuvering ship* over the course of the maneuver
- $\vec{i}_m$ - unit vector representing the direction of the *maneuvering ship*
- $\vec{v}_m$ - velocity vector of the *maneuvering ship*
- $\vec{i}_r$- unit vector representing the direction of the *reference ship*
- $\vec{v}_r$ - velocity vector of the *reference ship*
- t - time to complete the maneuver

The equation of motion for the *maneuvering* and *reference* ships is:

$$\vec{i}_r \, ||\vec{v}_r|| \, t = \vec{D} + \vec{i}_m \, ||\vec{v}_m|| \, t \tag{1}$$

where $\vec{D}$ is the relative motion vector $(\vec{R}_0 - \vec{R}_1)$. In Equation 1, two of the three variables $||\vec{v}_m||$, $\vec{i}_m$ or t are unknown, corresponding to the three possible types of maneuvers. From Equation 1 we can find the solutions to the different maneuvers, as follows:

1) Constant speed. Keeping $||\vec{v}_m||$ constant, we compute the course ($\vec{i}_m$) and the time to completion (t), by solving the system of two equations that results from projecting Equation 1 onto the (X, Y) coordinates.

2) Constant course. Keeping the course ($\vec{i}_m$) constant, we compute the speed ($||\vec{v}_m||$) and the time to completion (t), by solving the system of two equations that results from projecting Equation 1 onto the (X, Y) coordinates.

3) Constant time. Keeping t constant, we compute the course ($\vec{i}_m$) and speed ($||\vec{v}_m||$), by solving the system of two equations that results from projecting Equation 1 onto the (X, Y) coordinates.

Due to the fact that the simulated ships have realistic physics, we use a PD (proportional derivative) controller to slow down the ships as they approach their goal destination. The speed sent to the actuators is computed with the formula:

$$v_{mFinal} = v_m + K_p DiffSpeed + K_d * DiffAccel \tag{2}$$

where v_m is the speed computed from Equation 1, K_p and K_d are proportional and respectively derivative constants and $DiffSpeed$ and $DiffAccel$ are the difference in speed and acceleration between the maneuvering ship and the reference ship.

All four navigation behaviors, *approach, maintain station, move to* and *ram*, use the above equations, parameterized to fit their requirements.

C. Entity Avoidance

In typical robot/agent-based controllers, the role of the obstacle avoidance behavior is simply to avoid all obstacles. In most cases this is achieved by turning left when there is an obstacle to the right or by turning right when there is an obstacle to the left. To accurately mimic the actions of a human driving a ship, several important constraints apply.

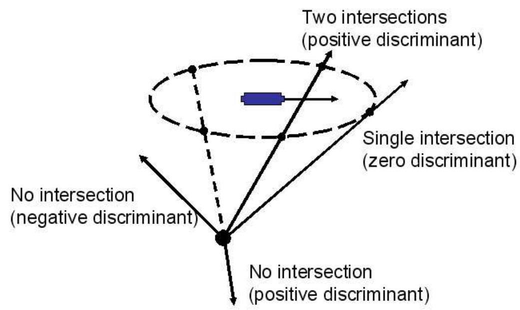


Fig. 7. Obstacle Avoidance

The most important navigation rule for avoidance is that a human looks ahead in time to determine whether he will hit an obstacle, behavior which cannot be achieved by a purely reactive controller. We implement such looking ahead capabilities into our avoidance behavior, as explained next.

For the obstacle avoidance behavior, each ship in the world (other than the avoiding ship) is represented by an ellipse that is centered about that ship's center of mass, rotated such that the major axis of the ellipse is parallel to that ship's heading, and whose major and minor radii are proportional to the length and width of the ship, respectively (Figure 7). The avoiding ship is represented simply as a point. Since the speed and heading of the avoidance ship as well as the speeds and headings of all other ships are known (in real life, this information can be obtained through passive sensing), we can look forward in time to find the positions of the ships at some point in the future, assuming that their speed or direction does not change. Along with this information, we can also obtain the equations of the ships' corresponding ellipses. A collision is predicted to occur when the point representing the own ship falls onto the ellipse representing another ship, or, to put it another way, when the (x,y) point representing the own ship satisfies the equation of one of the avoidance ellipses. Based on this information, the avoidance behavior finds whether a collision is imminent, the time to collision, and a revised speed or heading for the own ship that will avoid collisions with other ships.

