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Efficient Object Tracking in WAAS Data Streams

by

Trevor R.H. Clarke

Thesis

Presented to the Faculty of the Graduate School of
Rochester Institute of Technology
in Partial Fulfillment
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Dedicated to Robert Clarke
for his never ending support
in all my endeavors

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Trevor R.H. Clarke

Abstract

Wide area airborne surveillance (WAAS) systems are a new class of remote sensing imagers which have many military and civilian applications. These systems are characterized by long loiter times (extended imaging time over fixed target areas) and large footprint target areas. These characteristics complicate moving object detection and tracking due to the large image size and high number of moving objects. This thesis evaluates existing object detection and tracking algorithms with WAAS data and provides enhancements to the processing chain which decrease processing time and increase tracking accuracy. Decreases in processing time are needed to perform real-time or near real-time tracking either on the WAAS sensor platform or in ground station processing centers. Increased tracking accuracy benefits real-time users and forensic (off-line) users. The original contribution of this thesis increases tracking efficiency and accuracy by breaking a WAAS scene into hierarchical areas of interest (AOIs) and through the use of hyperspectral cueing

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1 Overview

Wide area airborne surveillance (WAAS) systems are a new class of remote sensing imagers which have many military and civilian applications. These systems are characterized by long loiter times (extended imaging time over fixed target areas) and large footprint target areas. These systems may be airborne or orbital and may contain sensors from any imaging modality (synthetic aperture radar (SAR), hyperspectral (HSI), thermal (TIR), and electro-optical (EO) systems have all been developed). The data streams generally have high spatial resolution and low temporal resolution. A system from Persistent Surveillance Systems, for example, generates 96 megapixel EO frames at about 1 frame per second. There are two major difficulties created by WAAS systems: a non-stationary camera makes tracking of moving objects difficult and tracking the many objects in a scene is computationally expensive. The main contribution of this thesis will be to adapt existing tracking algorithms to WAAS data streams. This is augmented by a target nomination algorithm used to reduce the size of the tracking space.

WAAS systems often circle a fixed target area in order to increase loiter time. This generates additional image motion which complicates object tracking. Existing tracking algorithms are designed for use in fixed camera situations or traditional unmanned aerial vehicle (UAV) full motion video (FMV). Much work has been done developing and adapting tracking algorithms for use with standard UAV video. Wenshuai Yu[1] has developed a framework for moving target detection and tracking for use with near real-time UAV video. Jiangjian Xiao[2] has shown two methods for tracking vehicles and people in UAV video. Isaac Cohen[3] has developed an algorithm which uses a directed acyclic graph of detected objects to register video and track objects even when the object tracks are partially obscured.

These systems fail to address the second major difficulty with WAAS streams. Large target footprints expose many targets (hundreds or more), many of which are partially obscured for portions of the video sequence. Identifying and accurately tracking this many objects is a computationally expensive operation. Human operators rarely need to track all of these objects simultaneously and concentrate on an area of interest for near real-time exploitation. Target nomination using supplemental HSI or other data will be explored as a way to shrink the tracking space. These techniques will be demonstrated on data from the Air Force Research Labs Angel Fire project, as well as data from aircraft mounted HSI sensors. The original contribution of this thesis is an increase in tracking efficiency and accuracy by breaking a WAAS scene into hierarchical areas of interest (AOIs) and through the use of hyperspectral cueing.

2 Thesis Objective

The objectives of this thesis are to determine the effectiveness of existing tracking algorithms on WAAS data, increase the efficiency of existing algorithms on WAAS data, and increase the accuracy of object tracks in WAAS data.

There is a large body of prior research dealing with object tracking in airborne video data. Most of this research deals with low spatial resolution, full frame rate EO video. A goal of this thesis is to gauge the applicability of these techniques to WAAS data, which has high spatial resolution and low frame rate. Existing algorithms will be modified to work on the lower frame rate WAAS data and their effectiveness judged against human derived object tracks.

The lower spatial resolution video data typically used for object tracking constrains the number of objects available for tracking. The high spatial resolution of WAAS data coupled with common uses of this data, such as large event security monitoring, lead to a large number of objects which need to be tracked. This can complicate tracking as there is a greater number of similar objects following similar tracks. Determining which object belongs to which track and maintaining the proper track can be difficult. This problem is also addressed by this thesis.

