

1 **Do AUVs Dream of Electric Eels?**

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5 Free-swimming autonomous underwater vehicles (AUVs) are unique from tethered remotely
6 operated vehicles (ROVs) and human-occupied vehicles in the amount of data-driven feedback a
7 human can provide during a mission. While free-space optical communications afford tether-
8 equivalent data rates at relatively close ranges (Farr et al. 2010), most AUVs employ acoustic
9 modems to maintain two-way communications with their operators while underway (Freitag et
10 al. 2005). However, the low bandwidths and high latencies inherent in underwater acoustics
11 prohibit the real-time transmission of data generated by imaging sensors such as cameras and
12 side-scan sonars. This has profound implications with regard to the *meaning* of the data an AUV
13 collects and the *trust* an operator has in the AUV's autonomy to react to data in the absence of
14 direct human oversight.

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16 Robots are fundamentally agnostic to the meaning of the data they collect, where meaning
17 implies the qualitative ideas a human attaches to quantitative values. As more and more meaning
18 is conveyed to the AUV, more and more trust can be built up by the operator. Thus, trust and
19 meaning form a cyclic feedback loop that is throttled by the bandwidth limitations of underwater
20 communication. Some of our recent work in marine autonomy has focused on co-robotic
21 frameworks that address this concept in the context of real-time AUV operations. We briefly
22 describe two frameworks for summary-based mapping and anomaly detection that reinforce

23 operator trust by enabling a human to impart meaning upon data while it is still being collected
24 by an AUV.

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26 **Summary-Based Mapping**

27 Online summaries (Ghirdar and Dudek 2010) are a useful tool for data reduction in real time
28 imaging pipelines, but their output lacks inherent meaning outside of a human's interpretation of
29 the content. Compression algorithms now make transmitting imagery via acoustic modem during
30 a mission a practical reality (Murphy and Singh 2010) but depend on a separate mechanism for
31 selecting which images to transmit. Marrying these two strategies, the robot can first transmit a
32 small number of images representing the classes that best represent the data collected thus far,
33 allowing a human to attribute meaning to them. Combining class membership of non-summary
34 images with navigational metadata enables the creation of simple maps whose indices
35 correspond to each of the summary classes (Kaeli and Singh 2015). An example of this is shown
36 in Figure 1 using 2,800 images collected by the SeaBED AUV in 2003 from the Stellwagen
37 Marine Sanctuary.

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39 Contrary to off-line algorithms that require all data to be collected prior to analysis, online
40 algorithms maintain a current summary of the data at any point in the mission. While they offer
41 less guarantees of stability or finding the optimal solution, they do provide a practical basis from
42 which an AUV can begin to adaptively sample its environment. Even in the absence of operator
43 feedback, pre-set classes can be stored to enable the AUV to search for certain substrates, ignore
44 entire areas, or transmit maps without the need for compressing imagery. At the end of a
45 mission, the operator possesses both an immediate high-level summary of the survey as well as

46 the ability to selectively download the most meaningful parts of the dataset first. Enabling
47 operators to begin interacting with data while a mission is underway makes the best use of both
48 the AUV's resources and the operator's time while at sea.

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50 **Anomaly Detection**

51 A robot can be trained to automatically detect meaningful objects of interest, but there are many
52 types of objects that are difficult or impossible to train a robot to search for. In these cases,
53 detecting anomalous regions that stand out from their surroundings can be useful for adaptively
54 resurveying potential targets in opposed to relying on human post-mission analysis and a
55 secondary deployment. We implement a two-tiered algorithm that first finds locally salient
56 regions that differ from their surroundings, then clusters these regions to learn which are globally
57 rare (Kaeli 2016). Applied to side-scan sonar imagery collected during the search for Air France
58 flight 447, shown in Figure 2, this approach detected several anomalous regions that include the
59 wreckage of the airplane.

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61 One possible implementation is to resurvey a set number of anomalies per track line. This
62 provides the operator with a richer data product while keeping the overall mission complexity
63 low, simplifying tracking and improving operator trust in the autonomy. Background classes can
64 be saved prior to deployment and subsequently ignored, or anomalies transmitted acoustically to
65 allow an operator to decide whether or not a resurvey is merited. Even in the complete absence
66 of human feedback, anomalies can serve as useful navigation landmarks, providing a stationary
67 and unique reference for the AUV to reset its accumulated navigation error.