The (x, y) position of any ship in time can be expressed as a pair of parametric equations, with time as a parameter. An ellipse can be uniquely described by its center point, its minor and major radii, and its orientation. For any given ship, we can safely assume that the radii will remain constant, as they are proportional to the dimensions of the ship, which are constant. Furthermore, we assume that the orientation of an avoidance ellipse will remain constant in the future, since ships usually do not change heading without reason. If one of these assumptions turns out to be false, such as when a ship is turning, the avoidance ellipse is recalculated based on the most recent values. The center point of the ellipse, like the point representing the own ship, can be calculated for some point in the future using the ship's current heading, position, and speed as in Equation 3:

$$\begin{aligned} h &= v_t * t * cos\theta_t + x_{0t} \\ k &= v_t * t * sin\theta_t + y_{0t} \end{aligned} \tag{3}$$

where h is the x coordinate of the ellipse's center, k is the y coordinate of the ellipse's center, v_t is target ship's velocity, t is the amount of time to look into the future, θ_t is the target's heading, x_{0t} is the x coordinate of the target's current position (x coordinate of current ellipse center), and y_{0t} is the y coordinate of the target's current position (y coordinate of current ellipse center).

The equation of a boat's avoidance ellipse (centered at (h, k) and rotated by θ_t) is given by equation 4 below:

$$\frac{((x_m-h)*cos\theta_t+(y_m-k)*sin\theta_t)^2}{a^2}+\frac{((y_m-k)*cos\theta_t-(x_m-h)*sin\theta_t)^2}{b^2}=1 \tag{4}$$

where x_m, y_m, h, k, and θ_t are the same as above, a is the major radius of the ellipse, and b is the minor radius of the ellipse.

We can find out if a point will fall on an ellipse by setting the x_m and y_m values representing the position of the points on the ellipse to the equations for the (x, y) position of the own ship and solving for time. The result is a quadratic equation in t, with x_{0m}, y_{0m}, v_m, v_t, θ_t, h, k, a, b as known parameters:

$$g(t) = q_2t^2 + q_1t + q_0 = 0 \tag{5}$$

Based on the possible solutions of Equation 5, the following cases occur:

1) If *both solutions are imaginary* (negative discriminant), then there will be no intersection at any time between the point and the ellipse, indicating no risk of collision.

2) If *both solutions are equal* (discriminant equal to 0), then there is only one point of intersection with the ellipse, meaning that the own ship is traveling tangentially to the avoidance ellipse of the ship to be avoided. In this case, there is no danger of the ships themselves colliding, as the own ship never makes its way inside the avoidance ellipse of the other ship.

3) If *the discriminant is positive*, there are three possible cases: i) If both solutions are positive, the own ship will intersect the avoidance ellipse twice: once to enter the ellipse and once more to exit it (in this case, some evasive action must be taken to avoid a collision); ii) if both solutions are negative, there is no risk of a collision (intuitively, this would mean that there was an intersection at some point in the past, but there is no danger in the future); and iii) if one solution is negative and one solution is positive, then the own ship has intersected the avoidance ellipse once in the past, and will intersect it once more in the future (this indicates that the own ship is within the avoidance ellipse of the other ship, and must take immediate and drastic evasive maneuvers to avoid a collision and leave the avoidance ellipse.)

If evasive action must be taken, the following options are considered. If the own ship is within the avoidance ellipse of another ship, this is seen as an emergency situation and the own ship will try to move behind and away from the other ship as quickly as possible. If, however, the danger of collision is sufficiently far away in the future, the obstacle avoidance behavior can make smaller adjustments to the heading or speed of the own ship to eliminate the danger of colliding with the other ship. To achieve this, the obstacle avoidance behavior computes a heading and/or speed that results in a zero discriminant for Equation 5 (case 2 above), resulting in a quadratic equation in v_m, with x_{0m}, y_{0m}, x_{0t}, y_{0t}, v_t, θ_t, a, b as known parameters. Navigation rules favor a change speed rather than heading, thus the behavior first attempts to find a new speed that satisfies the constraint:

$$f(v_m) = r_2 v_m^2 + r_1 v_m + r_0 = 0 \tag{6}$$

If the equation has two valid solutions (speeds are positive and less than or equal to the maximum speed of the ship), the behavior returns the highest speed. If only one solution is a valid speed, that speed is used. If neither solution is valid, then the heading must be changed to avoid a collision. To find a valid heading, the behavior first finds whether the collision would still be imminent if the own ship turned five degrees to the left. If not, then the behavior continues to test potential headings, in increments of five degrees, until it finds one that avoids a collision, at which point it uses the same process to find a corresponding heading to the right of the current heading. This results in two headings (one to the right, and one to the left) that avoid a collision. The heading closest to the current heading is the one passed to the actuators.

