

Real-Time Anomaly Detection in Side-Scan Sonar Imagery for Adaptive AUV Missions

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Abstract—Autonomous Underwater Vehicle (AUV) operations are inherently bandwidth limited but increasingly data intensive. This leads to large latencies between the capture of image data and the time at which operators are able to make informed decisions using the results of a survey. As AUV endurance and reliability continue to improve, there is a greater need for real-time data processing to inform on-board adaptive mission planning. In this paper, we present an anomaly detection framework based on saliency and rarity and demonstrate it using existing side-scan sonar datasets collected by an AUV. Salient regions are first identified using a novel method with analogies to keypoint detection in traditional image processing. Models of these regions are then learned to determine rarity using an online approach for real-time use during a mission. The algorithm we present will be implemented in field trials later this year. This approach to adaptive mission planning enables an AUV to both resurvey anomalies at higher resolutions and selectively transmit imagery for operator analysis and feedback within the scope of a single deployment.

Keywords—side-scan sonar; anomaly detection; autonomous underwater vehicle; adaptive mission planning

I. INTRODUCTION

Seventy percent of the Earth’s surface is covered by water, below which lie diverse ecosystems, rare geological formations, important archeological sites, and a wealth of natural resources. Understanding and quantifying these areas presents unique challenges for the robotic imaging platforms required to access such remote locations. Low-bandwidth acoustic communications prevent the transmission of images in real-time, while the large volumes of data collected often exceed the practical limits of exhaustive human analysis. As a result, the paradigm of autonomous underwater exploration is plagued with a high *latency of understanding* between the capture of image data and the time at which operators are able to gain a visual understanding of the survey environment. Furthermore, this latency is extended when secondary AUV missions must be planned to resurvey targets of interest identified in post-mission analyses. Real-time anomaly detection capabilities will dramatically reduce this latency by enabling AUVs to adaptively resurvey potential targets and selectively transmit imagery for operator feedback within the span of a single mission.

An anomaly is something that is both salient, standing out from its immediate surroundings, and rare, unlikely to be found elsewhere. Typical targets of seafloor searches, such as shipwrecks or other man-made objects, fit well into this definition. Since the shape and structure of such objects are often unpredictable and altered from their original form, it is difficult to train automated algorithms to detect and classify them. Thus, an anomaly-based approach to seafloor searches offers a promising practical framework for AUVs exploring unfamiliar environments. We first discuss related work in clustering and surprise-based summaries. Next, we introduce our framework for anomaly detection, followed by an example implementation for and demonstration on side-scan sonar data. Lastly, we discuss our approach in the context of real-world AUV mission scenarios.

II. RELATED WORK

Traditional clustering techniques, such as K-means [1], affinity propagation [2], and Latent Dirichlet Allocation (LDA) [3], are said to be “offline” because they operate on a complete dataset that has already been collected. In contrast, “online” techniques operate on a data stream as it is being collected, making it an appealing choice for real-time robotic exploration for two reasons. First, it allows the data to be processed continuously throughout the mission, reducing the overall computational load. Second, at any point in time it provides a model of the environment explored thus far.

A drawback to online methods is that they offer less guarantees of stability and are ultimately dependent upon the order in which images are presented to the algorithm [4]. The worst-case scenario would be for the most extreme data points to occur first, followed by interior points which become poorly represented. Fortunately, natural environments are often highly redundant with substrate domains that are spatially consistent relative to the sensor field of view. One possible approach uses incremental clustering of topic models using LDA [5]. We are particularly interested in prior work on navigation summaries [6], which operate on the concept of “surprise.”

An event can be said to be “surprising” because it happens unexpectedly. The idea of what is expected can be modeled as a probability distribution over a set of variables and considered as *prior* knowledge about the world. When a novel event occurs, it augments this body of knowledge and creates a

slightly different *posterior* knowledge of the world. If the amount of knowledge added by any single event is large enough, that event can be said to be unexpected and thus is “surprising.”

This concept has been formalized in a Bayesian framework as the difference between the posterior and prior models of the world [7]. For measuring this difference, the Kullback-Liebler divergence, or relative entropy, was shown to correlate with an attraction of human attention,

$$d_{KL}(p||q) = \sum_x p_x \log (p_x / q_x) \quad (1)$$

where p_x is the posterior model, q_x is the prior model, and x is some observed variable over which distributions can be computed. This can be thought of as the inefficiency in using q to approximate p . Rather than modeling the prior knowledge as a single distribution over a set of features, we follow [6] and model it over each member of a set of distributions or “cluster centers” whose purpose is to represent or summarize the data.

