Spectral Anomaly Detection with Machine Learning for Wilderness Search and Rescue

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***Abstract*—In wilderness search and rescue missions, unmanned aerial vehicles (UAVs) may be deployed to collect high-resolution imagery which is later reviewed by a responder. The volume of images and the altitude from which they are taken makes manually identifying potential items of interest, like clothing or other man-made material, a difficult task. For this reason, we created a program that automatically detects unusually-colored objects in aerial imagery in order to assist responders in locating signs of missing persons. The program uses the Reed-Xiaoli (RX) spectral anomaly detection algorithm to determine which pixels in an image are anomalous and then generates an "anomaly map" where brighter pixels signify greater abnormality. While the RX algorithm has previously been proposed for search and rescue missions, up until now it has not been evaluated in a high-fidelity setting with real responders and real equipment. We tested the program on 150 aerial images taken over the Blanco River area in Hays County, Texas after the May 2015 flooding and demonstrated the results at the 2015 Summer Institute on Flooding. Early feedback from responders suggests that RX spectral anomaly detection is a valuable tool for quickly locating atypically-colored objects in images taken with UAVs for wilderness search and rescue.**

Keywords—machine learning; anomaly detection; unmanned aerial vehicles; search and rescue; emergency informatics

I. Introduction

Unmanned aerial vehicles (UAVs) are an invaluable asset to wilderness search and rescue operations as they are able to capture high-resolution imagery of large stretches of land in a short period of time. But despite the usefulness of the data collected, the hundreds or thousands of images amassed by the UAVs can quickly become overwhelming to the responders who have to sift through them manually, searching for signs of missing persons or other objects of interest. The task is a demanding one not only because of the amount of images taken but also because the targets are generally small and ill-defined: much of what responders look for in the images is anything that seems "out of place," such as a piece of clothing. These difficulties combined with the stress and time-sensitivity of search and rescue missions motivate the use of *anomaly detection* to locate out-of-place objects in aerial imagery.

Anomaly detection, in machine learning, is the process of identifying items or events that deviate from an expected model or pattern. It differs from other kinds of target detection in that the definition of items to target is much fuzzier: rather than looking for a specific pattern like someone's face, anomaly detection establishes what is "normal" in a given dataset and then classifies everything that falls outside that norm as an anomaly. Since target objects that responders look for can be as vague as "anything that looks out of place," anomaly detection complements responder efforts quite well. In particular, *spectral anomaly detection* is well-suited to wilderness search and rescue imagery since objects of interest will often have a different color than their surroundings, and so spectral information can be leveraged to locate anomalies.

Algorithms for spectral anomaly detection are generally intended for hyperspectral imaging applications, but our work repurposes these algorithms for high-resolution RGB images. Previous research has suggested that hyperspectral anomaly detectors can be used successfully for search and rescue (e.g. [1]); however, no research to date has used images from real search and rescue events. This paper contributes the results of spectral anomaly detection on actual wilderness search and rescue images such as the one in Figure 1. It also describes the feedback received from responders during a demonstration of the results and provides direction for future research on anomaly detection algorithms for wilderness search and rescue.

Figure 1: One of the images taken over the Blanco River area during a UAV flight after the May 2015 flooding in Texas. An abnormality (metal pole) is marked with a yellow arrow.

II. Literature Review

Perhaps the best-known hyperspectral anomaly detector is the Reed-Xiaoli (RX) algorithm, introduced in 1990 by Reed and Yu [2]. RX assumes that background clutter in an image can be modeled as a Gaussian process and that although the mean may fluctuate greatly throughout the image, the

