Intelligent Adaptive Underwater Sensor Networks for Mine Countermeasures

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Mine hunting field experiment

Mine hunting – a common approach used in mine countermeasures. It relies on detecting and classifying a target on the sea bottom, using a sonar sensor, followed by an appropriate disposal procedure. Typical minehunters are ships using towed sonar array for imaging. They are manned vessels with complex hull structure to reduce their signature.

Autonomous Underwater Vehicle (AUV) – a robot that travels underwater without requiring input from an operator. AUVs are considered a future alternative for mine hunting. AUVs are small and remove the personnel from the mine field. They are potentially more cost efficient and can cover larger areas.

Figure 1: Capitas AUV equipped with a side scan sonar used for field experiment in the North sea at the coast of Denmark

Side Scan Sonar – typical sensor used for imaging of large areas of the sea floor. It is mounted on the hull sides of the AUV. The resolution is range dependent. Directly underneath the AUV, is a zone that is not illuminated. The blue circle on Figure 3 is the target from Figure 2. Typical operational frequency is from 100 to 500 kHz. It defines the range and resolution of the imagery.

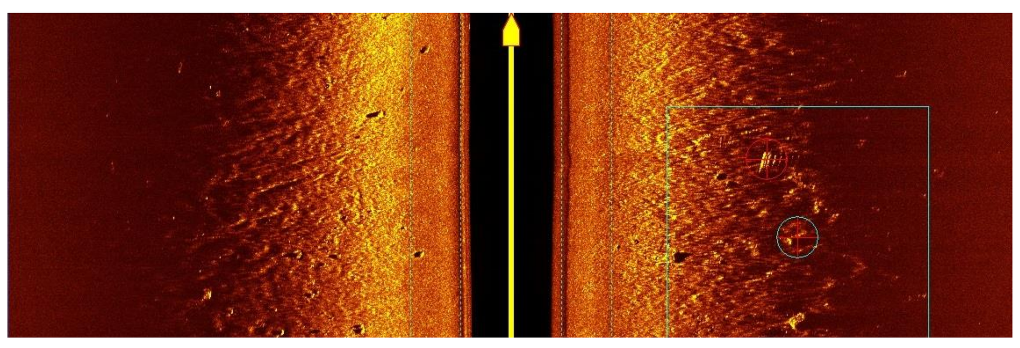


Figure 3: Still from a side scan sonar mounted on the AUV from Figure 1. The blue circle shows the target from Figure 2. Any guess what the red circle shows?

Targets on the sea bottom could remain undetected by a sonar deployed near the surface but an AUV can collect data from a closer proximity by diving near the sea bottom.

Figure 2: Metal cylinder with the size of a bottom mine used as a target

Why are AUVs not the default mine hunting approach? – the blue path on Figure 4 is what the vehicle was programmed to do. The red path was what was executed. Many problems remain an open research question, such as navigation, localisation, automatic target recognition, mission planning, cooperative operation.

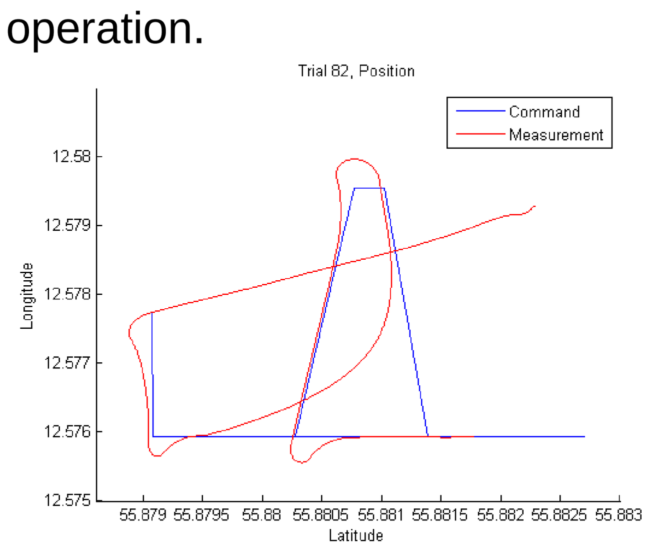


Figure 4: AUV path – planned vs measured

Multi-AUV mine hunting

Multi-AUV mine hunting – Using multiple platforms to execute the different tasks of the MCM procedure means that the vehicles can adapt their resource depending on the workload during the mission. Collaboration of multiple agents requires robust communication. The underwater channel is variable, the bandwidth and speed are low, as acoustic signals are used. This is one of the main reasons underwater applications are lagging compared to terrestrial counterparts.

