The volume of aerial surveillance video is outpacing the current, manual monitoring capabilities. DoD analysts need capabilities that reduce workload by identifying, summarizing, and creating alerts about critical events and patterns.

Initial Approach

Our initial approach (Figure 1) applied object detection, tracking, and stacked sparse LSTM auto encoders to identify unique segments of video for a summary.

Revised Strategy: Pattern of Life Analysis

Our revised strategy focuses on a common surveillance problem of identifying situations of interest relative to a specific area being observed (e.g., a compound). We are:

- selecting and training state-of-the-art classifiers and trackers on images and video representative of DoD aerial surveillance scenarios gathered during these scenarios
- analyzing extracted objects and tracks using statistical and machine learning techniques to summarize data, recognize interactions, and determine patterns of life at the compound

Analysts will be able to:

- set alerts for specific objects, activities, or patterns
- display summaries of detections over time and space
- summaries and alerts will be provided for increasingly complex forms of analysis, from recognition of the signatures of specific objects to prescriptions for suggested courses of action

Example: Anomalous Track Detection

As an initial step toward understanding tracks, we developed a LSTM-Autoencoder algorithm to detect unusual tracks. The algorithm takes as input sequences of spatiotemporal points (tracks) and calculates an anomaly score for each track.

The LSTM-Autoencoder works by learning a compact representation for each track, then attempts to reconstruct that track from the encoding. Behaviors which are under-represented in the training set will be difficult to reproduce and have a high reconstruction error.

To test our algorithm, we created synthetic track data using the SUMO traffic simulator on a set of streets surrounding the SEI (see Figure 3). Each generated track was a best path between a randomly chosen start and stop location. We inserted an additional hand edited track “ZigZag” that was not a best path to see if our algorithm could detect it.

Figure 4 shows the distribution of score values for all 974 tracks. “ZigZag” track is marked on the graph and had the 2nd highest observed anomaly score. The highest scoring track experienced multiple traffic jams at multiple intersections along its route. Another high scoring (anomalous) track was a vehicle making a u-turn.

Next steps include tuning autoencoder performance and testing against DoD data.