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1 Summary

The purpose of this program is to address the development of algorithms for adaptive processing of multi-sensor data, employing feedback to optimize the linkage between observed data and sensor control. The envisioned multi-modal adaptive system is applicable for intelligence, surveillance, and reconnaissance (ISR) in general environments, addressing base and port security, Leveraging our previously developed technology, SIG is developing second-generation methods to adaptively learn the statistics of dynamic object behavior in video, while focusing on defining system requirements for sensor deployment by using field data (vs. highly controlled indoor data). SIG is also working closely with its subcontractor, Lockheed Martin, to integrate additional technologies, such as object classification and recognition, to provide a more robust and discriminative system.

SIG is aggressively pursing follow-on funding and technology transition opportunities for persistent surveillance applications. In particular, under related IRAD efforts, we are working to address current shortfalls and develop new methods for activity recognition of vehicles and dismounts in persistent airborne EO/IR video imagery. An efficient framework is under development for joint classification and target tracking (JCT). The joint posterior density over target poses (e.g. position, velocity, heading) and target type is recursively estimated via a Bayesian formulation. It is assumed that appearance measurements provide information indicative of target class and kinematic measurements for indirect measure of target pose. An importance sampling approach is used to efficiently incorporate both types of measurements in refining estimation of the joint distribution. The methods are presented in the context of providing real-time analytic metadata to reduce data transmission requirements in support of persistent video-based surveillance. Included in this metadata are the joint-posterior distributions for target tracks and class which are utilized by an active learning cueing management framework to optimally task the appropriate sensor modality to cued regions of interest. Moreover, this active learning approach also **facilitates analyst cueing to help resolve track ambiguities in complex scenes.** We intend to leverage SIG's active learning with analyst cueing under future efforts with ONR and other DoD agencies. Obtaining long-term accurate target tracks is a key requirement for activity modeling. We propose adapting methods for activity manifold modeling, such that the posterior distributions of vehicle tracks themselves may be ultimately transformed into space-time probability manifolds. Such representations will enable further application of the active learning framework for semi-automated activity recognition with limited analyst cueing for anomaly and threat notification.

2 Recent Technical Developments

During the recent performance period we have made significant progress in developing a compressive sensing model to allow object detection and tracking directly in the compressed domain before image reconstruction.

2.1 Compressive sampling

The SIG C2CS effort at object tracking as seen in the previous sections has been shown to provide an effective approach for data compression if only moving foreground objects are of interest in a video scene. This would be appropriate for applications where the goal is to detect & track objects as well as to detect anomalous object behaviors. In such application, we could clearly compress high rate data streams based on selective representation of objects and background to send only data relevant to tracking objects.

The concept of compressive sensing (CS) also allows information to be extracted from sensor data (including video image sequences) using significantly fewer samples relative to conventional uniform sampling techniques. As indicated in our Year III planning letter, this related technology has been the subject of an effort to examine the approach of combining CS approaches to track objects in time-multiplexed video imagery.

2.2 Applications

In DoD surveillance applications, the Field-of-Regard (FOR) has become too large for a single imaging sensor to capture the activities for timely exploitation. Using a scanning imaging system will require large areas of the FOR to go un-sensed while the scanner is imaging another area. Multiple sensors or platforms will result in a possibly unmanageable data glut and require extra processing (such as sensor registration or mosaicing). For image-based Automatic Target Recognition (ATR) applications one has the distinct possibility that there is significant mismatch between what is being sensed, and what is optimal for the ATR to make a decision. For example, the imaging sensor is perhaps wasting photon collection resources to image irrelevant and confusing clutter information when more photon collection on the target of interest could increase the ATR performance. One would ideally want to use the imaging sensor to help determine the current position of the target at time samples determined by the object's velocity; while imaging other, static, portions of the scene at a lower sampling rate.