When a new distribution is observed, the amount of “surprise” it represents can be quantified in terms of how well it compares to the existing model of the world, the set of summary distributions. If this value exceeds a threshold, then the new distribution is added to the summary set. Then, the “least surprising” member of the existing summary set may be absorbed by the most similar summary set to maintain a static set size [8]. In this manner, a temporally global summary of the environment can be maintained at all times by the robot.

III. FRAMEWORK FOR ANOMALY DETECTION

The notion of an anomaly, both salient and rare, is also strongly tied to scale [9]. At one scale, an object such as a rock surrounded by sand will appear as anomalous. However, zooming out, the presence of many rocks, which will cease to be rare, will form a texture and cease to be anomalous. Zooming out even further, these rocks may represent ballast stones from an ancient shipwreck on an otherwise sandy bottom with the occasional rock, becoming anomalous again. As a result, we advocate for a scale-invariant framework that allows the operator to select a practical range of scales that may change depending on the goals of the each mission. Our approach, diagrammed in Figure 1, first detects potential anomalies by finding salient regions across multiple scales and then clusters these regions in an online summary framework to determine rarity.

A. Salience

Our first requirement for an anomaly is that it is salient, or stands out from its surroundings. In a multi-scale sense, this has strong analogies to keypoint detection, whereby stable features such as spots and corners can be detected as the extrema of a scale-space function such as the multi-scale Laplacian of Gaussian (LoG) [10]. The LoG of a grayscale image in this sense represents the difference between a pixel and its neighbors. However, we want to capture anomalies that not only differ in mean intensity from their surroundings, but also in texture as well. To do this, we can pass an image through a filter bank to create an image stack such that each pixel represents a histogram of features. The distance between

