Sensor Driven Online Coverage Planning for Autonomous Underwater Vehicles

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Outline

Outline

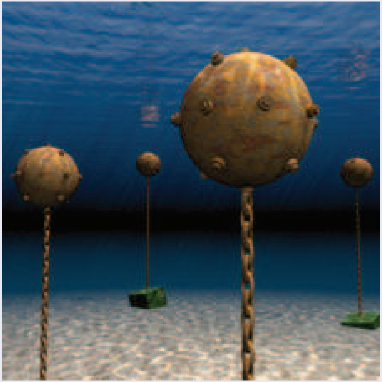
Introduction
Underwater Mine Countermeasures

Mine Countermeasures

AUVs have many advantages for countering undersea threats, such as:

- Increased covertness
- Reduced number of personnel required
- Safety of qualified personnel
- Increased efficiency

Moored Mine

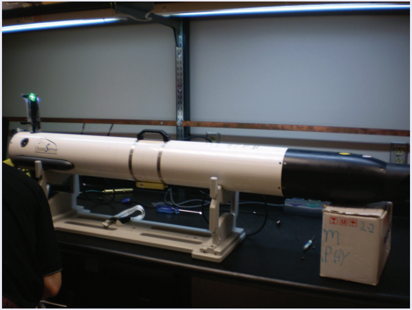


Autonomous Underwater Vehicles (AUVs)

Autonomous Underwater Vehicles

- Autonomous underwater vehicle (AUV) research began in the 1970s
- AUVs are used for surveying, mine countermeasures (MCM), bathymetric data collection and more
- Challenges: No GPS, communication very challenging, environment quite unstructured

The IVER2 AUV



Sidescan Sonar Sensor

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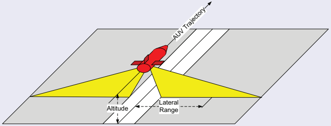
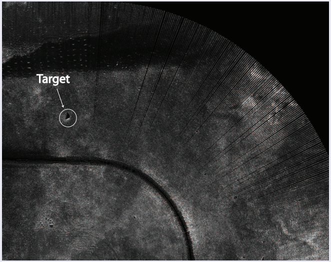
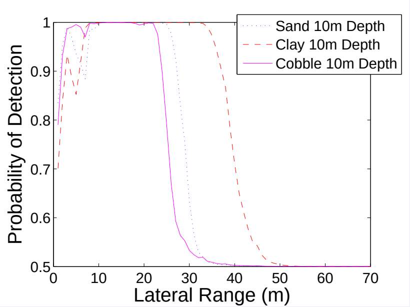


Data



$\mathcal{P}(y)$ Characteristic Curves



Objective of Work

- Current AUV seabed survey plans are generated manually by an operator before the start of the survey.
- These plans are usually highly structured ("lawn mower or zig zag")
- The performance of the sonar used for seabed survey is highly dependent on many parameters that are not necessarily known beforehand but can often be measured *in situ*.
- Can we develop survey planning strategies that do not require offline survey plans to be generated, that aren't restricted to the structured paths, and can adapt to parameters measured on the fly.

Outline

Path Planning and Coverage Path Planning

Free Configuration space (C_{free}): The set of all valid configurations that the robot can achieve
Workspace (W): The world that the robot exists in

General Path Planning

$$\tau : [0,1] \rightarrow C_{free}$$
$$\tau(0) = x_i,\ \tau(1) = x_g$$

- Tasks: Navigation, coverage, localization, mapping
- Past Approaches: Bug, potential fields, cell decomposition, sampling-based...

Coverage Path Planning

N sensor readings: $\{A_1, ..., A_N\}$

$$\bigcup_{i=1}^{N} A_i \supseteq W$$

- Heuristic methods
- Cell decomposition

Information Theory

The **Shannon Entropy** of an RV X: $H(X) = E[\log P(X)]$
The **Expected Conditional Entropy** of an RV X given Z:

$$\begin{aligned} \bar{H}(X|Z) &= E_z\{H(X|Z)\} \\ &= -\int P(Z) \int P(X|Z) \log P(X|Z) dX dZ. \end{aligned} \tag{1}$$

The **mutual information** I or **expected entropy reduction** (EER):

$$I(X,Z) = H(X) - \bar{H}(X|Z), \tag{2}$$

The **information gain** B of a control action U that will result in n independent measurements $\{Z_1, Z_2, ..., Z_n\}$:

$$B(U) = \sum_{k=1}^{n} I(X, Z_k). \tag{3}$$

Outline

Multi-Objective Function

The backbone of the proposed approach is an objective function that is evaluated over the domain of all possible desired headings: $\psi = \{0..360\}$:

$$\psi_d = \arg\max_{\psi} R(\psi) = w_B B(\psi) + w_G G(\psi) + w_J J(\psi), \qquad (4)$$

Where:

- R is the total utility
- B is the information gain
- G is the branch entropy
- J is the benefit of maintaining the current heading ($\propto -|\psi_c - \psi|$, ψ_c is current heading)
- w_B, w_G, and w_J are the weights tuned manually or with some metaheuristic method