3 Background

Object detection and tracking are difficult with WAAS data. Large spatial resolution increases the number of objects which need to be tracked and increases the computational requirements needed for detection and tracking. The low frame rate also complicates tracking as object motion predictions have greater variability from frame to frame.

Most object detection and tracking systems can be structured in a processing pipeline with a number of common steps. Not all steps are present in all systems but this pipeline provides a useful abstraction for comparison and evaluation of different techniques. The pipeline in Figure 1 will be used for discussion.

Many WAAS systems use multiple cameras to capture the image data. These images need to be mosaiced into a single frame. This is typically performed by the sensor's internal processing pipeline using a camera model specific to that particular imaging system. Generic mosaicing algorithms exist but this thesis will assume that the sensor specific mosaicing algorithms are sufficient and will concentrate on other portions of the tracking pipeline.

WAAS platforms are in motion relative to the ground so the apparent motion of objects in a video sequence consists of the actual object's motion combined with the motion of the WAAS platform. Some algorithms require the platform to be stable so algorithms are needed to stabilize a video stream relative to the ground. This stabilization may be accomplished by the platform's mosaicing algorithm but this stabilization is often coarse and may need refinement.

Object detection is a key step in the tracking pipeline. Detection algorithms may require multiple video frames or a single frame for detection. There may be different methods of detection for objects which are part of an existing track. A number of detection algorithms will be discussed in detail later in this section.

Figure 1: Tracking pipeline

The primary decision point in the tracking pipeline determines if a detected object is in an existing object track or if it represents a new object. This decision may be implicit in the object detection step if a separate algorithm is used to detect existing objects. Alternately, it may be an explicit step in the pipeline. There are a couple of classes of tracking algorithms in general use. Predictive tracking algorithms use existing information about a track and an object to estimate where that object will reside in the next frame. This prediction is used to search for objects within a threshold of the predicted location. The other class is matching algorithms. These algorithms attempt to associate newly detected objects with existing tracks using a variety of metrics. If a match is found, the track is extended; otherwise the object is considered new. Some algorithms may implement a hybrid approach using data from both methods.

The object prediction step is used in predictive tracking algorithms to predict the next probable location for an object. Matching algorithms use this stage to generate model parameters which will be used to match objects in the next frame.

A number of algorithms will be presented and discussed below. Basic information on the algorithm will be presented along with information on how the algorithm has been used in existing tracking applications. Some algorithms may encompass multiple stages in the tracking pipeline or just a single stage.

3.1 RX Filter

A common anomaly detection algorithm, often used as a baseline anomaly detector for comparison with other algorithms, was developed by Reed and Yu [4]. This algorithm is commonly called the RX detector (RXD), RX filter, or simply RX. The classic expression of RXD is shown in Equation 1 and is referred to as $K - RXD$.

$$\delta^{K-RXD}(r) = (r - \mu)^T K_{L \times L}^{-1} (r - \mu) \quad (1)$$

The K refers to the sample covariance matrix, r is the L length vector of spectral intensities at a particular spatial location and μ is the sample mean. A modification shown in Equation 2 uses the sample correlation matrix (R) and is sometimes used in optimized implementation since the sample mean is not needed. It is referred to as $R - RXD$ to distinguish it from the covariance version, $K - RXD$.

$$\delta^{R-RXD}(r) = r^T R_{L \times L}^{-1} r \quad (2)$$

Both forms of RXD are related to the Mahalanobis distance which measures the similarity between an unknown sample set and a known one. Further explanation of the properties and application of RXD can be found in [5] and a number of other introductory texts on hyperspectral data exploitation.

