Towards Adaptive Thresholding for Sub-Pixel Co-Registration and Anomaly Detection

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ABSTRACT

Automated change detection (ACD) is a technique that automatically discerns any area of change when comparing two images of the same geographic location over different moments in time. Within the ACD processing stream, co-registration ensures the areas depicted in two images coincide. The difficulty in co-registering sonar images of the seafloor can arise from a difference in vehicle trajectories, low resolution, and the presence of noise. Moreover, the changing features of the sea floor can further add to the difficulty. The successful co-registration of sonar images is important when comparing images, and is thus required in areas such as change detection and mosaicing. In this effort, a three-step co-registration process is used: co-registration by navigational alignment, fine-scale co-registration using SIFT, and local co-registration that corrects navigational differences. In this paper, we focus on the final step where phase alignment occurs. To eliminate unreliable unwrapped phase data, we introduce a novel histogram based adaptive thresholding technique which rejects errors in phase alignment occurring in the across-track direction of the vehicle. Further, an adaptive thresholding technique is applied to the change-map generated following the co-registration stage. To isolate pixels of interest related to anomalies or targets, a thresholding method is applied in conjunction with principal and independent component analysis (PCA and ICA).

We will demonstrate the effectiveness of these adaptive thresholding techniques in sub-pixel co-registration and target detection.

Keywords: Thresholding, change detection, synthetic aperture sonar, independent component analysis

1. INTRODUCTION

The detection of changes in an underwater environment with synthetic aperture sonar (SAS) systems provides a very powerful tool in military and environmental monitoring applications. With tools such as coherent change detection (CCD) and incoherent change detection (ICD), automated change detection (ACD) techniques discern changes in the seabed from multi-pass imagery.[1] The CCD tool generates a coherence map by predominantly exploiting the phase signal from co-registered multi-temporal imagery to discern the presence of a new seabed feature. Because of the dependance on the data being coherent, the CCD tool is not always reliable. On the other hand, ICD generates a log-ratio difference map to expose the presence of significant changes introduced that may occur between passes. Unlike the CCD tool, it is difficult for the ICD tool to isolate subtle changes. Therefore, the application can dictate which tool will provide more meaningful results. In this study, threshold methods, inspired by the zero-detect method, are applied to various stages of the ACD process. Improvements will be made throughout the ACD processing stream.

With the CCD tool, a zero-detect like threshold method will be applied to the sub-pixel co-registration stage of the ACD process. By isolating unreliable phase data, improvements will be made to the sub-pixel co-registration in the across-track direction. For the case of the ICD tool, the detection of targets is enhanced. A zero-detect threshold method is applied to the ICD change-map to distinguish between target and non-target pixels. Further, a principal and independent component analysis (PCA and ICA) method is applied for preliminary false alarm reduction and feature extraction. This uses pertinent attributes to reduce, isolate, and identify target feature information from multiple snippets in the data sets. Assigning a user defined threshold is an extremely challenging

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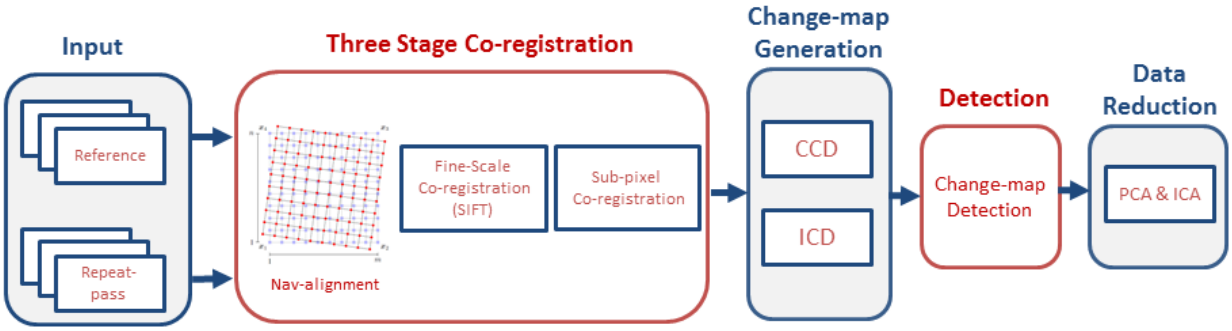

Figure 1: The end-to-end Image-based Automated Change Detection (ACD) processing stream. The steps highlighted in red will be explored in this discussion.

problem due to the automated process of change detection. Thus, to develop a data adaptive solution, new methodologies are needed to perform thresholding from the data.