Rendezvous Point (RP) method – assuming the communication constraint is the major limitation to enable AUV collaboration, the rendezvous point (RP) method was developed. It is applied in an underwater sensor network of AUVs by setting multiple meeting points in space and time for all vehicles. This is a robust way to allow exchanging world information between the nodes and enable distributed decision making

RP simulation scenario

- Scenario – MCM at a nearshore strip – 3 vehicles which can have tasks to search for contacts or revisit detections with high resolution sensor; tasks are defined at RP based on available detected contacts
- Aim - maximise search area while revisit all contacts
- Loss – time to reach RP
- RP scheduling applied – decide time and location based on detected contacts – trade-off between loss and coordination

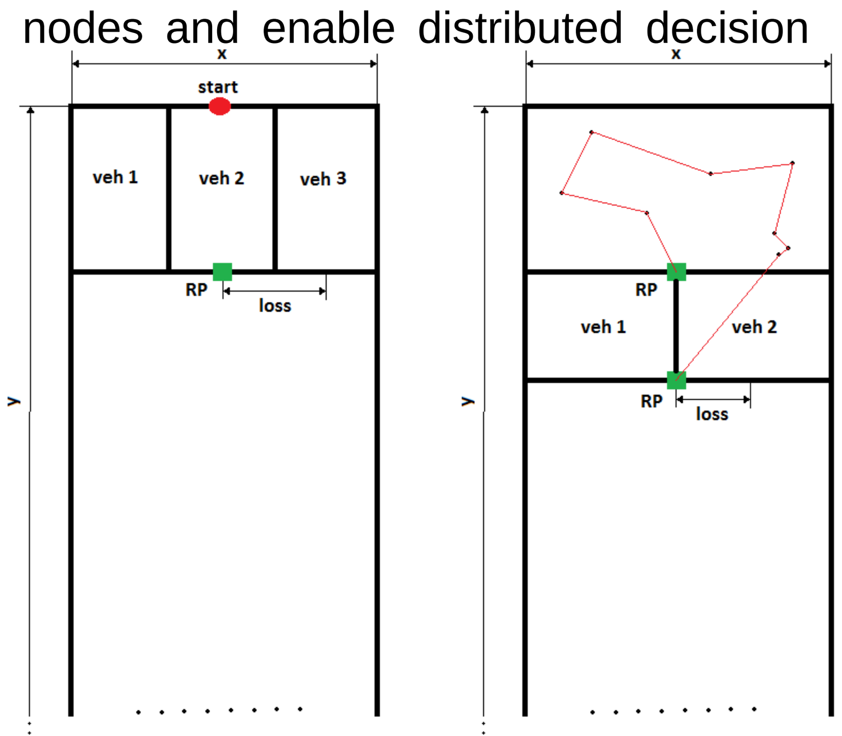


Figure 5: MCM Scenario

Methodology and output

Markov Decision Process (MDP) - a mathematical framework for modelling decision making in situations where outcomes are partly random and partly under the control of a decision maker. MDPs are useful for studying a wide range of optimization problems solved via dynamic programming and reinforcement learning.

MDP definition - Markov Decision Process is a discrete time stochastic control process (Figure 6). At each time step, the process is in some state **s**, and the decision maker may choose any action **a** that is available in state **s**. The process responds at the next time step by randomly moving into a new state **s′**, and giving the decision maker a corresponding reward $\mathbf{R_a(s, s')}$. The probability that the process moves into its new state **s′** is influenced by the chosen action. Specifically, it is given by the state transition function $\mathbf{P_a(s, s')}$. Thus, the next state **s**' depends on the current state **s** and the decision maker's action **a**. But given **s** and **a**, it is conditionally independent of all previous states and actions; in other words, the state transitions of an MDP satisfies the Markov property.