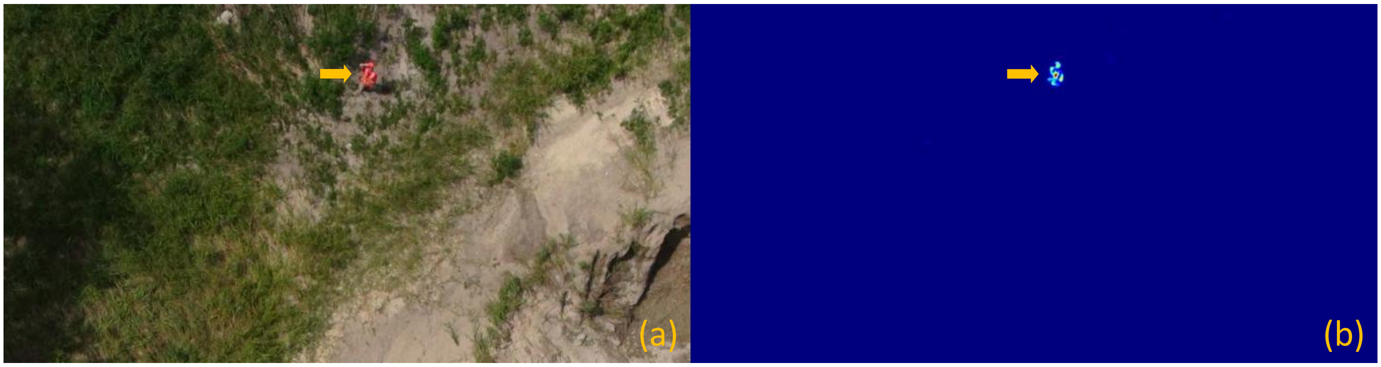

Figure 2: Running our anomaly detection program on image (a) produces the anomaly map in (b). The orange clothing of the responder and its corresponding pixels on the anomaly map are marked with yellow arrows.

covariance will vary much more slowly. The mean and the covariance may be estimated globally with the entire image or locally with subdivisions of the image partitioned by a sliding window. Either way, the output of the RX algorithm is the squared Mahalanobis distance of each pixel from the estimated background model. It is given by the following formula:

$$\delta_{RXD}(r) = (r - \mu)^{\mathrm{T}} K_{LxL}^{-1}(r - \mu)$$

where r is a pixel, μ is the background mean, L is the number of spectral bands, and K_{LxL} is the background covariance.

RX has been successfully utilized in many hyperspectral applications and is considered the benchmark anomaly detection algorithm for multispectral and hyperspectral data [3]. Even so, possible pitfalls with the RX algorithm have prompted researchers to develop alternate spectral anomaly detectors. Some of these alternatives are direct enhancements to the RX algorithm that strive to improve background model estimation [4, 5]. Others use support vector data descriptions to classify the data in a way that is similar to the RX algorithm but removes the need for a background covariance matrix to be inverted [6, 7]. Finally, some researchers have experimented with cluster-based anomaly detection to mitigate the window size restrictions that RX can impose [8, 9].

While these spectral anomaly detection algorithms were successful in their various applications, we still chose to use the original RX algorithm. The reason for this was that one of the main disadvantages of RX — the computational cost of inverting large background covariance matrices — all but disappears when using RGB images rather that hyperspectral images since there are only three spectral bands as opposed to dozens. With this issue out of the way, its simplicity, speed, and wide acceptance make the RX anomaly detector a very appealing algorithm that is well-suited to our application.

III. Approach

We decided that the best way of using RX spectral anomaly detection for search and rescue would be to show responders the map of RX scores next to the original image (see Figure 2). The advantages of doing this rather than keeping the RX scores "behind the scenes" and flagging anomalies directly on the image are that (1) no expensive clustering or segmentation operations are needed to find anomalous regions, and (2) there is no risk of drawing over useful information on the original image. Moreover, the fact that responders typically review the images from a UAV flight out in the field provides an incentive for having a high-contrast map of anomaly scores readily available to responders: screen glare can wash out colors and make the images difficult to see, so having a map that relies more on pixel intensity than pixel hue can greatly increase the odds of finding an anomaly (see Figure 3).