The work presented in this paper investigates the detection of targets in the scene using the zero-detect threshold method. Chiang et al first introduced this method in,[2] where a hyperspectral image was filtered by analyzing its histogram. Assuming the histogram of an image has a Gaussian-like distribution, the outliers were generally caused by small targets that created ripples on either side of the tails of the Gaussian distribution. By starting from the center of the distribution and moving towards the extremes, the value where the histogram is zero is the desired threshold. In this paper, zero-detect like methods are applied to various stages of the ACD processing stream to isolate pixels of interest.

This paper is organized as follows: Section 2 provides an introduction and the importance of exploiting data adaptive thresholding. The formulation of the automated method for finding the zero-detect threshold is described, and its applications to sub-pixel co-registration and anomaly detection are introduced. Section 3 will briefly describe the data reduction method using PCA and ICA as it applies to the anomaly detections from the ICD tool. In Section 4 the preliminary performance results of zero-detection threshold applied to SAS images are presented. Conclusions and discussions are made in Section 5.

2. ADAPTIVE THRESHOLDING IN SAS IMAGERY

Thresholding is the process of converting an input image into a binary image with the use of an optimal value. The purpose of thresholding is to extract pixels of interest. In this discussion, pixels of interest are first referred to as the quality of the phase data. Then, the pixels of interest are discussed with reference to target detection. That is, one objective of binarization is to determine the pixels of interest to be used to complete the across-track sub-pixel co-registration. Further, another objective is to detect changes over muliple passes.

Threshold values can vary depending on the particular area observed. Therefore, adaptive thresholding can be an important step in the automated change detection (ACD) processing stream. For sonar systems, such as the SAS systems, change detection is the process by which regions of interest are identified through the comparison of current (repeat pass) data with historical (initial pass) data.[3] The end-to-end automation of the ACD task discussed here involves the following: reference and repeat-pass co-registration, change-map generation, target detection through change-map detector,[1,4] and finally feature extraction and false alarm reduction. A block diagram of end-to-end ACD processing is illustrated in Fig 1.

2.1 Zero-Detection Threshold

In this discussion, zero-detect like methods are applied at various stages of the ACD processing chain. The zero-detect method, introduced by Chiang et al,[2] employed projection pursuit for target and anomaly detection. In addition to being applied to SAS images for target detection, a similar technique will be used to aid in the co-registration of two sonar images on a sub-pixel level. The idea introduced by[2] began with a histogram of the

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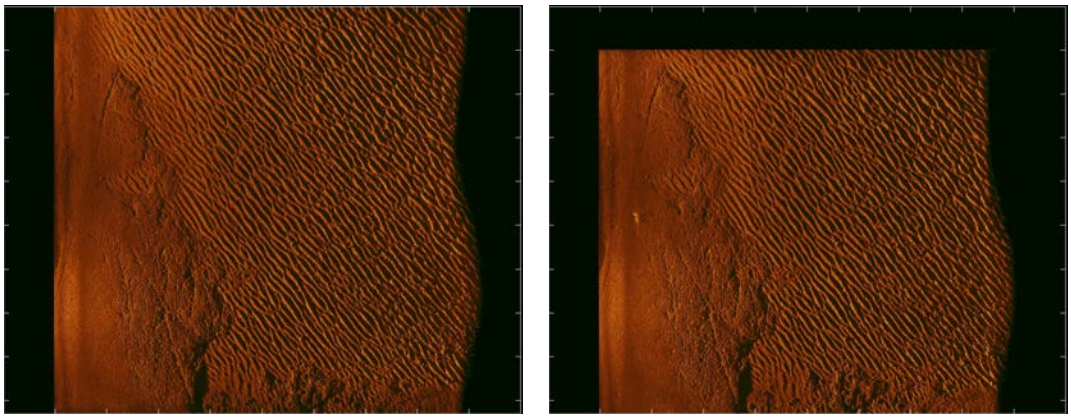

(a) Initial pass. (b) Repeat pass.