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69 **Conclusion**

70 Many of the greatest advances in autonomy over the past few decades, from unmanned aerial
71 drones to commercial airline autopilot systems, have borne the most fruit when autonomy is used
72 to enhance operator perception rather than fully replace human oversight (Mindell 2015).
73 However, this paradigm is particularly difficult in underwater robotics due to the extreme
74 limitations of the communications channel, which slow not only the feedback loop of meaning
75 and trust between vehicle and operator but also the time constant for development as well. One
76 of the challenges facing developers of marine autonomy will be to design behaviors that, while
77 they may inherently occur unpredictably, still prove tractable to human operators in the field.
78 As a result, we advocate for the parallel development of co-robotic approaches that blur the
79 traditional lines between AUVs and ROVs, hastening the cycles of meaning, trust, and
80 development while creating smarter and more precise tools for understanding the oceans.

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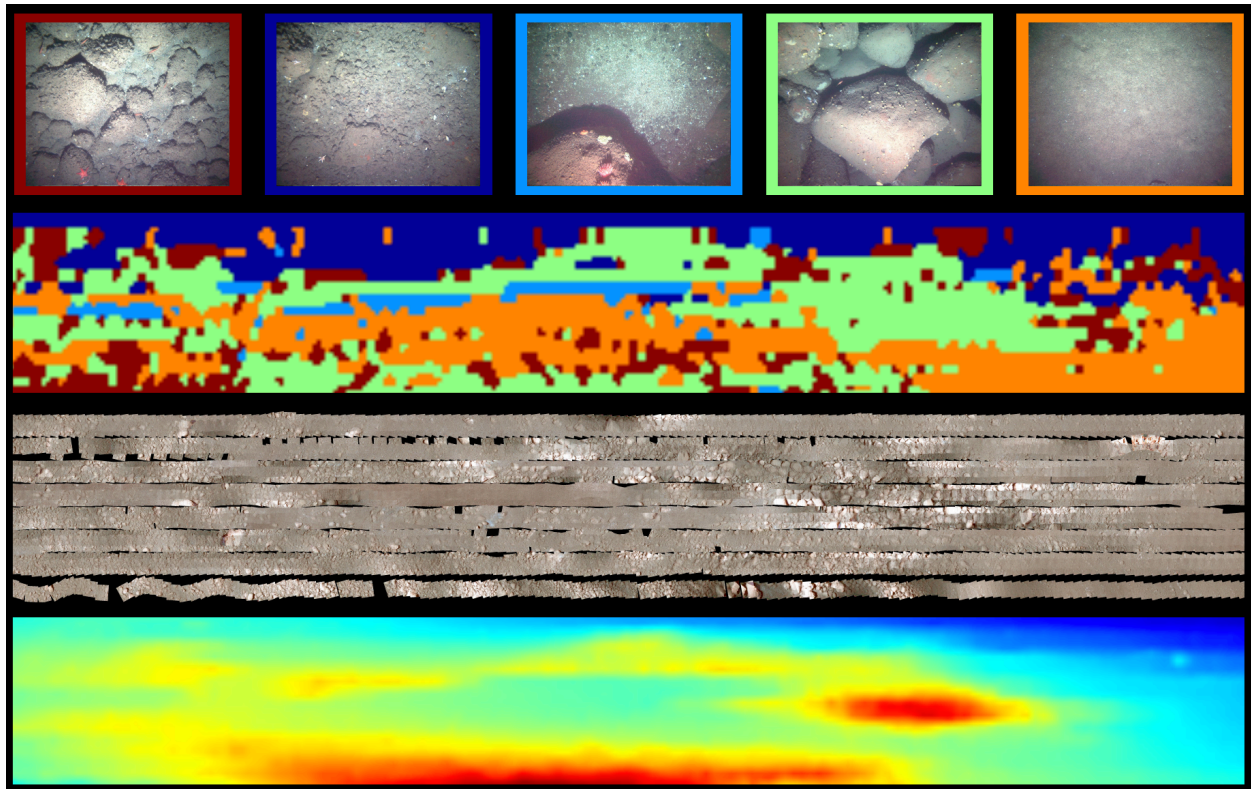
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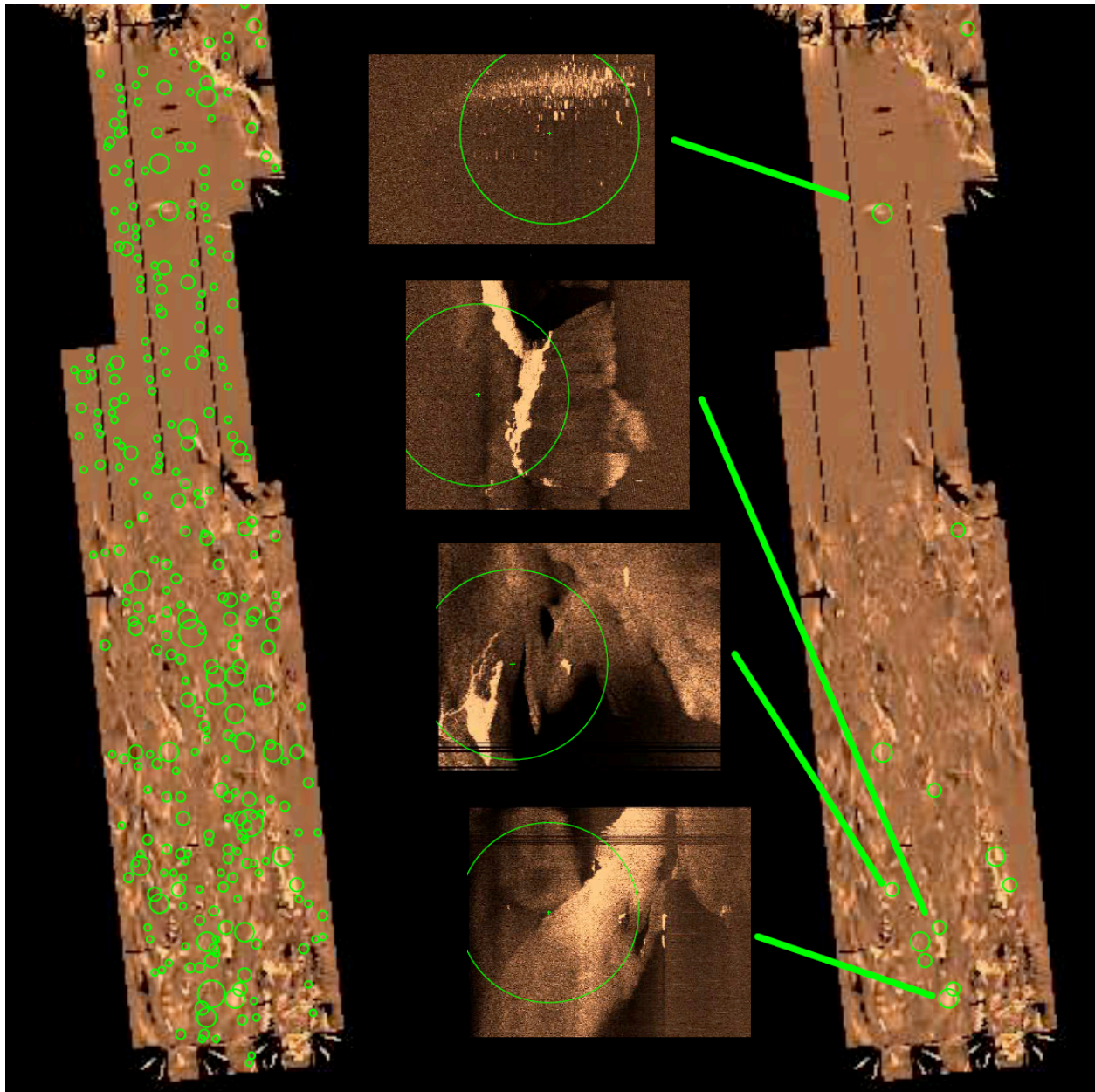
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101 **Figure 1. From to top to bottom: five images the algorithm selected that best**
102 **summarize the dataset; summary-based map color coded by image class;**
103 **photomosaic of the entire mission; bathymetry of the survey area. While the robot**
104 **only understands the data in the context of “Class 1” or “Class 2,” a human is able to**
105 **attribute meaning such as “rocky” or “sandy” to the images and relate that meaning**
106 **to the broader context of habitat or geomorphology.**

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109 **Figure 2. Locally anomalous regions detected in a side-scan sonar survey (*left*) are**
110 **subsequently filtered to select only those that occur at a particular rarity and scale of**
111 **interest (*right*). Sample detections (*center*) include the wreckage of Air France flight**
112 **447 (*top*) along with numerous geological formations.**