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UUV Human Response to System Faults

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1. General Problem and Context

Current cyber-physical systems (CPSs) involve a human-machine interaction for operation, and studying this interaction is important in assuring the safety of CPS. The public view of the state and progress of autonomous vehicles is somewhat inaccurate. New autonomous features feel very advanced to the public, but in reality, no systems in use have actually reached level 5 autonomy. Autonomous vehicles (AVs) are measured in 5 levels of autonomy, with 1 meaning assisted automation and 5 meaning full automation (Taeihagh and Lim 2019). Therefore, current cyber-physical systems require at least partial human operation. While operator error and technical system error can both pose a threat to safety critical systems, unique problems can arise from human-machine interaction. Modeling system errors is an important step in studying and preventing system failures. Many CPSs have extensive system models to track and prevent possible faults, but the nature of modeling human operation makes it difficult to integrate human-machine interaction into these models (Ibrahim 2019).

Unmanned underwater vehicles (UUVs) pose less of a human safety threat than other CPSs; however, their high cost adds risk to their operation. UUVs are often used to follow underwater pipes which transport oil and gas and search for possible cracks or leakage. Damages to these pipes can be caused by corrosion, ship anchors, improper construction, flawed materials, or tectonic activity. These pipe damages pose a large environmental and safety threat. Human monitoring of these pipes would be extremely dangerous and expensive. Therefore, unmanned underwater vehicles are used to monitor these pipelines and detect any signs of damage. Some programs can be used to complete aspects of this UUV mission autonomously, but because of the high cost of possible crashes into the pipe or seafloor and the lack of assurance in autonomous operation, successful human operation of these UUVs is extremely important. One possible fault arising from human-machine interaction could occur when the operator fails to recognize any system error or reacts incorrectly to it. Recording and modeling human response to possible faults in UUVs offers insight into how systems and their signals could be adjusted to enhance operator and system compatibility.

2. Description of the Specific Human/Cyber-Physical System

When a human interacts with any partially autonomous system, there is often the problem of mode confusion. Mode confusion can cause system behavior to deviate from intended behavior because of a discrepancy in the operator's understanding of how the system works and how the system works in reality. Causal models can be used to represent human decisions, but very different models such as temporal failure propagation graphs (Abdelwahed, 2008) are used to represent a system and possible faults. Integrating these models into a system poses a difficult but necessary task to ensure successful operation and prevention of mode confusion. In order to build these models, research on human response to different types of system faults is necessary. In these models, different pathways can indicate whether the human operator noticed the fault and whether the fault was interpreted correctly.

3. The Challenges of Reaching a Functional System

Because experimenting on real physical UUVs would be extremely expensive and impractical, simulation is often used to study these systems. Gazebo and rViz are two 3D visualizers which can be used to simulate the launch and operation of a UUV. The Gazebo graphical user interface (GUI) gives a clear, high-quality, omniscient view of the vehicle. For a real underwater environment, this clarity is unrealistic.In real operation, there are cameras attached to the UUV, but a detached full view of the system is not possible. Because of the uncertain underwater environment, even these cameras cannot be relied on. Therefore, UUVs often use a combination of sonar imaging and gauge readings for operation. Sonar imaging strings together scan-lines using a waterfall-like manner. Sonar imaging in combination with a depth and speed gauge gives a more realistic simulated operator view. UUVs are often operated with a joystick providing control of pitch, yaw, roll, and thrust (Blue Robotics 2020). For my research, I was able to use the UUVSim Github (https://github.com/uuvsimulator) repository with slight adjustments to launch the simulation of a remotely human operated unmanned underwater vehicle. The simulated vehicle works similarly to the BlueROV2.

4. The Technical Problem and the Research Setting

In order to study human-machine interaction in cyber-physical systems and identify potential safety risks, I introduced machine gauge failures to this UUV simulation and monitored the human operator response. First, I had to adjust the visualization components of the launch to create the more realistic gauge and sonar view. The UUVSim repository uses

Robot Operating System (ROS) (https://www.ros.org/) to simulate the UUV. ROS includes a gauge package that can be installed to visualize realistic gauges. Once installed, I was able to set ROS parameters to tell the gauges specific topics to listen to. For example, to create an altimeter gauge telling the distance from the vehicle to the seafloor, I had to publish messages with the altitude of the vehicle, which is gathered from the Doppler velocity log (DVL) vehicle sensor. The speed gauge is created in a similar manner. I created a 'republisher' node to contain the speed and altimeter data in one central location. To record how humans respond to system faults, I used the 'republisher' node to introduce random faults in the speed and altimeter gauge. I did this through a random seed for fault time and to indicate which gauge to fail. Upon launch, the gauge to fail functioned as normal until this random time at which the node no longer republished the message to the desired topic. This simulated a fail-stop failure in the gauge in which the gauge remained indefinitely at the same speed or height reading. This randomized fault injection creates a fair experiment because the operator has no knowledge of what fault will be introduced or when. Therefore, the human cannot preemptively adjust the vehicle operation to account for a fault.

The "Assured Autonomy" research team at Vanderbilt has developed the ALC toolchain (https://alc.isis.vanderbilt.edu/redmine) to assist in the modeling and development of safer CPS. The toolchain has an extensive modeling component including temporal failure propagation graphs (TFPG). To increase the accuracy of the system, I added two additional software sensor blocks and two additional hardware blocks. TFPG modeling in the toolchain has signal input and output ports which also allow for fault and anomaly modeling. To represent the randomized system fault injection in a temporal failure propagation graph (TFPG) format, I introduced fault blocks and fail-stop anomalies which flow to the ‘republisher’ block output ports representing speed and altimeter gauge failures. These extensions allow the study of human reactions to system failure in a tele-operated UUV.

5. Future Research

To collect data and analyze how humans respond to random system failures, this vehicle should be simulated using this realistic operator visualization with randomized fault injection. The human should operate the vehicle with the safety condition of not crashing into the seafloor or the pipe and the performance condition of following the pipe. The simulation should be run in varying underwater environments with straight and bent pipes. The data of human operation and response to faults can then be analyzed in conjunction with the autonomous operation of the vehicle. Analysis should include how the machine and human respond differently to system faults to highlight the unique problems generated by human-machine interaction.

To extend this research, the data could be used in the toolchain to train a learning-enabled component (LEC). Data from human operation could then be compared to UUV performance when under control of this LEC to observe discrepancies in how the human and learning-enabled machine respond to system faults. I also believe more faults could be introduced that correspond to hardware components of the system such as fins and thrusters. Introducing these hardware faults and recording human and machine response for further analysis could give more insights into human response to different types of faults.

References

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