Figure 2: The co-registered initial (a) and repeat pass (b) images of an area.

data. Starting from the center of the (Gaussian-like) histogram and moving towards the tails of the histogram, the method searches for values where the histogram is zero. The location of the zero determines the threshold by which to form a binary image such that pixels exceeding the threshold are set to 1 and 0 otherwise. A projection map is created by using the binary image to mask those pixels that exceed the threshold. Following the same process, the resulting projection map is used to find a new threshold and corresponding binary and projection map. The process will continue until either no zero is detected or no significant changes from the previous projection are made. In the following subsections, more detail will go into how similar threshold methods are applied to the ACD process.

2.2 Thresholding for Sub-Pixel Co-Registration

In the first step of the ACD processing stream, two images are co-registered in a three stage process. The co-registration step follows the process developed in[1] and is used to create coherent and incoherent change-maps necessary for the ACD processing stream. In the first stage, the historical and repeat pass images are coarsely co-registered by aligning the navigation data. Because of possible errors from the navigation data, a second co-registration stage is required. The two images are then finely co-registered using the scale invariant feature transform (SIFT) algorithm. In Figures 2 and 3, the finely co-registered environments are displayed. In the case of Figure 2, the initial and repeat passes were separated by a couple of hours, and the passes displayed in Figure 3 were separated by a couple of days.

Although the images are now visually co-registered, in order to co-register the images for what is required of change detection, the final sub-pixel co-registration stage is required. In this stage, coherence is used to correct for any navigational errors not addressed in the first two stages, and the two images are locally co-registered. Further, the underlying phase data of the two images are co-registered. Now to determine the separation of reliable unwrapped phase pixels, a quality map is created using the locally co-registered historical and repeat pass images.[5] In,[2] the zero-detect method relied on data having a Gaussian shaped histogram. Since that is not the case with the quality map, which has a U-shaped distribution, another thresholding technique is used. The technique employed was used in,[5] where a threshold was determined according to the minimum of the histogram. Much like the zero-detect threshold method, however, the resulting threshold will produce a projection map and binary map with which will then be used to find a new threshold. A sequence of binary maps and projection maps are thus created. The process will continue until the difference in thresholds are less than some ε. The resulting threshold and its binary map are then used to mask the quality map to form a weighting matrix. Used in the same way as,[1] the weighting matrix aids in co-registering the two images in the across-track direction. In Section 4, the example in Figure 2 will be explored with regards to sub-pixel co-registration.

2.3 Thresholding for Anomaly Detection

In this case, pixels of interest in an incoherent change-map are a result of two events: a new object appearing in the repeat pass that was not in the initial pass or a removed (or moved) object that was in the initial pass but

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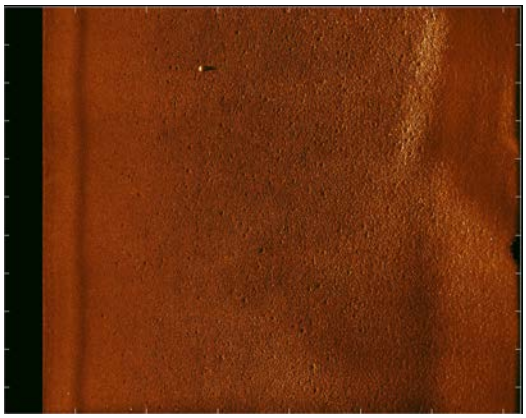
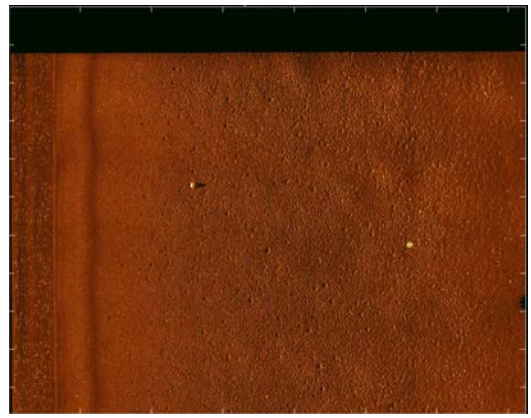
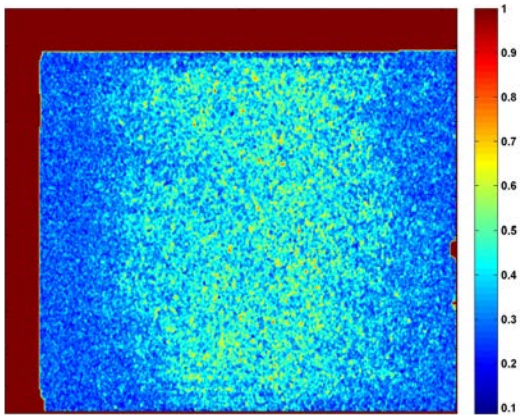