Information Gain Behavior

Define a proposed track starting from the AUVs current location (x, y) and extending out a distance r and angle ψ:

$$\begin{aligned} \mathcal{C} : [0,1] \rightarrow C_{free}, s \rightarrow \mathcal{C}(s) \\ \mathcal{C}(0) = (x, y) \\ \mathcal{C}(1) = (x + r\cos(\psi_d), y + r\sin(\psi)) \end{aligned} \tag{5}$$

Then evaluate the expected information of the paths:

$$\bar{H}(T_{ij}|Z_k^{ij}) = E_{z_k}\{H(T_{ij}|Z_k^{ij})\} \tag{6}$$

$$\bar{I}(T_{ij}, Z_k^{ij}) = H(T_{ij}) - \bar{H}(T_{ij}|Z_k^{ij}) \tag{7}$$

$$\bar{I}(W, Z_k) = \sum_{(i,j) \text{on } \mathcal{C}^{\perp}} \bar{I}(T_{ij}, Z_k^{ij}) \tag{8}$$

$$B(\psi) = \sum_{k=1}^{n} \bar{I}(W, Z_k) \tag{9}$$

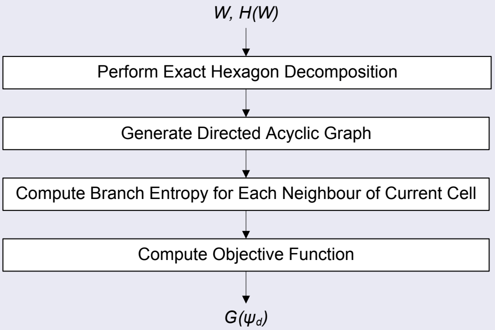
The Branch Entropy Behavior

Overview

Behaviour Objectives

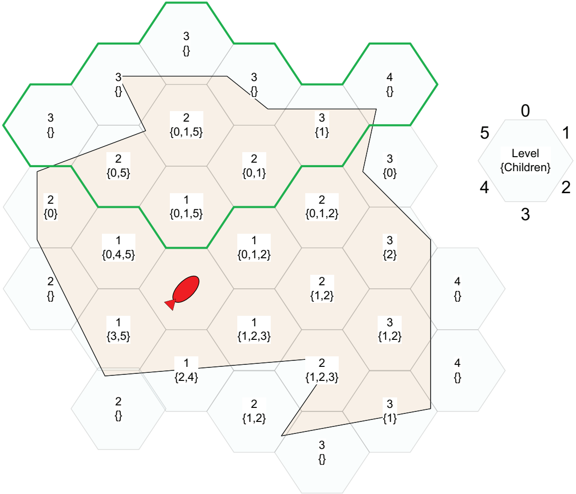
- finish sections before it leaves them.
- find the areas of the workspace that are not covered.
- not get stuck in infinite loops.

Algorithm Flowchart



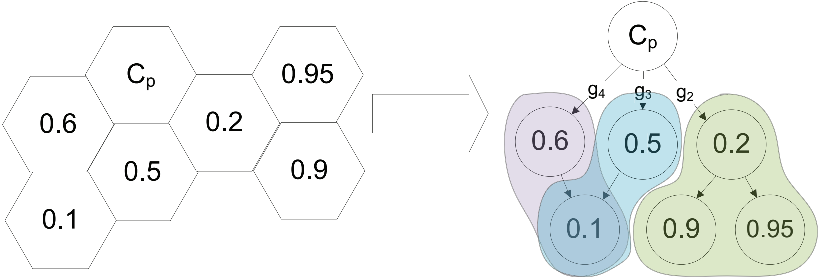
The Branch Entropy Behavior

The Hexagon Decomposition

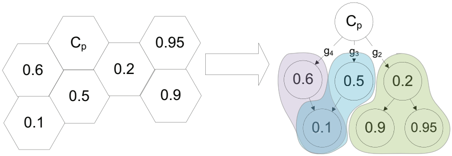


The Branch Entropy Behavior

Hexagon Decomposition → Directed Acyclic Graph



Calculating the Branch Entropies



The Branch Entropy Equation

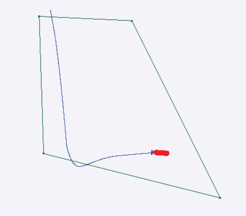
$$g_k = \frac{\sum_{l=2}^{L}(L-l+1)\frac{\sum_{i=1}^{m_{lk}} \hat{H}_i}{m_{lk}}}{\sum_{l=1}^{L-1} l}$$

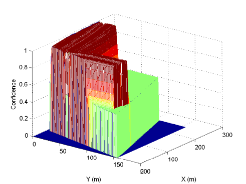
Simple Example

$$\begin{aligned} g_4 &= 1/3((2)(0.6) + (1)(0.1)) \\ &= 0.433, \\ g_3 &= 1/3((2)(0.5) + (1)(0.1)) \\ &= 0.367, \\ g_2 &= 1/3((2)(0.2) \\ &+ (1)(1/2)(0.95 + 0.90)) \\ &= 0.442. \end{aligned}$$