The solution to avoid one ship could potentially generate collisions with others. Our approach uses a mechanism to deal with avoiding multiple ships, as follows: for every ship on a collision course with the own ship, the avoidance behavior puts in a list all the valid speeds and headings that will avoid that ship. After all the ships have been analyzed and the list is built, the behavior iterates through the list and eliminates the routes that collide with other ships. The only elements remaining in the list will be the speeds or headings that avoid collisions with all the other ships in the simulation. Since speed changes take priority over heading changes, if there is at least one speed remaining in the list, that speed will be passed to the actuator with the current heading. If there is more than one potential speed in the list, the highest speed is passed to the actuators. If no speed changes remain in the list, then the potential heading that is closest to the current heading is passed to the actuators along with the current speed.

D. Land Avoidance

To determine whether or not a ship is in danger of colliding with land, the avoid land behavior uses the speed of the ship, as indicated in (John V. Noel 1988). This speed is to determine the approximate distance that the ship can travel in four minutes, to check if there is any land within that distance, in all directions from the ship. If no land is present in that area, there is no land to avoid. However, if there is land in front of the own ship, the behavior computes a heading that will take the ship away from land and a speed that makes the nearest land be outside of the four minute range. To achieve this, the behavior uses the distance and bearing to the nearest land in the front 180-degree field of view. The new speed is calculated to be that distance divided by four minutes, to ensure that the nearest land will lie outside of the four minute range. The new heading is calculated to be that bearing plus or minus 90 degrees, whichever is closer to the current heading. This ensures that instead of continuing to head toward land, getting slower and slower until the ship grounds itself, the ship will turn parallel to the land, following its contour until there is no more land to avoid or until the land avoidance behavior is turned off.

VI. TRIGGERS

Triggers are used to encode in a behavior network controller important situations in the training scenario. Typically, they are used with the purpose of changing a boat's behavior when that situation occurs.

During the controller authoring stage, the trigger information is recorded in the behavior-based controller, as a trigger condition, as described in Section IV. Triggers can be created through the triggers panel of our interface, shown in Figure 8. The following types of triggers are available: *distance between entities*, *entities within a certain range*, *hull strength* of a particular ship, or an arbitrary *instructor flag*. The panel allows the user to specify the parameters for each trigger, such as, for example, the entities between which the distance is to be monitored. The name and current value (updated every tick) of all created triggers is displayed on the triggers panel main window. Triggers can be created, monitored, or deleted at any time during either authoring or execution.

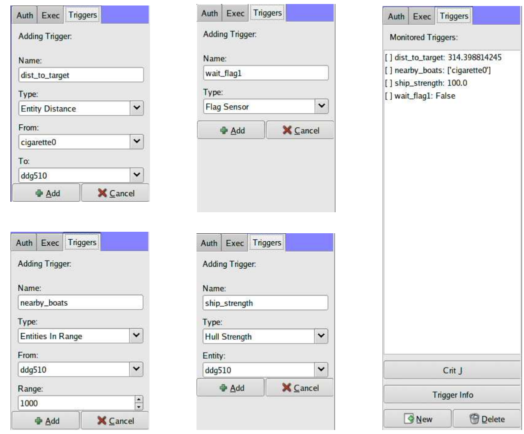


Fig. 8. Trigger types and panel.

All triggers, with the exception of the *instructor flag* triggers, do not require user input (i.e., setting the trigger) during execution. For these, the *true* or *false* value of the trigger is automatically computed from the parameter information. In contrast, an *instructor flag* trigger requires user input both during authoring and execution. Such a trigger usually represents an event whose occurrence the instructor wants to specify himself, such as the start of a scenario. At execution stage, this trigger will be set by the instructor at the appropriate time when the students are fully prepared to begin the exercise. The instructor flag triggers are particularly important for the naval training application, as they allow the instructor to activate specifi c stages of the scenario at the time that will provide the best training experience for the students.