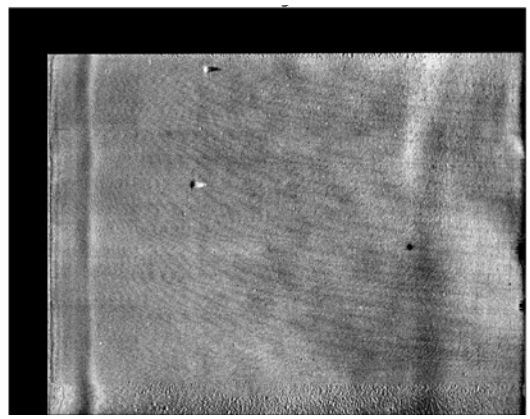
(a) Initial pass.



(b) Repeat pass.



(c) Coherent (CCA) change-map.



(d) Incoherent (ICD) change-map.

Figure 3: The co-registered initial (a) and repeat pass (b) images of an area and their corresponding coherent (CCA) and incoherent (ICD) change-map, (c) and (d), respectively. The object in the initial pass was moved and a new object is present on the right side of the repeat-pass image.

not in the repeat pass. With the magnitudes of the two (locally) co-registered initial and repeat passes, A and B respectively, the ICD change-map $\boldsymbol{\omega}$ is the log-ratio difference map such that

$$\boldsymbol{\omega} = c \cdot \log\left(\frac{A}{B}\right)$$

for some scaling constant c. Therefore, any object removed from the initial pass will appear to be a bright intensity (possibly followed by a dark intesity) in the ICD change-map. Likewise, any object added will appear as a dark intensity (possibly followed by a bring intensity) in the ICD change-map. This section will demonstrate how this adaptive threshold method can be used in anomaly detection.

In Figure 3, an inital pass and repeat pass image is shown with their corresponding coherent and incoherent change-maps. Since an object was moved, a bright intensity appears in the incoherent change-map where the object was removed. An object was also inserted into the scene after the initial pass. A dark intensity appears in the incoherent change-map where the new object was inserted and where the old object was moved. The presence of bright or dark intensities will alter the skewness of the image, which is used to determine the threshold of each successive zero-detect threshold step.

Before the zero-detect threshold is applied, the data is first sphered and whitened. When the zero-detect threshold method is applied, the zero that corresponds to the more dominant feature is found in each zero-detection step. That is, depending on the skewness of the change-map (or projection), the search will begin on the left or

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right tail of the histogram. If the skewness of the incoherent change-map is negative, the search for the first zero will begin on the left side of the Gaussian-like histogram. Likewise, if the skewness is positive, the search will move towards the right tail of the histogram. If there is both a removed and an inserted object, the skewness will be determined by the more dominant feature. As was mentioned at the beginning of the section, the zero-detect threshold method will return a series of binary images and next projections (masked change-maps) that can provide a level of pixel significance. The area corresponding to a change is then used to determine if anomalies detected are relevant to the application. In our case, small regions, that can be attributed to noise or small changes on the sea floor, can be ignored. Similarly, very large regions in the binary map can be ignored as they can be attributed to environmental factors such as ripples in the sand or even fish. Using these factors, the binary images are filtered, and the union of these filtered binary images are used in target detection. Section 4 will introduce an example of how this level of significance will aid in anomaly detection.

3. DATA REDUCTION THROUGH PCA AND ICA

Although the ICD tool has been useful in discerning changes, the resulting detector products from these tools suffer from false detections and clutter noise features that are difficult to discern from a target of interest. In this case, detected products (snippets) correspond to the detections made from the union of filtered binary images. The locations of those detections are used to create snippets from the initial and repeat pass. In order to reduce the number of detections to represent the target of interest, thus ignoring any anomalies due to noise, PCA and ICA are applied to the detected snippets for each image. The process briefly described here was first introduced by G-Michael et al.[6]

The first step in false alarm reduction is preprocessing, which may include transforming and projecting the original data into the transformed variable space. Transforming and reducing the dimensionality has shown to improve target detection by considering only the most informative variables. The best known method to reduce the data in this fashion is PCA. It is generally considered as a transformation that decorrelates data with the use of second order statistics. It does so by ranking its principal components (PCs) according to the magnitude of its eigenvalues.