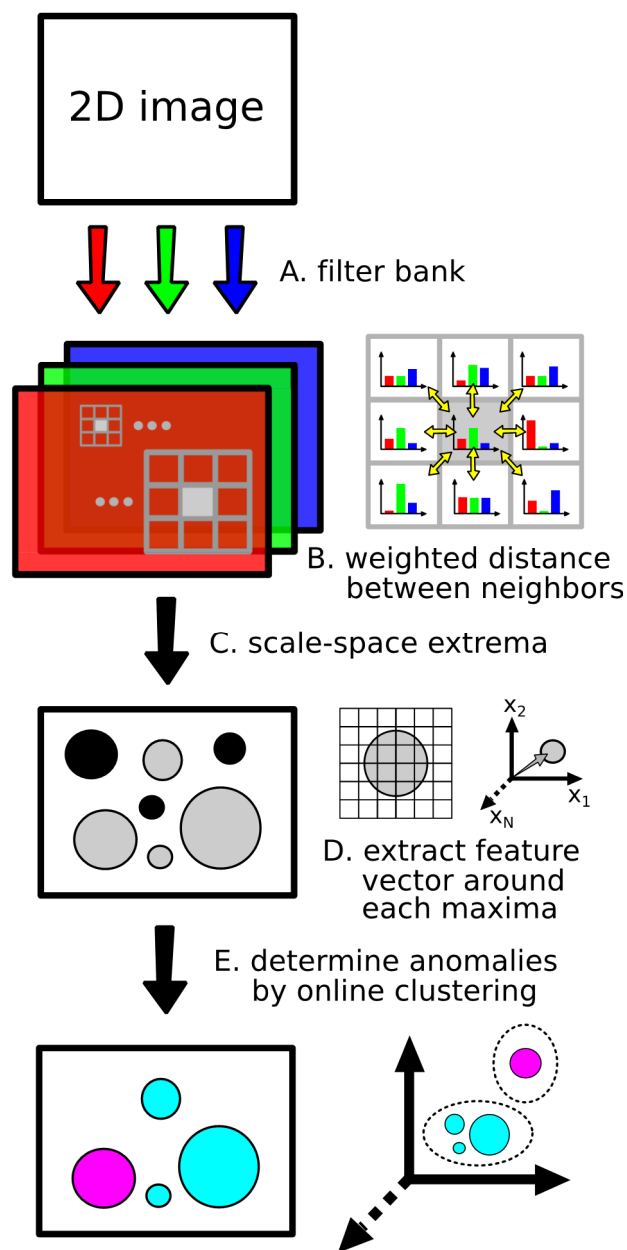


Figure 1. Anomaly detection framework. (A) A 2D image is passed through a low-dimensional filter bank to produce a stack of images such that each pixel can be viewed as a histogram of features. (B) The weighted L_1 norm is computed between each pixel’s histogram and its neighbors’ histograms at multiple scales across the image. (C) The scale-space extrema of this metric are detected. Minima (black circles) correspond to regions that locally are most similar to their surroundings. Maxima (gray circles) correspond to regions that locally are least similar from their surroundings, which are considered to be salient and potential anomalies. (D) The region around each of these potential anomalies is then characterized with a higher-dimensional feature vector. (E) These feature vectors are then clustered using an online summary based approach. Groups with lower membership (violet) are considered more anomalous than groups with higher membership (cyan).

a region’s histogram p_i and its neighbors’ histograms $q_{i,n}$ can be computed across multiple scales using a weighted L_1 norm.

$$d_1(p, q_{n \in N}) = \sum_n w_n \sum_i |p_i - q_{i,n}| \quad (2)$$

The extrema of the resulting scale-space can then be found. Minima represent regions that are locally most similar to their surroundings, while maxima represent regions that are locally least similar to their surroundings. These maxima can therefore be considered locally anomalous. However, further treatment is required to determine if they are also globally anomalous.

B. Rarity

The region around each potential anomaly is then characterized using a higher-dimensional feature vector. We make a subtle distinction of a “higher” dimension here, relative to the previous feature bank for determining saliency. Generally speaking, the more dimensions a feature space has, the greater discriminatory power a clustering algorithm can have, at the expense of additional computational complexity. Since it can be assumed that global anomalies are a subset of all local anomalies, we are able to dramatically reduce the computation load by first detecting local anomalies using a low-dimensional feature space. This frees up resources to use more complex feature spaces that would be much slower to compute and compare between every pixel in the image.

The feature vectors of the local anomalies are then clustered using an online summary based approach. A summary set of previously observed local anomalies is maintained by the algorithm. If a new local anomaly exceeds some threshold of “surprise” relative to the summary set, then it becomes a member of the summary set. If not, it is absorbed as a member of one of the existing summary sets. Members of summary sets with large memberships are themselves not rare in the global sense. Thus, only members of summary sets with a single member can be said to be truly rare, global anomalies.

IV. IMPLEMENTATION AND RESULTS

Figure 2 details our strategy for implementing this anomaly detection framework for side-scan sonar surveys from an AUV. Each sonar ping builds up a row of an image buffer. Once full, the image is treated like the 2D image in Figure 1 with features computed and local anomalies detected. However, both these features and anomalies can be projected into the coordinate frame of the map using the navigational information of the AUV. Global anomalies can then be detected over a very broad range of scales. The resolution of the map at this stage will be much less than the resolution of the image buffer. This approach softens the effect of any navigational errors between track lines that could otherwise blur finer scale anomalies if not initially detected within the sensor’s field of view.

A. Side-Scan Sonar

Side-scan sonar is a ubiquitous oceanographic imaging sensor that emits a narrow beam of sound perpendicular to a platform’s direction of travel. The sound bounces off the seafloor, with closer echoes arriving back at the sensor before further echoes. With knowledge of local sound speed, this time series can be mapped into the spatial domain. Successive pings form an image that can provide a trained operator with an understanding of the bottom topography and any objects lying on the seafloor.

Sonar imagery is prone to several artifacts that are somewhat unfamiliar to those experienced only in traditional