During authoring, triggers are set by clicking the Critical Juncture button. With the exception of the *instructor flags*, all other triggers will record as parameters the corresponding values computed at the time when the button was pressed. During execution, the *instructor flags* are set by selecting the check-box next to the desired flag and clicking the Critical Juncture button.

The set of triggers can easily be extended to capture additional events happening during a task execution. This can be achieved in two ways: by introducing new types of triggers (done by the system designer) or by creating arbitrary triggers using the *instructor flags* (done by the user).

VII. Controller Authoring Approach

To create new controllers for a particular boat, the instructor uses the *Authoring* panel of the Control Panel interface (Figure 3) to start or stop the relevant behaviors (Figure 5). While the behaviors are executed, the authoring tool continuously monitors the status of the behaviors' postconditions. To build the controller we add to the network task representation an instance of all behaviors whose postconditions have been detected as true during the demonstration, in the order of their occurrence. At the end of the teaching experience, the intervals of time when the effects of each of the behaviors were true are known, and are used to determine if these effects were active in overlapping intervals or in sequence. Based on the above information, the algorithm generates proper dependency links between behaviors (i.e., *permanent*, *enabling* or *ordering*). This learning process is described in more detail in (Nicolescu & Matarić 2001), with application to the mobile robot domain.

The process for authoring a controller proceeds as follows:

1) The user starts the authoring by pressing the *Record* button.
2) If any triggers are needed, the user first creates all the triggers to be used during that session. While a scenario is being recorded, if the user wishes to indicate changes in behavior based on some particular event in the world, he/she navigates to the triggers panel, clicks on the check-box next to the appropriate trigger to indicate its relevance, clicks the Critical Juncture button, and then starts the desired behavior.
3) To start a behavior, the user selects the appropriate behavior panel, selects its parameters and clicks the *Start* button. At this time, the button's label changes to *Stop*, which the user can press to indicate the end of that behavior. The user activates and de-activates behaviors in sequence such as to follow the steps of the controller task.
4) The user ends the authoring process by pressing the *Save* button.

During playback of the same scenario, the system will monitor the state of all triggers. When the state of the execution trigger approaches that of the user-created trigger, the system switches the boat's behavior according to the demonstration. With respect to the avoidance behaviors, the system will run the controller as was indicated during authoring: if no avoidance behaviors were included, the corresponding boat has a potential for collision either with land or other boats.

VIII. Experimental Results

In this section we describe the performance of our system during behavior performance testing and during controller authoring, and also present field results from the use of our system in real navy training. This experimental validation demonstrates the main capabilities of our system: autonomous control of multiple boats, compliance to navigation standards and authoring of complex controllers.

A. Behavior Performance

The behaviors that involved the underlying navigation capability (*approach*, *maintain station*, *ram*, and *move to* have been thoroughly tested throughout the experiments listed below. Their performance correctly and faithfully demonstrated compliance to the rules of ship navigation.

We successfully tested *avoid entities* in numerous situations, including the following: 1) moving own-ship from one side of stationary/moving target ship to the other side, 2) moving own-ship from one end of stationary/moving target ship to other end, 3) moving own-ship from one side of two stationary/moving ships whose ellipses overlap to the other side and 4) moving own-ship from one side of a crowded group of moving and stationary ships to the other side. These represent the most probable situations to be encountered by a boat in high-traffic areas. Currently, the system can run up to 80 ships with both avoidance and navigation behaviors in real time. This performance provides a realism of behavior that enables an effective learning experience for the trainees.