3.2 Nested Spatial Window Target Detector (NSWTD)

NSWTD is an anomaly detection algorithm for hyperspectral data discussed in [6]. It can be used for object detection in a tracking pipeline. A group of three concentric spatial windows is used to detect objects which are statistically distinct from their background. A spatially large window contains a medium sized window and a small window. The two smaller windows represent potential target sizes and the large window will be used to calculate the background statistics. NSWTD uses a metric known as orthogonal projection divergence (OPD) shown in Equation 3.

$$\begin{aligned} OPD(s_i, s_j) &= \sqrt{s_i^T P_{s_j}^\perp s_i^T + s_j^T P_{s_i}^\perp s_j^T} \\ P_{s_j}^\perp &= I_{L \times L} - s_k (s_k^T s_k)^{-1} s_k^T \quad \forall k = i, j \end{aligned} \quad (3)$$

Where I is an identity matrix, s^T is the signal to noise ratio maximization operator from orthogonal subspace projection[7] and s_i, s_j are vectors representing pixel spectra.

The OPD equation must be calculated twice, once between the inner and middle windows as in Equation 4 and once between the middle and outer windows as in Equation 5.

$$\delta_1^{2W-NSW}(r) = OPD(m_{in}(r), m_{d,1}(r)) \quad (4)$$

$$\delta_2^{2W-NSW}(r) = OPD(m_{mid}(r), m_{d,2}(r)) \quad (5)$$

Where $m_{d,1}$ is the mean of the outer window minus the inner window and $m_{d,2}$ is the mean of the outer window minus the middle window. Finally, the three window NSW is calculated by Equation 6.

$$\delta^{3W-NSW}(r) = \max_{i=1,2}(\delta_i^{2W-NSW}(r)) \quad (6)$$

This gives a metric for each pixel which can be thresholded to determine if the pixel is anomalous. According to [8], the NSWTD algorithm is faster than other, common anomaly detection algorithms such as RX while providing good detection results for targets of varying sizes.

3.3 Spectral Angle Mapper (SAM)

SAM is a common hyperspectral classification algorithm[9]. It can be used for object detection in a tracking pipeline or it may be used as an input to a matching-based object tracking algorithm. Spectra are compared pair-wise by treating the spectral vectors as points in n-dimensional space, normalizing to unit vectors, and calculating an angle between the two vectors. Since the vectors are normalized, this method is invariant to illumination level. SAM is a way to quickly determine similarity between two spectra and is a useful filter when the spectral angles are thresholded against a fairly high target angle. Other spectral comparison algorithms provide more accurate similarity results but SAM is extremely fast and is a good first cut for similarity filtering of pixels.

3.4 Optical Flow Estimation

Optical flow is the apparent motion of objects, surfaces, and edges between frames. This motion is typically caused by motion of the camera and motion of individual objects in the scene. A number of methods are available for estimating optical flow but they generally fall into two categories.

Dense estimation techniques map all pixels in the first frame to corresponding pixels in the second frame. Dense techniques are quite accurate and provide motion vectors for all the data in a frame but are generally very computationally expensive. They are typically used on very small scenes or subsets.

Sparse estimation techniques map a subset of pixels from one frame to another. This subset may be an actual subset of pixels chosen by some external criteria or it may amalgamate pixels into blocks and calculate the motion of the blocks. While less accurate, sparse techniques are generally effective for calculating camera motion since a majority of pixels will have the same flow vectors.

The Lucas-Kanade (LK) [10] method was originally proposed as a dense estimation method but has since been adapted to become a sparse estimation method. LK can be used as a sparse estimator since it only relies on spatially local information when estimating a pixel's motion. The motion of a subset of pixels can be calculated and these can be used as an estimate for the motions of the other pixels.

The local information is derived from a small window around the pixel in question. This has a serious drawback in that large motions which fall outside of this window can not be calculated. A pyramidal version of LK can be used to overcome this deficiency. LK is first run on a low detail version of the image, in essence a series of image blocks. This accounts for larger motions since a window of a fixed size encompasses a larger percentage of the frame at a lower detail level. This is repeated on one or more additional detail levels until the full detail frame is used.

LK make a few assumptions about the frames.

1. Brightness consistency - A pixel or object from one frame to another has fairly consistent brightness levels.
2. Temporal persistence - A pixel or object makes only small movements. Small is not an exact qualifier and relates to the overall size of the frame.
3. Spatial coherence - Neighboring pixels belong to the same surface, project to nearby points on the image plane, and have similar motion.