One drawback of using PCA is that some features may not be captured by second-order statistics. In order to mitigate this issue, we depend on the high-order statistics-based component analysis transform, ICA. ICA is an unsupervised source separation process.[7,8] It differs from PCA in that PCA decorrelates the sample data covariance matrix in such a manner that the data set can be decomposed into a set of uncorrelated and orthogonal components where each component is oriented by an eigenvector. On the contrary, ICA looks for components which are statistically independent rather than uncorrelated. Thus, ICA requires statistics of orders higher than the second order.

Following the zero-detect threshold method, the detected snippets are processed by PCA and ICA. The results of these methods are explored in the next section.

4. EXPERIMENTAL RESULTS

To demonstrate how zero-detect like methods were applied in various steps of the ACD process, SAS data was collected with the high frequency projector. Two passes were taken by following a linear sonar track. The analysis of the co-registration performance is first considered, followed with a discussion regarding anomaly detection.

4.1 Sub-Pixel Co-registration

The example discussed here illustrates the zero-detect inspired method as it applies to sub-pixel co-registration. As mentioned previously, the initial and repeat passes in Figure 2 are separated by a four hour latency time. Following local co-registration, the phase of the repeat pass is unwrapped and co-registered with the initial pass. In Figure 4, the resulting wrapped and unwrapped phase maps from Figure 2 are displayed. The effects of local co-registration and sub-pixel co-registration on the incoherent change map and the coherence of the passes are displayed in Figures 5 and 6, respectively. Notice that with each successive co-registration step, the coherence of the two images increase throughout the image. Although the incoherent change-map was improved when the images were locally co-registered, a significant change was not displayed when the phase was aligned. This is expected as the incoherent change-map does not rely on the aligned phase.

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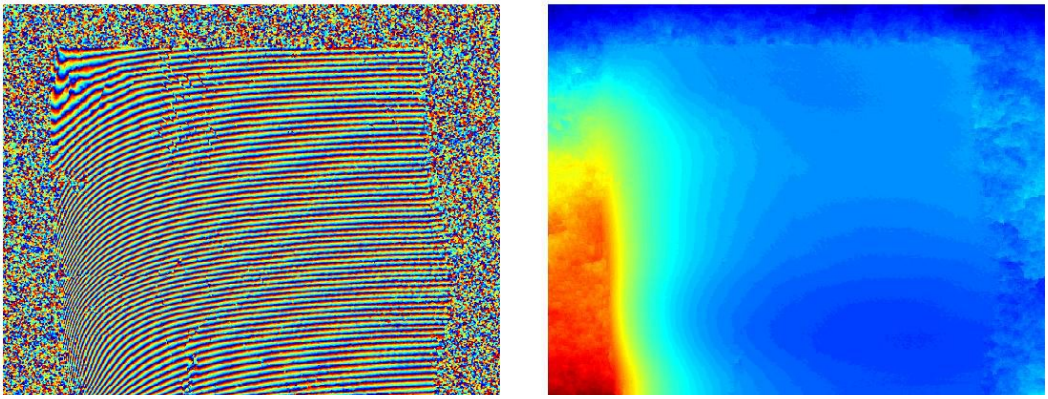
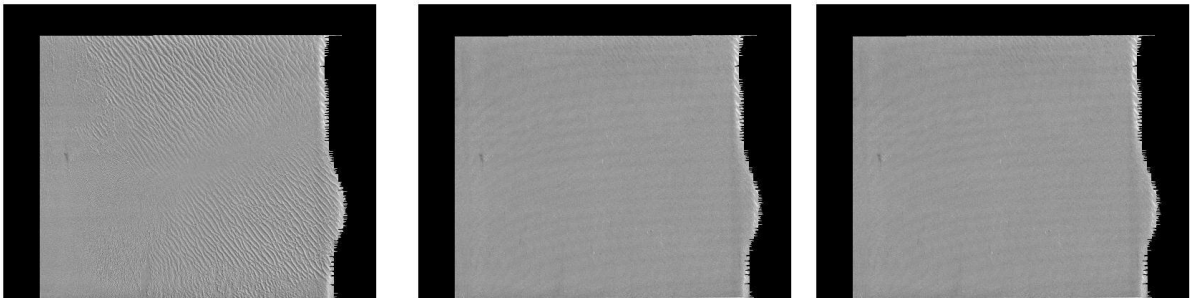