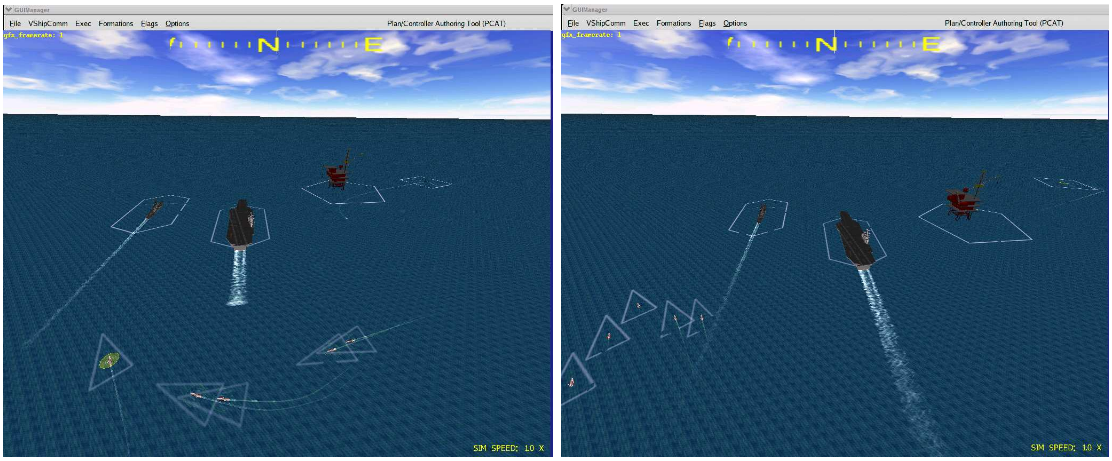


Fig. 9. Behavior performance evaluation: Destroyer maintains station with respect to aircraft carrier; V-formation avoids big ships while moving west.

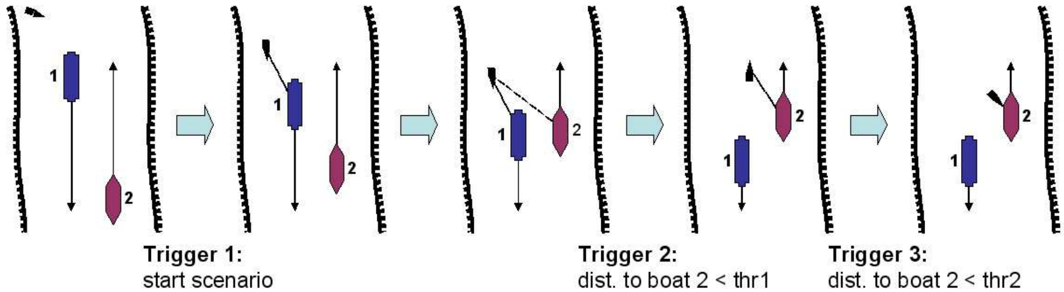
We successfully tested the *avoid land* behavior in the following representative situations: 1) moving own-ship from point far away from land to point near land, 2) moving own-ship from point near land to point farther away from land, 3) moving own-ship to a point within a land mass (triggered avoidance and did not move onto land), 4) moving own-ship to a point on the other side of a land mass.

By attaching *Maintain station* behaviors to several boats, in a layout such as required by a formation, we enabled autonomous group behavior, for large number of boats. Currently, we can organize any number of boats (as allowed by the computational power of the computer) in the following formations: *line*, *row*, and *V-formation*. The boats involved in a group maintain their assigned formation while performing other tasks, such as moving to a new location, or approaching a target. While performing these maneuvers, the group avoids obstacles, keeping the formation together. Figure 9 shows a group of 5 boats in *V-formation*, moving to the left of a destroyer and aircraft carrier, while performing obstacle avoidance. The bottom figure shows the formation regrouped after avoidance. The boats can dynamically switch between formations.

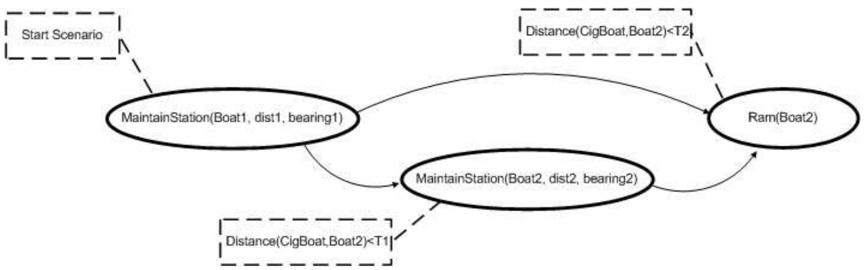
B. Controller Authoring

We have performed a large number of authoring experiments with different scenarios, with all controllers being learned correctly. Below we give detailed description of two examples, which are relevant for the training of conning officers.