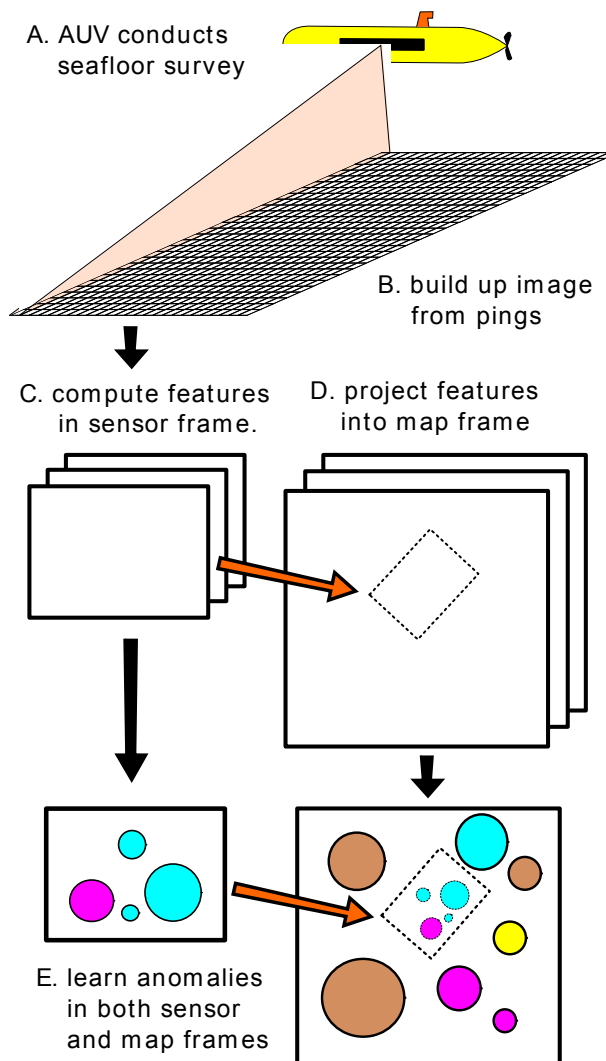


Figure 2. Implementation of our anomaly detection framework for AUV-based side-scan sonar surveys. (A) An AUV conducts a typical seafloor survey, (B) building up rows of an image buffer with each successive side-scan sonar ping. (C) When the buffer is full the image will enter the anomaly detection framework shown in Figure 1. Detected anomalies will exist in a coordinate frame relative to the sensor. (D) The feature histograms can also be projected into the coordinate frame of the map using the navigational information of the AUV. Anomalies that are larger than the sensor’s field of view can now be computed. (E) Anomalies in the sensor frame can also be projected into the map frame so that the final map can contain anomalies over a very broad range of scales.

optical image formation. Because the ping loses intensity the further it travels, the image suffers from lower intensity at the outer pixels. Also, because of the shallow grazing angle, even mild seafloor topography can result in shadow zones analogous to shining a flashlight across a hole. To robustly account for these phenomena in an unsupervised setting, we normalize each ping with a simple running mean filter. Pixels with low values represent shadows, values near unity represent the background substrate, and high values are assumed to be hard

objects or substrates like metal or rock. We use these classes plus gradient values as the low-dimensional feature histogram from which to detect scale-space extrema as local anomalies.

B. Concept of Operations

Figure 3 shows a graphical depiction of this framework in practice. During a typical mow-the-lawn type side-scan sonar survey, an anomaly might be detected. Before the AUV accumulates significant navigation error, an adaptive mission is initiated with a low-altitude pass to capture high-resolution imagery of the anomaly. In practice, the thresholds for how salient or rare an anomaly must be to merit this secondary survey can be balanced against the endurance of the AUV and the remaining area that must be covered.

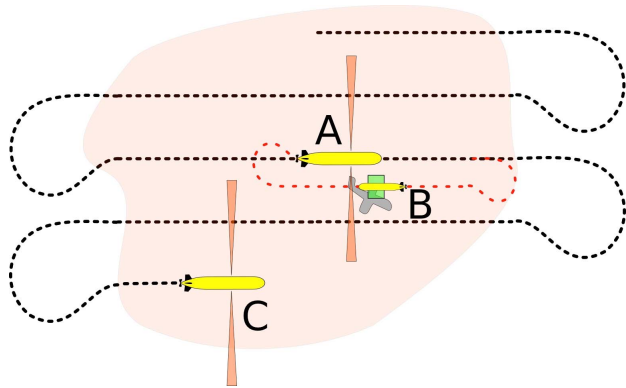


Figure 3. Concept of operations. (A) During a typical mow-the-lawn type survey, an anomaly is detected. (B) Before significant navigation error is accumulated, an adaptive mission leg is planned at a lower altitude to capture high-resolution imagery of the anomaly. (C) The survey continues.