These assumptions can be represented by equations 7 where I is the intensity of pixel $x(t)$ at frame t .

$$\begin{aligned}
 f(x, t) &\equiv I(x(t), t) = I(x(t + dt), t + dt) \\
 \frac{\partial f(x)}{\partial t} &= 0 \\
 \frac{\partial I}{\partial x} \Big|_t \left(\frac{\partial x}{\partial t} \right) + \frac{\partial I}{\partial t} \Big|_{x(t)} &= 0 \\
 v &= - \frac{I_t}{I_x}
 \end{aligned} \tag{7}$$

Starting with the brightness invariance and temporal persistence and applying the chain rule for partial differentiation we end up with the second to last equation. We substitute I_x , v , and I_t for each term to indicate the spatial brightness derivative, the velocity, and the temporal brightness derivative. This yields the final form which is the basis for LK. The form indicated is the one dimensional case but can be easily extended to two dimensions.

The change in space for a given time period is measured by finding strong corners in the edge image of each frame. We search for corresponding corners in a local window and calculate an initial estimate. Since brightness will be somewhat variable, the corners will not correspond exactly

so we use Newton's method to refine the estimate using edge information in the spatial window. A more in depth derivation of LK is available in [11] including a discussion of the strengths and weaknesses of the technique.

3.5 RANSAC

Random sample consensus (RANSAC) [12] is a method used to fit a model to observed data. RANSAC is an iterative method which is robust against outliers.

The algorithm works by randomly selecting a number of points from the observed data and fitting a model to those points. Each point in the data which is not in this set is tested against the model estimate. If the calculated error is less than a threshold it is added to a set of consensus points. The algorithm is halted when the size of this consensus set exceeds a threshold or a maximum number of iterations has occurred. The model with the largest consensus set is selected.

While robust, RANSAC has no upper bound on execution time. The maximum iteration count is used to force an upper bound but exiting the algorithm this way results in a sub-optimal model. It is possible to calculate the probability that RANSAC will generate a model with a maximum error value and a maximum number of iterations. This information can be used to adjust these two parameters in order to control the execution time or the margin of error.

3.6 Hyperspectral Cueing

Cueing as it relates to video tracking uses the video data or other, external data to mark candidate objects or areas of interest. The supplemental data reduces the search space for the primary tracking algorithm or supplements the primary tracking algorithm to increase the object detection accuracy. Hyperspectral cueing uses external hyperspectral imagery to locate areas of interest and to increase tracking accuracy. Anomaly detectors such as K-RXD locate areas of interest based on spectral dissimilarity. These areas of interest are intersected with the pixels flagged during motion estimation. The other use of hyperspectral imagery is to supplement tracking of identified objects. Objects in two frames of data are compared using a signature comparison algorithm such as SAM. Comparing the spectral signatures of two objects provides additional information when determining if these are the same object and thus constitute part of an object track.

3.7 Wang Tracking Algorithm

The tracking algorithm used by Wang, et al. [13] is a hybrid object tracking algorithm which uses matching-based and prediction-based techniques. Four values are examined to decide if an object is a candidate for addition to a track: object trajectory, object size, grayscale distribution, and object texture. Wang's tracking algorithm requires a stabilized video stream. Stabilization is accomplished by calculating an edge image for each frame and using a few coincident frames to

estimate the bilinear projective model for the camera motion. [14][15] Object detection in Wang's method utilizes a wavelet transform and the bilinear predictive camera model to remove camera motion. The resultant differences between various levels of the wavelet pyramid identify objects. Wang's end goal is a motion prediction system which is used to compress video streams. Other portions of the compression utilize the wavelet transform, so this is a process with zero additional cost. The wavelet transform can be computationally expensive and will not be discussed in further detail. It was used by Wang since the wavelet transformed needed to be calculated for a non-tracking algorithm thus the data was already available for used for object detection. The object tracking portion of Wang's pipeline is of primary interest for this thesis.