Scenario 1: sneak attack (Figure 10). After a *Scenario Start* trigger, a small boat moves into position with respect to big ship #1, then maintains station with respect to it, such that it is hidden from view from ship #2. Big ship #2 navigates in opposite direction from ship #1 in a channel. When a *Distance* trigger1 between the ship #1 and ship #2 fires, the small boat switches to maintaining station ahead of ship #2. When a second *Distance* trigger between the small boat and ship #2 fires, the small boat switches to ramming ship #2. The network controller,



a) Diagram of task sequence



b) Network controller for scenario 1

Fig. 10. Scenario diagram and controller network for scenario 1.

shown in Figure 10 b), represents all these successive stages, with the appropriate behaviors being activated by proper precondition links and trigger conditions. Figure 11 shows two snapshots from the execution of the scenario, with a cigarette boat, a container ship (Ship #1) and a destroyer (Ship #2).

This describes the execution of the sneak attack during training. However, how did the network controlling the behavior of the small boat come about? Below we describe the authoring of this network by providing step-by-step details on the scenario's authoring by an instructor.

1) Using the mouse menu, create three ships.
2) Position and orient ships as described above and shown in Figures 10 and 11.
3) Mouse select the small boat whose network is being authored.
4) Press the red start-record button on the behavior network authoring panel.
5) Create three triggers.
   a) Create three distance triggers using the trigger creation panel. Trigger #2 between ship #2 and small boat and trigger #3 also between ship #2 and small boat.
   b) Create Scenario start trigger.
6) Command ship #1 to move towards the harbor entrance.
7) Command ship #2 to move towards in-harbor ports.
8) Command small boat to maintain station with respect to ship #1. At this stage all three vessels are moving.
9) Fire trigger #2 when ship #2 approaches within 150 yards of the small boat. Trigger #2's threshold is now

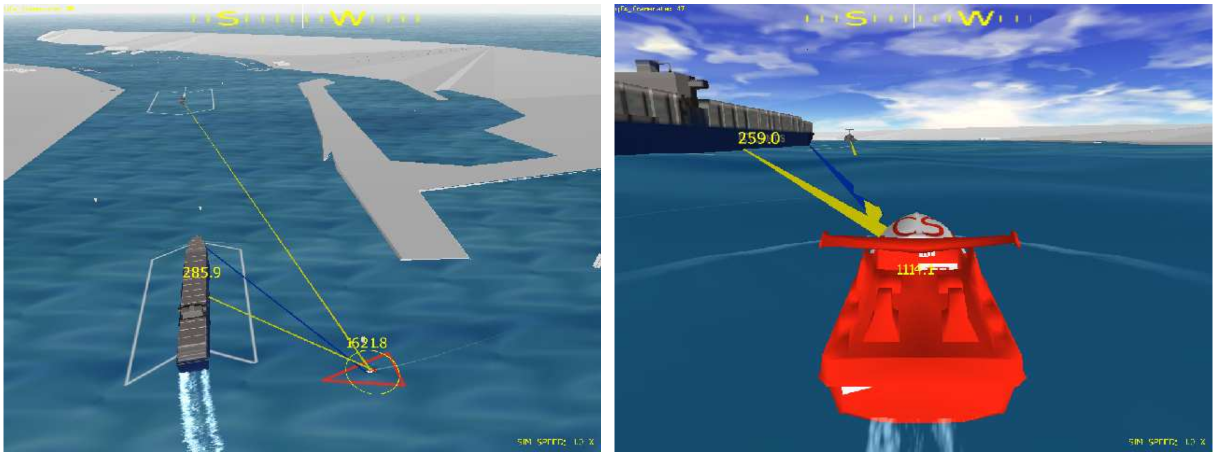


Fig. 11. Snapshots of the task execution in a simulated San Diego harbor. Left: Small boat gets into position w.r.t. Ship1 (distances to big boats are shown with yellow lines). Right: View from the perspective of the small boat.

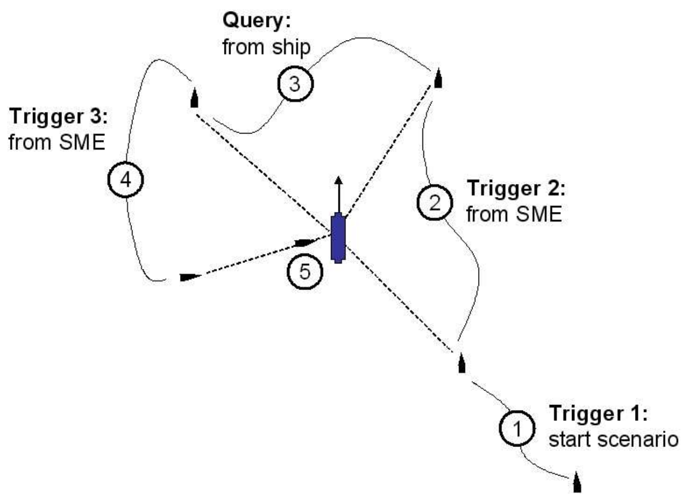
recorded as 150.