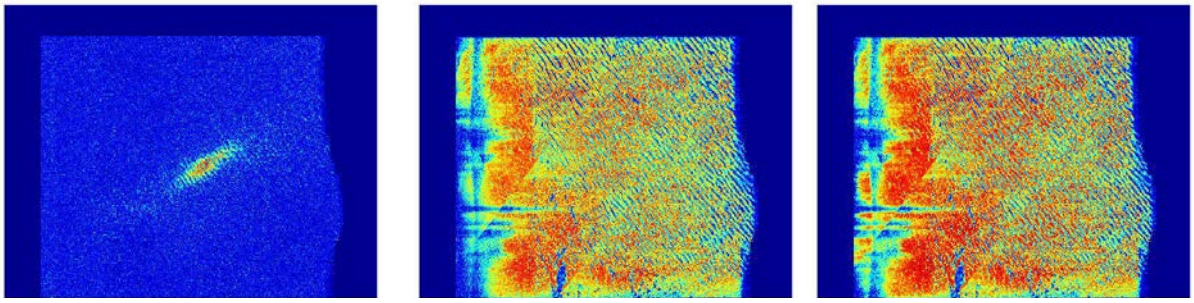
(a) Wrapped Phase. (b) Unwrapped Phase.

Figure 4: The wrapped and unwrapped phase of the repeat pass from Figure 2.



(a) Finely co-registered. (b) Locally co-registered. (c) Sub-pixel co-registered.

Figure 5: The results of the incoherent change-map (a) without sub-pixel co-registration, and (b) with local co-registration, and (c) with sub-pixel co-registration together with zero-detect inspired threshold method.



(a) Finely co-registered. (b) Locally co-registered. (c) Sub-pixel co-registered.

Figure 6: The local coherence estimates for the initial and repeat pass (a) without sub-pixel co-registration, (b) with local co-registration, and (c) with sub-pixel co-registration together with zero-detect inspired threshold method.

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4.2 Anomaly Detection

The following example demonstrates the zero-detect method as it applies to anomaly detection. We refer to Figure 3, with intial and repeat passes separated by a two day latency time. Although not addressed in,[2] the choice of bin size was important in finding a threshold. The use of 10,000 bins proved to be appropriate in detecting the target pixels, the number of which was small compared to the size of the image. The bin size should be small enough to be able to find a zero value in the histogram. Where some anomaly detections rely on user defined thresholds that often take into account anomalies not corresponding to targets, such as biologics or other environmental changes, the zero-detect method could isolate features according to their intensities.

Figure 7 demonstrates the series of projections and their corresponding binary images and filtered binary images as a result of applying the zero-detect method to the ICD change-map from Figure 3. Notice in the first binary image, the two targets inserted into the scene as well as the shadow of the removed target are represented. Comparing the binary imaged to the filtered binary image, the noisy pixels are removed as well as the shadow of the target in the initial pass. Here, a level of significant pixels is displayed. In the second step of the zero-detect threshold method, a large portion of the binary map now corresponds to a highlight in the top right quadrant of the initial pass image. Although this does exceed the threshold found through the zero-detect threshold, the region does not represent an area containing pixels of interest. As a result, the area is ignored. Although the second filtered binary image still consists of noisy pixels, notice that the target in the initial pass is captured. By using the sequence of filtered binary maps found in Figure 7, the size of the closed detected regions not only distinguish noisy pixels but also areas that possibly correspond to biologics.

If a union of the two filtered binary images are taken, the resulting image is filtered through a detector to capture snippet detections. As a result, 48 snippet detections are located. Figure 8 represents those snippets from the repeat pass, many of which correspond to clutter noise features. Although many false alarms are represented, when PCA and ICA is applied to the 48 snippet detections, the resulting detections corresponding to the targets in the repeat pass are filtered, Figure 9 (b). The snippet represented here corresponds to the largest eigenvalue in Figure 9 (a). Similar results, not displayed here, are found when PCA and ICA are applied to the snippet detections from the initial pass image. Thus, relevant changes between the initial and repeat pass are isolated.

