**Anomaly Detection in Hyperspectral Imagery: Statistics vs. Graph-based Algorithms**

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**INTRODUCTION**

- In hyperspectral imagery, an anomaly is an observation (pixel spectrum) which deviates from a “normal” image spectrum. An anomalous spectrum suggests that an unexpected material is present within the scene.
- Numerous algorithms have been developed to detect anomalous pixels in hyperspectral imagery, but their performance varies drastically based on scene content and the assumed background model.
- Anomaly scores in multivariate statistics-based algorithms (RX and subspace-RX) should theoretically approximate a chi-squared distribution; however, this is rarely the case with real hyperspectral imagery.
- In this work we quantify differences in the distributions of anomaly scores found with RX, subspace-RX and TAD. We also look for general trends in performance with scenes of varying content and complexity (shown right).

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**ANOMALY SCORES AND DISTRIBUTIONS**

- Anomaly scores are displayed below for the three scene subsets and the three tested algorithms. In the images, darker pixels are more anomalous. In the graphs, dashed lines indicate a best-fit Gaussian distribution for RX and subspace-RX, and the solid line shows the expected distribution, dependent on the degrees of freedom (DOF). The solid green line shows the expected threshold for anomaly detection assuming the $\chi^2$ distribution, determined with $L = \chi^2_p((1 - \alpha)^{1/2} / \alpha)$, where $\alpha$ represents the probability of detecting an RX score larger than $L$.
- **Visual inspection of the charts below show that the subspace-RX scores approximate a $\chi^2$ distribution much more closely than the RX scores.** As expected, the most anomalies were found in the urban scene, and the least in the rural scene.
- **The theoretical distributions also predict the total anomaly count expected for each scene.** With 360° DOF (RX), no outliers were expected to be found from a $\chi^2$ distribution, and the Gaussian fit proved to be a better match. In the case of subspace-RX, very few outliers were detected, and the results closely fit both the Gaussian and $\chi^2$ distributions.
- **The TAD results show a very clear set of anomalous pixels at the tail-end of the distribution.** This is possible because rather than comparing to a single statistical background model, the graph-based TAD algorithm allows for multiple backgrounds, and makes no statistical assumptions on the data.
- **The distribution of TAD scores appears to be best-fit by a Gaussian; however, more results are needed to confirm this observation.**
- **Another interesting feature is that each scene has a similar number of anomalies.** It was originally expected that more complex scenes would be more susceptible to anomalous pixels.

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**ALGORITHM COMPARISON**

- **Images below show 95th percentile anomalous pixels, color-coded by algorithm (left).** (White indicates no detected anomalies). The diagonal wall in the upper right of the urban image stands out visually when the scene is assumed to be normally distributed, as evidenced by the strong detections in the RX and subspace-RX algorithms. However, this wall was flagged as a background component by TAD, which instead highlighted other areas in the scene.
- **The strongest agreement between all three algorithms is in the upper-right of the rural image.** Meanwhile, there is very little agreement between the algorithms in the suburban image.
- **These results show what kind of detections can be expected from each algorithm under differing scene content.**

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**CONCLUSIONS**

This work provides the first comparison of anomaly score distributions between common statistics-based anomaly detection algorithms and the graph-based Topological Anomaly Detector (TAD). Results show that anomalies are much easier to detect using a graph-based background model instead of assuming a statistical distribution.

Comparisons were also made between the algorithms’ performance on scenes of differing content and complexity. As expected, more anomalies were detected in more complex scenes for the two statistical detectors. On the other hand, the number of detected anomalies was similar for all scene complexities with TAD.

Future work will study TAD distributions in more imagery and attempt to determine if the number of detected anomalies is consistently similar in scenes of varying complexity.