10) Command small boat to maintain station 100 yards ahead of ship #2, causing the boat to begin swinging out from behind ship #1 and towards the bow of ship #2 (our target). This maintain station behavior and its parameters will now be associated with trigger #2 and will activate when trigger #2 fires during execution.
11) Fire trigger #3 when the small boat is within 150 yards of ship #2 recording trigger #3's threshold as 150.
12) Command small boat to ram ship #2. This ram behavior and its parameters are then associated with trigger #3 and will activate when trigger #3 fires during execution.
13) Press the save button on the behavior network authoring panel.

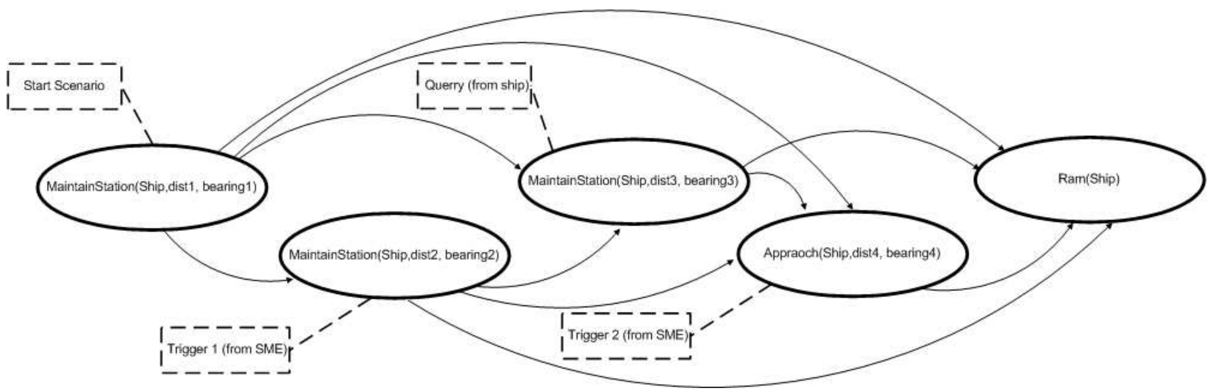
Once saved to a file, the constructed behavior network can be used for sneak attacks in San Diego. It may also be used in other contexts and scenarios although, as with any program, some "debugging" and fine tuning (such as changing distance trigger thresholds) may need to be done.

Scenario 2: zig-zag attack (Figure 10). After a *Scenario Start* trigger, a small boat moves into position with respect to a big ship, then maintains distant station south-east of ship; on *Trigger 1* (from SME), the small boat changes to maintaining station north-east of big ship; upon a *Query* trigger from the big ship, the small boat moves to maintaining station north-west of big ship; at *Trigger 2* (from SME), the small boat approaches the big ship at the east and then rams it. The network controller for this scenario, shown in Figure 12, encapsulates all the above stages: the three successive steps of *maintaining station* with respect to the big ship, followed by *approach* and *ram*. The first four behaviors have corresponding triggers that enable their activation, based on the conditions demonstrated during authoring.

During training of navy officers, the learned behavior network controllers are assigned to specific boats, which will navigate autonomously under the control of the behavior network. Using the CAT interface, the instructor has also the opportunity to adjust variables of the controller during the execution of the scenario, providing an additional



a) Diagram of task sequence



b) Network controller for scenario 2

Fig. 12. Scenario diagram and controller network for scenario 2.

level of flexibility for training.

The impact of our system to the offi cer training experience has multiple levels. First, it allows for increased scenario complexity, in that our solution can handle up to 80 simultaneously running boats, relieving the instructor from controlling them by hand. This number is currently achieved by parallelizing the control of the entities in the simulation. Second, our system provides improved adaptability from the scripted scenarios, by allowing flexibility in task execution, while exhibiting realistic behavior, consistent with the navigation rules of the road. Third, by automating the navigation of the boats in the simulation, we allow for larger student to instructor ratios, thus increasing the effi ciency of training.