C. Experimental Results

This framework was applied to a side-scan sonar survey conducted in 2011 by a REMUS 6000 AUV off the coast of Brazil, shown in Figure 4. The feature vectors used in this experiment are much smaller than we are currently exploring for real-time implementation. Many global anomalies were detected in the map frame with characteristic scales ranging from 100 to 800 meters. Among these detected anomalies was the wreckage from Air France flight 447.

V. DISCUSSION

When analyzing the results presented in Figure 4, one might assert that, although we have detected the wreckage, the false positive rate is quite high, as many geological features have also been identified as anomalous. On the contrary, there is no false positive rate, nor true positive or any rate, because our algorithm is not trained to detect wreckage, rocks, or any particular target! It merely discovers in the data regions that have been quantified as being both salient and rare. For this to be of practical use, one has to be comfortable with the notion that whatever they are looking for fits these criteria. At the very least, the algorithm is extremely good at detecting where interesting things aren't, which too could be useful in planning multi-resolution surveys in a limited amount of time.

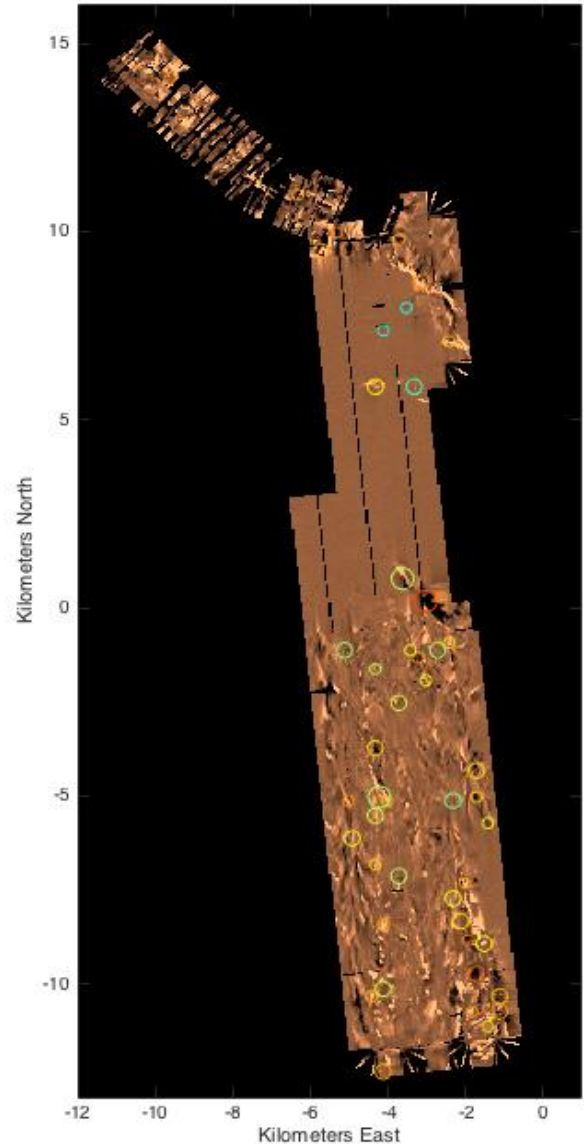


Figure 4. Side-scan sonar mosaic showing detected global anomalies in the map frame. The characteristic scales have been limited within a range of 100 to 800 meters. The yellow circle near the top is the wreckage from Air France flight 447.

Certainly, after several surveys and with post-mission human analysis, the summary set of this framework could begin to be seeded with “uninteresting” classes like rocks so that these are no longer recognized as global anomalies. Further still, depending on the mission, several summary sets developed from known targets such as previously imaged shipwrecks can be included and tagged as “more interesting” with the hope that, despite variation between circumstances, that a target of interest might resemble one of these sets. The feature vector itself might be manufactured to preferentially discriminate between natural and man-made objects.

An overarching goal of this research is to reduce the number of separate AUV deployments required to confidently identify and even survey a desired target. To this effect, more traditional trained classification could take place on the high-resolution imagery collected from the adaptive survey. For instance, a classifier trained to identify easily recognizable parts of airplanes that may remain intact during crashes, such as wheels and window shapes. If these are recognized during the secondary survey, a tertiary survey could even be planned to exhaustively image the debris field after a positive identification is made. Similarly, mission-time feedback could be provided if the anomalies or high-resolution imagery was acoustically telemetered [11] to operators on a support ship. It is this latter approach to enhancing autonomy while still connecting a human in the loop that hallmarks many of the advances in robotics over the past many decades [12].

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