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Anomaly Detection in Remote Optical Imagery

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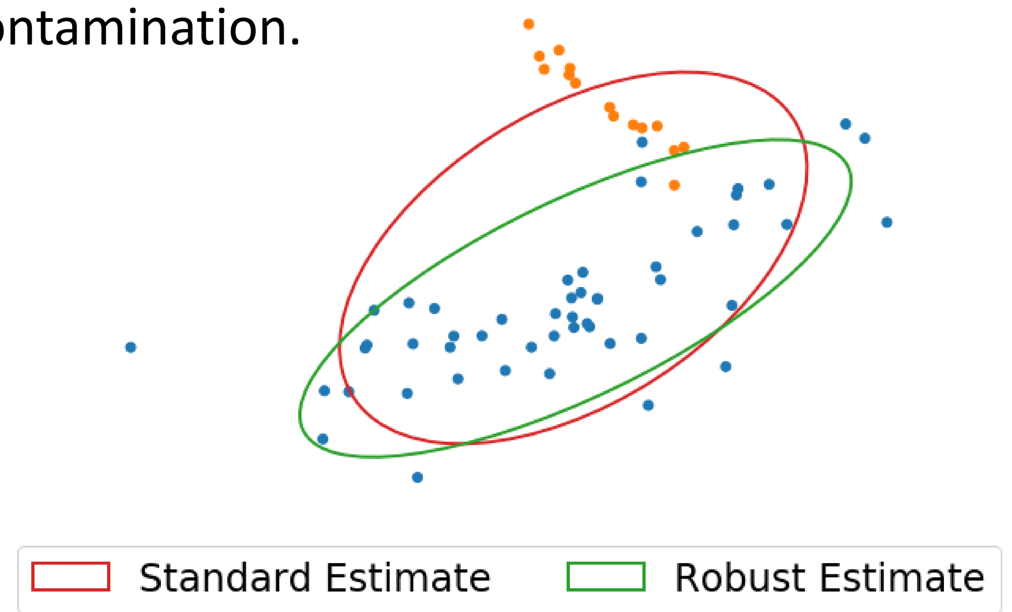
Introduction

Remote optical imagery, including panchromatic, multispectral, and infrared, can be acquired during a Comprehensive Nuclear-Test-Ban Treaty (CTBT) on-site inspection (OSI) to search for anomalies and artifacts and can increase an Inspection Team's efficiency and effectiveness at selecting search zones. For example, optical imagery can reveal large scale patterns that may be indicative of OSI relevant activities, but are not directly apparent from ground based visual observation. Although powerful, analyzing large volumes of imagery can be prohibitively intensive, particularly under CTBT-imposed manpower and time limitations. This work examines automated statistical techniques for anomaly detection in remote optical imagery, which increase the throughput of OSI-relevant information while reducing manual processing.

