Using AI for automatic detection of underwater objects in sidescan sonar imagery

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Context

1. Explosion of data sources
   a. AUV/ASV
   b. Satellite imagery

2. Explosion of data processing requirements

3. Need for automation
   a. Reduce delays, up to real-time
   b. Reduce costs
Automated detection paradigms

- **AI**
  - **Supervised Learning**
    - Known Targets (Classic ATR) ➔ **Convolutional Neural Networks**
  - **Unsupervised Learning**
    - Unknown targets (regions of interest) ➔ **Computer Vision**
    - Targets with very high variability
Convolutional Neural Networks

- Supervised method: rapid detection of known (labeled) objects.
- Require training data and training.
- Models do not generalize well.
- Black boxes, hard to debug.
- Mostly solved: Just throw training data, TensorFlow and GPUs at it.
Computer Vision

- Unsupervised method: will detect objects with no prior knowledge.
- No need for training data or training.
- Based on analytical, geometrical and statistical principles which makes them more transparent.
- Less precise.
- May requires human intervention to sort things out afterwards.
Technique
Theoretical bases

1. Images can be decomposed in micro-features such as corners, edges and color blobs (Harris)

2. The density of micro-features has as tendency to increase around objects (Viola & Jones)
Simplified example

- Corners are marked in blue
- Edges are marked in red
- Color blobs are marked in yellow

*The density of micro-features drastically increases where objects are present. This reduces the detection problem to a clustering problem.*
Algorithm

1. Image synthesis
2. Micro-features search
   1. F.A.S.T. (corners)
   2. M.S.E.R. (color blobs)
3. Clustering micro-features
Phase 1: Image Synthesis

“Slant-range” Correction

Histogram Normalization
Phase 2: Micro-features search
Phase 3: Clustering & Denoising
Applications
Underwater Archaeology

- Mostly inference-driven from indirect evidence
  - Debris
  - Traces
- Maximizing survey surface and minimizing post-processing costs is a determining success factor

*Shipwreck of the Scotsman and debris field, Le Bic, Canada*
Boilers from the SS Germanicus, Le Bic, QC, Canada
Ocean Waste Management

- Abandoned, lost or derelict fishing gear affects nearly 80% of right whales (Knowlton & Al. 2012)
- The volume of ghost fishing gear is estimated to be several millions of tons.
- The large variety of fishing gear makes supervised detection unfeasible.

*Crab trap and rope, Rimouski, QC*
The algorithm can generate a real-time map of potential waste markers.

A simple manual review of detected zones allow for fast and focused retrieval efforts, a very significant efficiency gain.
Inventory map of abandoned aquaculture structures, Paspébiac, QC
Conclusion

Automated detection of underwater objects opens a lot of promising applications in terms of operational capacities. It significantly lowers the cost of field operations through the ability to use force multipliers such as ASVs and AUVs without the hurdles of increased post-processing costs, and provides faster and more accurate actionable intelligence to operators and decision makers.
Thank you

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