5. CONCLUSIONS AND DISCUSSION

In this paper, zero-detect inspired methods are introduced. In both applications, the thresholding methods proved to be an effective technique at locating pixels of interest. In the case of sub-pixel co-registration, an improvement in coherence is observed. For anomaly detection, the use of the zero-detect method in conjunction with PCA and ICA demonstrated significant improvements in target detection. It proved to be effective at not only locating breakpoints between background and targets for use in detecting changes in the incoherent change-map but also in target feature selection and identifying outlier target pixels during target detection. This method was demonstrated to be the robust choice when employing false alarm reduction method. These results will be important for the false alarm mitigation technique of the incoherent map detector by significantly improving the SNR of potential change patterns, reduction of false alarms, and anomalous activities against the seafloor background, such as underwater IED detection. The future effort will focus on expanding the work presented in this paper and focusing on the continuation of testing on SAS images from different seabed sediment types.

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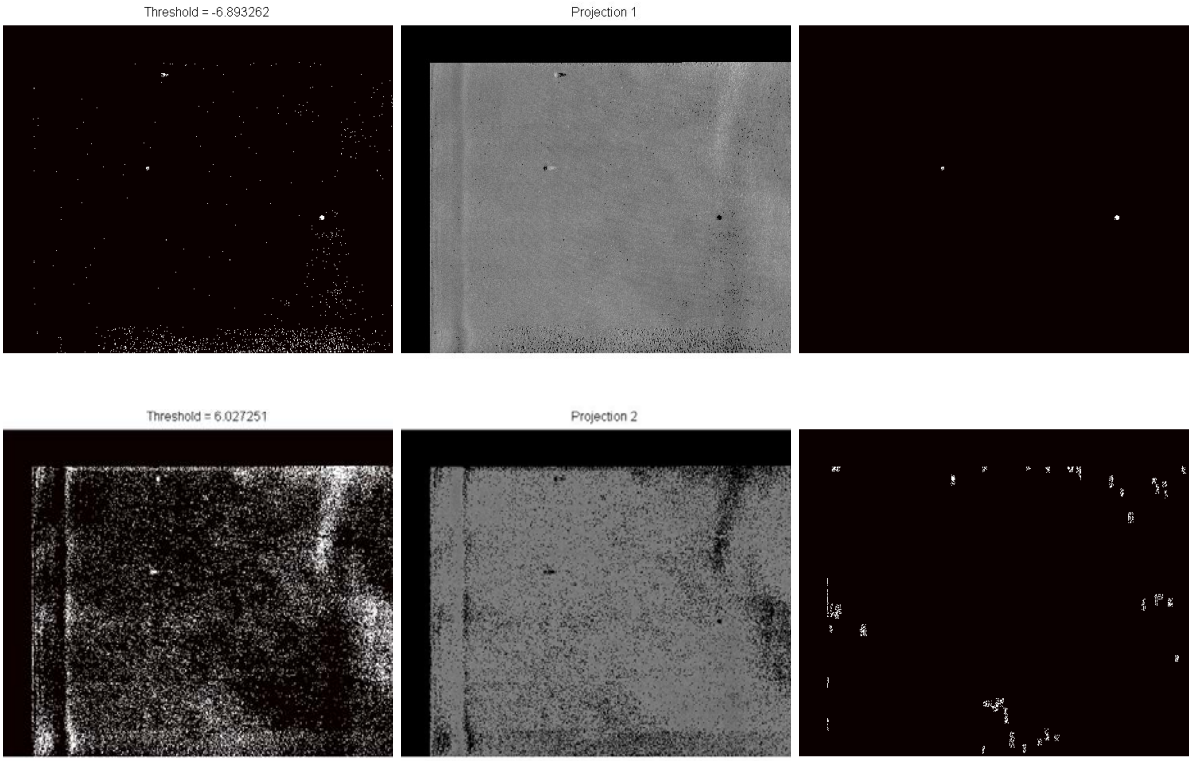

Figure 7: Each row represents a step in the zero-detect threshold method for the example found in Figure 3. The first column represents the binary images from each step. The second column represents the projection maps, and finally the third column represents the refined binary image used in anomaly detection.