2.3 Sampling Approach

Figure 1 shows the basic approach to compressive imaging that we are investigating for object detection and tracking. Here, the traditional sampling approach is shown as an array of 128x128 pixels where each pixel is integrated over a period of 128 high resolution time steps. The assumption is that there might be some object motion that might be detectable by the high resolution sensor, but that using traditional single-pixel integration will fail to resolve the moving objects. In the proposed compressive sampling approach, however, each output value is not a single integrated pixel, but instead a liner combination of 128 values at each time interval is created to form 128 "super-pixels" at each time step. These values collected at each of the time steps can them be processed to reconstruct details (e.g. moving objects) that could not be resolved using the traditional single pixel integration approach.

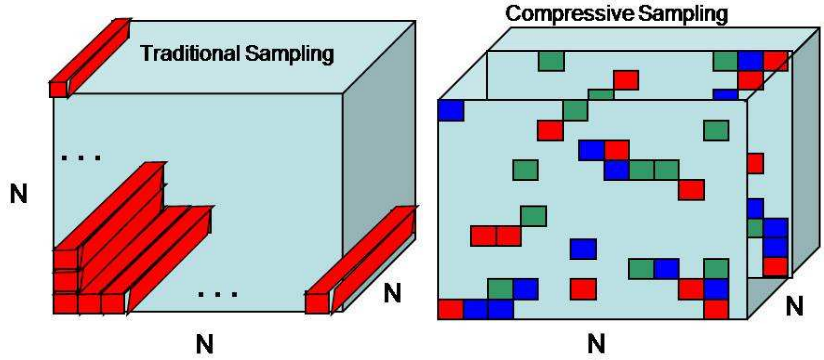

Figure 1: Left – The traditional methodology for sampling a video frame. We integrate the photons along the red rectangular elements to arrive at a pixel intensity value. Right – A compressive sampling architecture. The collections of all same colored "pixels" are integrated together as a large "super-Pixel". There are N super-Pixels collected at N different time intervals. The spatial distribution of the same colored pixels are randomized.

2.4 Initial Results

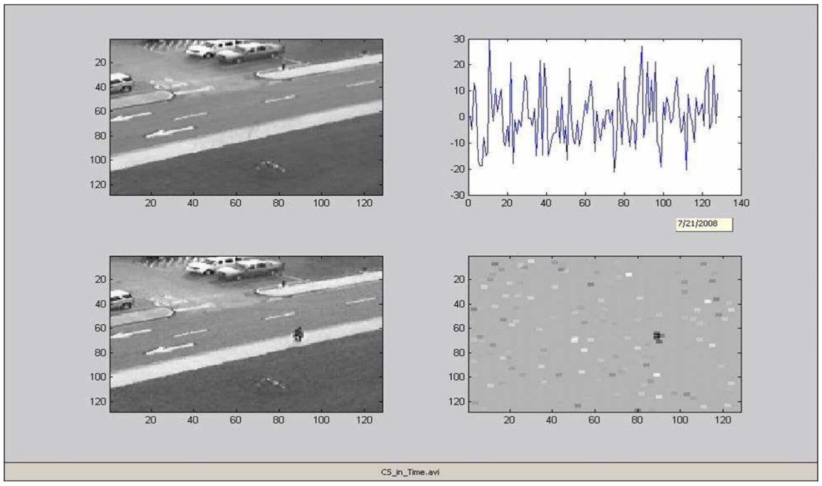

Figure 1: Top Left: The information scene by a traditional camera. Top Right: the vector of data collected during the compressive sampling (linear function of each image). Bottom left: The ground truth video. This is unobservable to the system as we are assuming the motion is too fast from traditional sampling. Bottom right: The successive estimates of the difference imagery collected and estimated.

Figure 2 shows an initial result of the compressive imaging approach whereby the difference between successive images is found before image reconstruction. Note that each 128x128 pixel image is compressively samples by only 128 samples at each frame.

3 Future Directions

During the next reporting period, we will continue work on using the concepts of compressive sensing to address object detection and tracking. We will continue the work on transition of the C2CS technology for airborne persistent surveillance applications, as well as for integration with systems that use analyst-in-the-loop technology for analyst cueing. We will also prepare the final report for the SIG C2CS effort to close out the contract period.