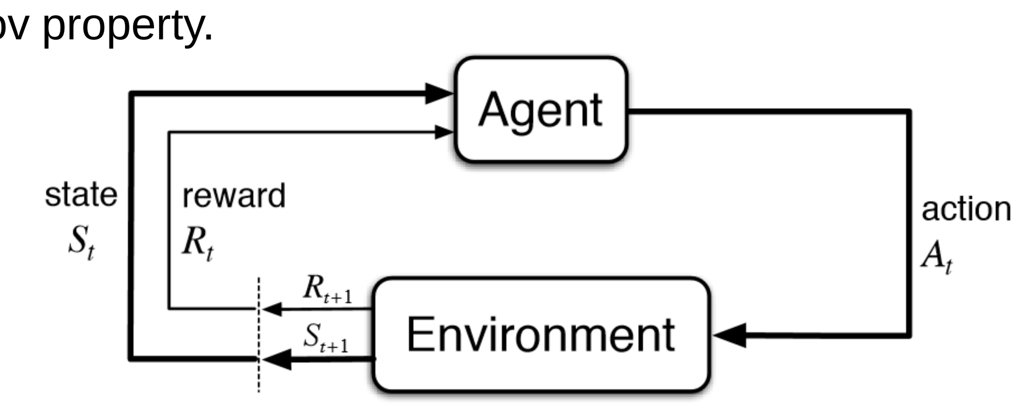
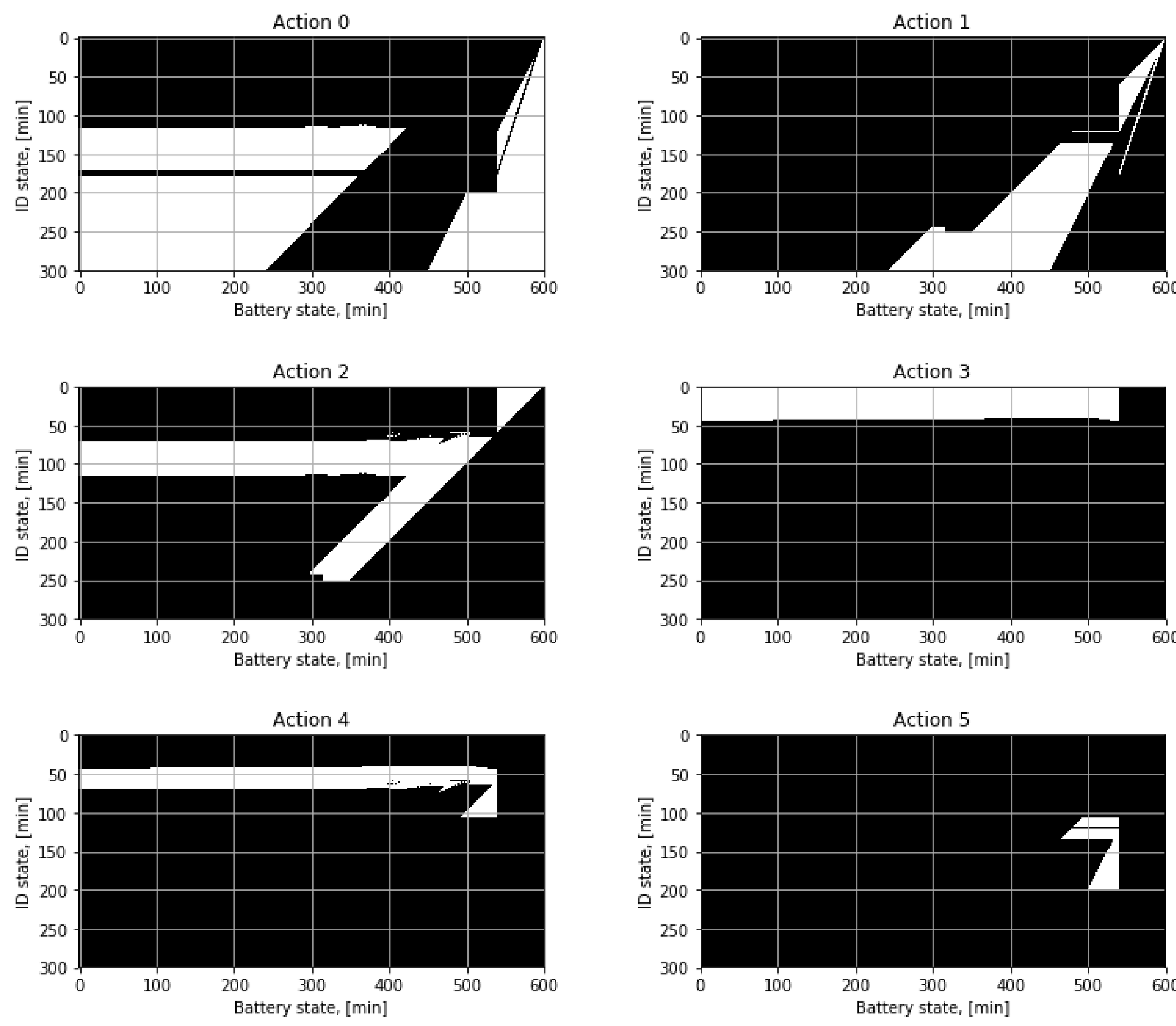