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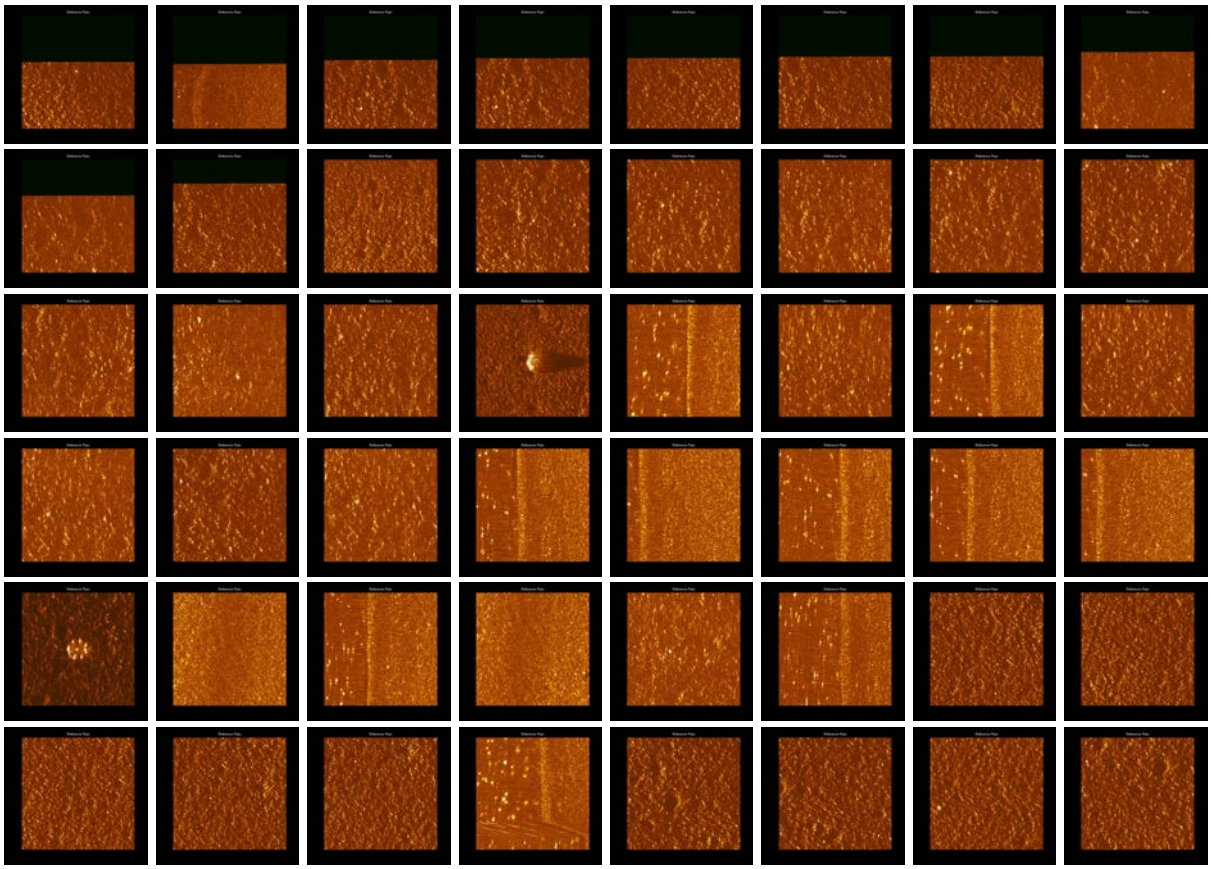
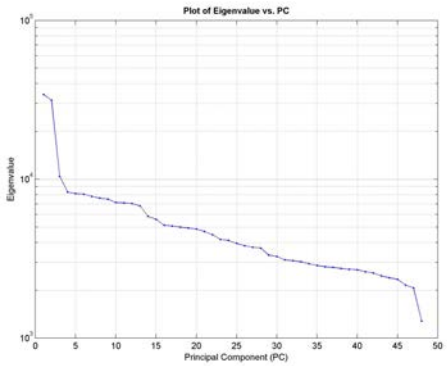
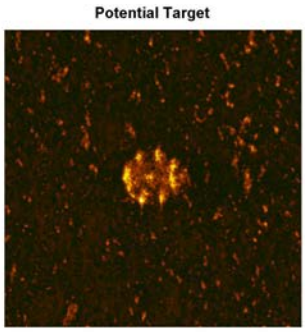


Figure 8: The resulting snippets from the repeat pass image that correspond to the anomaly locations resulting from the zero-detect thresholding method.



(a) Eigenvalues used in PCA to determine the significant principle components.



(b) A resulting snippet following the PCA-ICA method that indicates a detected target.

Figure 9: The corresponding (a) scree plot for the repeat pass snippets and (b) a resulting target following the PCA-ICA method.

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