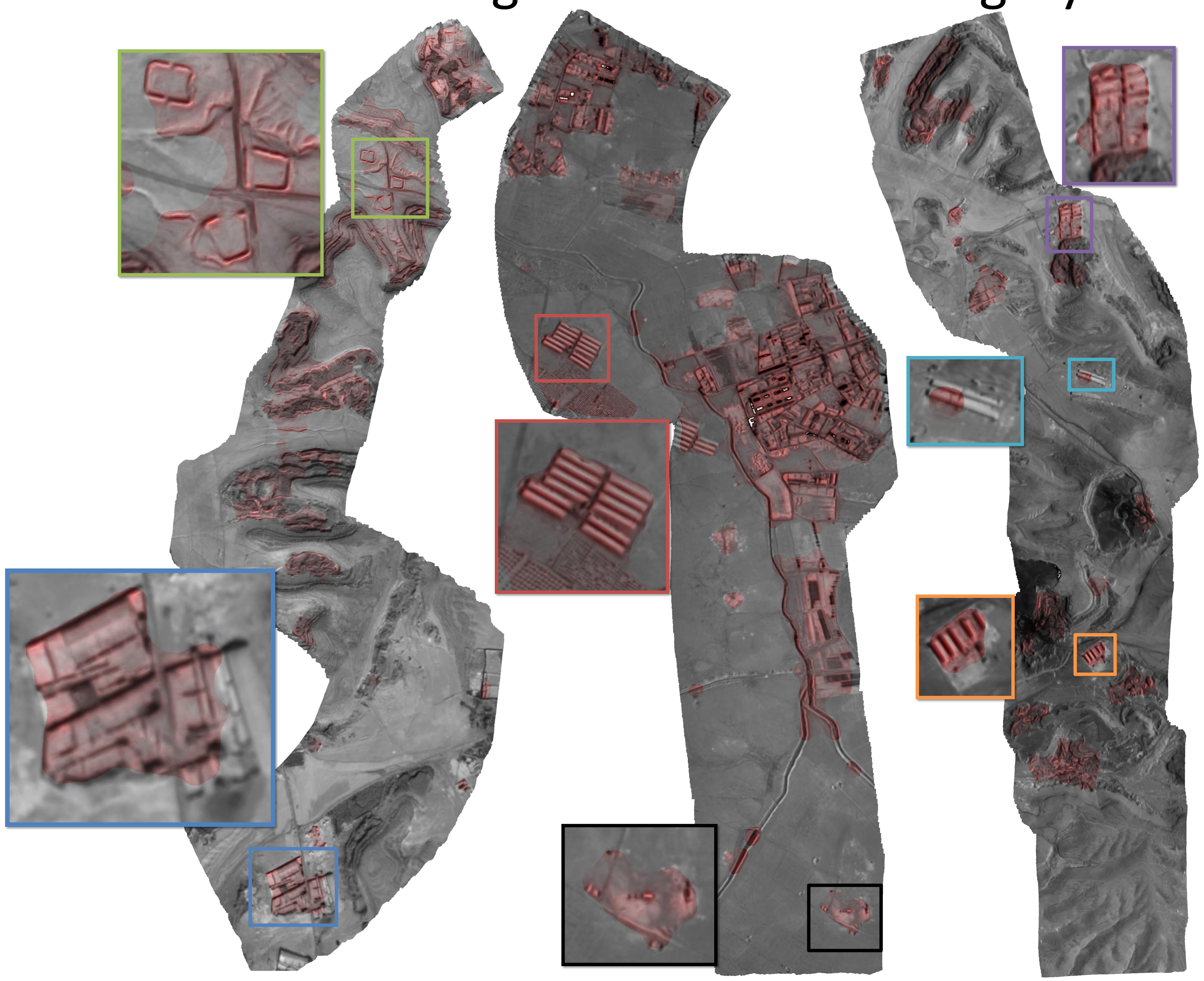
Anomaly Detection

The most common anomaly detection algorithm is the Reed-Xiaoli Detector[1]. The RX-D algorithm estimates a multi-variate normal distribution of the background, and tags data with low probability as anomalous. If data used to estimate the background model contains anomalies, then parameter estimates can become polluted. This is problematic in remote imagery: anomalies and background co-exist in scene. We employ least-median regression[2] and robust statistics for estimation of mean and covariance. This is robust up to 50% anomaly contamination.



Model estimate pollution by anomalies (orange) present in data (blue).

Results on Long Wave Infrared Imagery



Detected anomalies (red) from long-wave infrared imagery scenes collected as part of the multispectral field exercise 2013 in the Hashemite Kingdom of Jordan. Each scene is composed of 400-1,000 individual images.

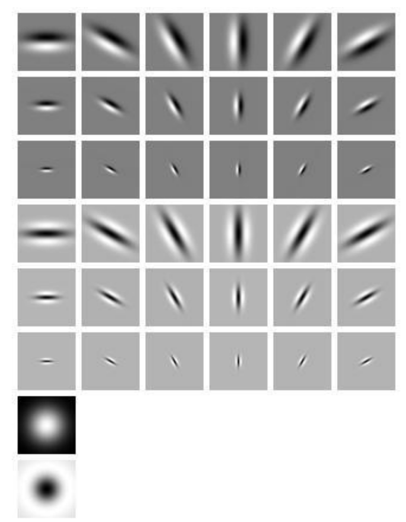
Acquire Imagery → Orthomosaic Scenes: SIFT key point algorithm[4] and perspective transforms → Compute texture: MR8 nonlinear texture filterbank[3] → Estimate Statistics: Least-median regression[2] → Detect Anomalies: RX-D[1]

Processing workflow for anomaly detection in single band LWIR. Since this data consists of a single band, we compute the local "texture" for analysis. For data with additional spectral content (e.g. multi- or hyper-spectral imagery), spectra can be used directly.

Conclusion

Automated statistical algorithms for anomaly detection can be of great utility to an inspection team. These techniques can be used to generate anomaly maps of areas that differ significantly from background, thereby reducing the regions to be reviewed or inspected manually and enhancing the utility of remote optical imagery for OSI. Robust estimation of the background model allows for application of anomaly detection algorithms to remotely sensed imagery, in which both anomalies and background exist.

MR8 nonlinear texture filterbank[3]. Response to this orientation-invariant filterbank can be interpreted as a proxy for texture.



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