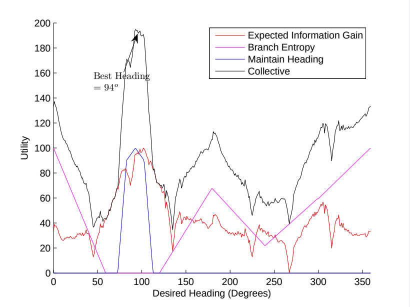
The Combined Objective Functions

Simulated Path





Multi-Objective Optimization



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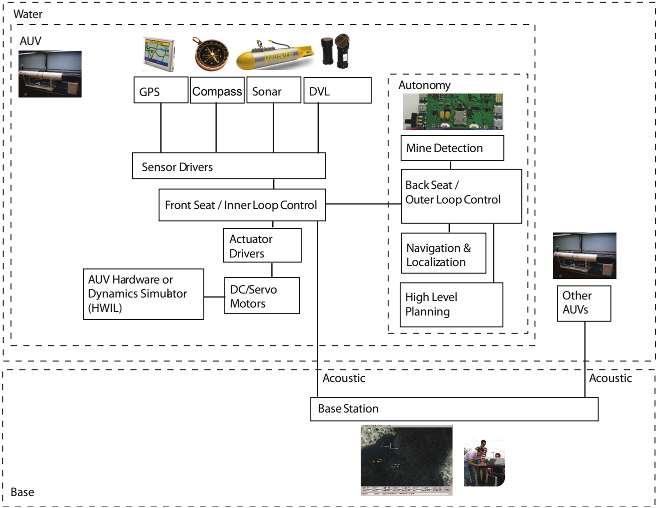
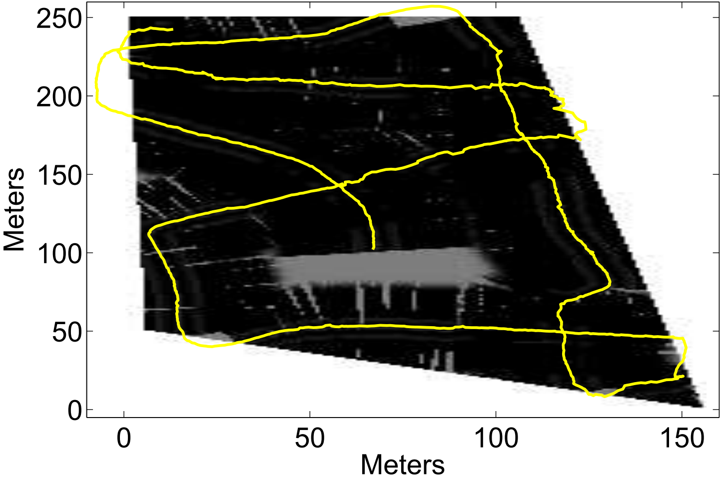
Experimental Setup



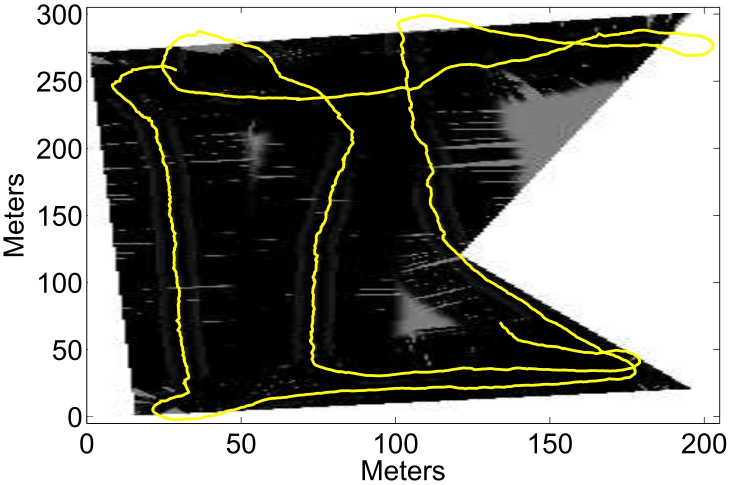
Hardware Trials

Outline

Hardware Trials



Hardware Trials



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Advantages of Proposed Approach

The proposed approach has the advantages that:

1. The total paths and times required to cover a workspace are shorter in many cases.
2. There is no need for pre-programmed waypoints.
3. The AUV will maintain heading for better data mosaicing in the presence of currents or erratic waypoint tracking behavior caused by poor navigation or controller performance.
4. It is adaptive to any changes in environmental conditions that can be detected *in situ*.
5. It is able to generate paths for complex and non-convex environment shapes such as would typically found in harbours.
6. Fast and scales linearly with environment size (after initialization)

Thank you!

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