Another crucial design choice was to use global RX scores rather than local RX scores with a sliding window. Since local RX iteratively computes a new inverse covariance matrix and mean for a small area neighboring each pixel, it is much more computationally complex than global RX, which only does these operations one time. Speed is of the utmost importance during wilderness search and rescue missions not only because of increasing danger to missing persons but also because the area that needs to be search grows over time, and so global RX is the preferred choice of algorithm. Thus our approach was to calculate global RX scores for each image, threshold the scores to remove noise, and then display the map of anomalies next to the original image. Technical details of the implementation are given in the following section.

Figure 3: Screen glare can wash out colors and make it even more challenging to find objects of interest. The white piece of debris circled in (a) is hard to see, but the corresponding anomaly map pixels circled in (b) are more noticeable.

IV. Implementation

Using the Python programming language, we created a cross-platform standalone application with a simple graphical user interface. The application prompts the user to select a directory of images, and then it processes each one serially. Processing an image consists of the following steps:

1. Before doing anything else, the image is resized if one of its sides exceeds a predefined maximum size length. In our implementation, this was set at 1024 pixels. Aspect ratio is maintained when resizing.
2. Global RX scores are calculated and saved.
3. A chi-square percent point function is defined to threshold the RX scores. Any image pixel that has a probability of less than 0.1% with respect to the background model is kept; all other pixels have their RX scores set to zero.
4. The matrix of RX scores is normalized to a [0, 1] range and converted into a colormap RGB image. Our application uses the standard colormap called "jet" where low scores are dark blue and higher scores are progressively brighter teals, yellows, and reds.
5. The colormap of RX scores, which we refer to as an "anomaly map," is concatenated with a copy of the original image to form a single image.
6. The final image is saved in a program-generated folder within the directory that the user selected.

We used the Spectral Python (SPy) library, version 0.16.0, to implement the RX algorithm within our program. All image manipulation was done with standard numeric and scientific libraries for Python, including numpy and scipy.

V. Field Experiment

A Sony HDR-PJ780VE camera mounted on a UAV was used to take 150 high-resolution images (6544x3680 pixels) over the Blanco River area in Hays County, Texas after the May 2015 flooding. Mostly the images consisted of felled trees, branch piles, sand, mud, and water, but 56 of them also had synthetic objects like pipes, fabric, and plastic tape. We transferred the images to a laptop with an Intel Core i5-2410M CPU running at 2.30 GHz and ran our program on them. Each anomaly map was 1024x575 pixels and took an average of 2.23 seconds to generate and save to file. The images and anomaly maps were then shown to responders during the 2015 Summer Institute on Flooding, a workshop that brought together representatives from 12 agencies, 15 universities, and 5 companies to discuss lessons learned from the Texas floods and to conduct field work with new protocols and technologies for preventing, responding to, and recovering from floods.

VI. Results and Discussion

In total, 1.14% of the image pixels were flagged as having some degree as abnormality. All of the synthetic anomalous objects found by a group of seven students who had studied the images were highlighted in the corresponding anomaly maps with bright pixels. Noise in the anomaly maps included sunlight reflections off water, deep shadows, and bright green foliage, particularly when there were few neighboring trees, but the overall success of the program yielded very positive feedback from the responders. They said that an application like this is something they have wanted for a while now and expressed great interest in using it out in the field.

VII. Conclusion

Spectral anomaly detection is an effective tool for quickly locating unusually-colored objects in images taken with UAVs for wilderness search and rescue. Our research has shown that the global RX spectral anomaly detector successfully identifies regions with abnormal colors in real search and rescue images.

Future work will consist of further high-fidelity testing as well as a user study to verify whether having an anomaly map placed alongside the original image increases the amount of objects with atypical colors found by responders. Additional directions to go with this research include the integration of spectral anomaly detection with computer vision techniques (e.g. straight line detection) to increase the confidence in the anomalies detected, or the application of other thresholding and filtering techniques to reduce the amount of noise in the anomaly maps. Adapting the global RX algorithm to run even more efficiently on RGB images or in general would also be a highly useful path for future research.

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