C. Field Results

Currently, this system has been deployed at the Surface Warfare Offi cer's School (SWOS) in Rhode Island, and is used in conjunction with the existing control interface on the Full Mission Bridge Simulator (FMB). The FMB is a mock-up of a real ship bridge, located in the center of a cylindrical projection wall, on which the graphics image is projected in 360 degrees. The bridge is equipped with realistic consoles and instrumentation, which the navy officer students use for realistic training.

To date, the following scenarios have been tested:

- **Scenario 1:** testing the performance of the Controller Authoring Tool by having an expert drive a destroyer (DDG51) in an open ocean scenario, while maneuvering to try to escape from a CAT-controlled cigarette boat that was maintaining station with respect to the DDG51. The expert could not lose the cigarette boat, which also did not crash into any other boat in the scenario despite the expert's efforts to make it do so.
- **Scenario 2:** students practiced "shouldering" with a Navy RHIB in a port transit escort scenario. Because CAT-controlled boats avoid other entities while carrying out their major objective (in this case, maintaining station), when the escorting Navy RHIB comes close to the maintaining cigarette boat, the RHIB essentially nudges (or shoulders) the cigarette boat away (without actual contact). The cigarette boat then comes back to maintain station. This behavior can only be obtained with CAT controlled boats and increased the realism of the simulation. SWOS was impressed with this emergent behavior.
- **Scenarios 3 through 5** are tactical scenarios, one in open ocean and two in littoral waters. Each of these three scenarios had between 21 to 40 vessels most of which followed fixed paths. Simulation officers only controlled a small subset, between two and five, of these vessels at any one time during a training. In the open ocean scenario, although there are more than twenty vessels, they are far apart and thus relatively easy to avoid. There is no land to avoid either. We were also able to implement formations during long transits that move boats and ships into position. CAT maintains these boats in formation while approaching their targets. Formations work simply. A designated lead boat is asked to approach a ship, the rest of the boats in the formation maintain station with respect to the lead boat giving the impression of a formation. Once the boats in formation come within a threshold distance of their targets, they split and maneuver as separate entities running different behaviors.

According to our subject matter expert, the open ocean scenario has been the most successful, since our behavior based controllers handle open ocean avoidance best. There were still some collision problems in tight maneuvering situations associated with littoral waters. The level of workload in this scenario has been reduced through spreading out tasks. Currently, the hardest aspect of controlling scenarios is the weapons, but this is due to the integration with the existing training system.

Without behavior based controllers, SWOS was restricted since the simulation officers found it difficult to control more than four vessels simultaneously. Adding behavior based controllers allowed experimentation with adding more boats to the scenarios. Initially, we could control more boats but our graphics were lagging with low frame rates. Since our goals was to start running these scenarios with more boats, we have now improved the graphics frame rate and optimized the controllers in order to be able to control up to eighty (80) entities with acceptable frame rates.

In terms of net workload savings, since we have to control AI and weapons separately, SWOS added an instructor for these tests. So neither instructor has to work as hard, but to date the results have been improved scenario realism and complexity and not manpower savings. Better systems integration with existing systems at SWOS will address this issue.

Regarding the realism of behavior of the CAT-controlled boats, one of the student groups was asked after training if they noticed anything peculiar about boats in the scenario. The answer from the entire group was that "We thought the boats behaved realistically".

IX. Conclusion

In this paper we presented an approach to efficient and realistic design of serious game simulators, with application to ship navigation. The goal of this system is to provide the infrastructure needed to train conning officers to drive big ships in the context of high-traffic, potentially dangerous situations. Developing such a system poses significant challenges and in this paper we presented an integrated solution to three of the major requirements for a successful training simulator: 1) the *efficiency of the training system*, 2) the *readiness of response* of the boats and 3) the *realism of the behavior* of the automated boat controllers. To address these challenges we developed a *Controller Authoring Tool* that enables the development of intelligent, autonomous controllers that drive the behavior of a large number of boats. This eliminates the necessity of having large number of personnel for a single student's training, significantly reducing the costs involved. We developed a Behavior-Based Control architecture that provides responsive automated controllers, and we incorporated expert ship navigation knowledge to provide realistic behavior for the automated boats. To demonstrate our approach, we presented experimental results describing the main capabilities of our system.

X. Acknowledgments

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