Figure 6: Markov Decision Process: agent-environment interaction. This decision making framework is often used for solving reinforcement learning or planning problems.

Rendezvous Planning for Multiple Autonomous Underwater Vehicles using a Markov Decision Process - The MCM scenario we are studying uses 3 AUVs. For the limited battery time they have, their goal is to maximise the area they can search with the constraint that every detection has to be revisited. Two tasks are defined: search and ID (relocating targets and collecting additional data to help classify and identify the object). Following the RP method idea, the vehicles meet so they can exchange target locations, decide how to allocate tasks and appoint time and location for their next meeting point. The RP schedule and the MCM application goal constraints define the input functions for the MDP framework.



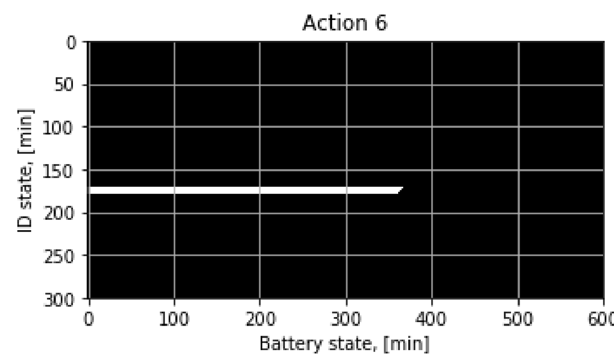


Figure 6: Optimal policy solution of the multi-AUV MCM problem. The state space is represented by the AUV battery life limit (x axis) and the workload during the mission (y axis). Each of the seven graphs represents an action. White colour means an action is selected.

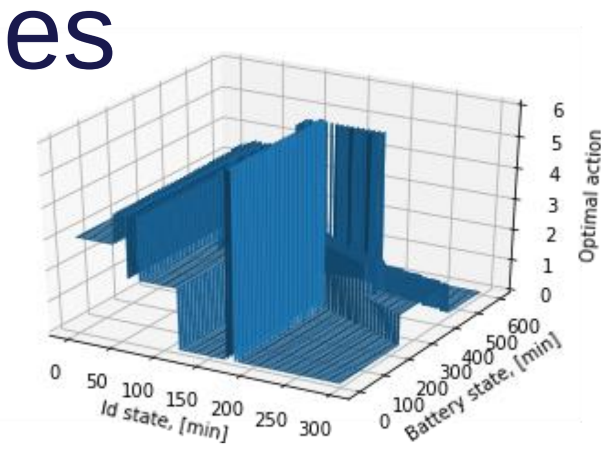
The main contribution of this work is that our model is capable of computing a solution for the MDP in manageable time, with potential to reach real time execution. We achieved this by discrediting the action and state spaces without losing vital mission information. The other critical element is that utilising the RP method made the decision making intervals very few throughout the mission and we managed to define our MDP with a finite horizon until we reach mission completion.

Achievements

- Designed a strategy to tackle UW commutations limitations – the Rendezvous Point method
- Developed the Rendezvous Point method to tackle the underwater communication problem and enable cooperative behavior for multiple AUVs
- Developed a Markov Decision Process formulation for the multi-AUV mine hunting problem for near real time operation

Future work and Outcomes

- Validate parameter choice in sea trials
- Validate simulation results in a mixed reality simulation and a real AUV
- Be able to advise on future MCM system designs



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