Object position is defined in Equation 8 as the centroid of a detected object.

$$\begin{aligned} c_x &= \left(\sum_{(i,j) \in O} p_{i,j} \cdot i \right) / \left(\sum_{(i,j) \in O} p_{i,j} \right) \\ c_y &= \left(\sum_{(i,j) \in O} p_{i,j} \cdot j \right) / \left(\sum_{(i,j) \in O} p_{i,j} \right) \end{aligned} \quad (8)$$

Where O is the set of coordinates of an object area and $p_{i,j}$ is the value of the edge image at position (i, j) . Object motion over a few frames is assumed to be a straight line with constant acceleration. Three frames are used to calculate speed v and acceleration a in Equation 9. These values predict a location for the current frame which is compared to the candidate object.

$$S = vt + \frac{1}{2}at^2 \quad (9)$$

With an adequate framerate, object size does not change significantly from frame to frame. A dispersion value as calculated by Equation 10 is a metric for measuring object size. This equation determines how far from the object centroid a nearly uniform gray level extends. (c_x, c_y) represents to object centroid from Equation 8.

$$disp = \left(\sum_{(i,j) \in O} \sqrt{(i - c_x)^2 + (j - c_y)^2} \cdot p_{i,j} \right) / \left(\sum_{(i,j) \in O} p_{i,j} \right) \quad (10)$$

Grayscale distribution (the width of the grayscale histogram) of an object is fairly constant for objects of interest assuming the lighting conditions are constant from frame to frame. Grayscale distribution is calculated as $(g r_m, g r_h, g r_l)$ the mean of groups of pixels in the entire range, upper 10% of the range, and lower 10% of the range respectively.

The object texture measures grayscale variation across an object. Wang estimates texture by calculating the mean of the 10% of pixels with the largest values in the edge image. The method

of calculating the edge image is not discussed, but a reasonable assumption is that a common edge detection method such as the Laplacian method or Sobel method can be used.

The four metrics discussed above are calculated for candidate objects and existing tracks (as the object in the track for the previous frame). The difference between these sets of values is thresholded and metrics outside the threshold are ignored. At least three of the four metrics must be within the threshold for consideration. If no objects fit this criteria for a certain track, it is terminated. If there is an unambiguous correspondence between a single object and a single track, the track is extended. If multiple objects are candidates for a track, or multiple tracks are candidates for an object, a weighted cost is calculated for each potential object and track pairing using Equation 11. The w variables represent the weights and the f and t superscripted variables represent the metrics for the current frame and the track. Wang was not clear how the weights were determined, but it is implied that values were chosen which performed well with a set of sample data.

$$\begin{aligned}
dif = & w_{tr}(|c_x^f - c_x^t| + |c_y^f - c_y^t|) \\
& + w_{disp}(|disp^f - disp^t|) \\
& + w_{gr}(|gr_l^f - gr_l^t| + |gr_m^f - gr_m^t| + |gr_b^f - gr_b^t|) \\
& + w_{tx}(tx^f - tx^t)
\end{aligned} \tag{11}$$

Wang's algorithm is not expected to work well with WAAS data as stated due to the assumption of a reasonably high frame rate in multiple steps in the algorithm.

3.8 Cohen Tracking Algorithm

Cohen and Medioni [3] present an alternate method for object detection and tracking as well as elimination of camera movement using optical flow. This system performs object detection and matching-based object tracking.

Instead of directly modeling the 3D parameters of the camera motion, Cohen estimates the induced optical flow of coincident frames. A small set of feature points (x_i, y_i) in the image are tracked from a reference image I_0 to a target image I_1 . These two images are registered by computing the transformation $T_{I_1 I_0}$ which warps I_0 to I_1 . The parameters are estimated using an iterative minimization of the least square criterion as in Equation 12.

$$E = \sum_i (I_0(x_i, y_i) - I_1(T(x_i, y_i)))^2 \tag{12}$$

An affine model is used to approximate T and is calculated for at least three different detail

levels in an image pyramid. This transformation is incorporated into the optical flow calculation according to Equation 13.

$$\nabla I_i \nabla^T I_i w = -\nabla I_i \frac{dI_i}{dt} \quad (13)$$

Where $w = (\mu, v)^T$ is the optical flow. This equation can be used to extrapolate the normal to the optical flow in Equation 14.

$$w_{\perp} = -\frac{(I_{i+1}(T_{i+1,j}) - I_i(T_{i,j}))}{\|\nabla T_{i,j} \nabla I_i(T_{i,j})\|} \cdot \frac{\nabla T_{ij} \nabla I_i(T_{ij})}{\|\nabla T_{ij} \nabla I_i(T_{ij})\|} \quad (14)$$

$w_{\perp}$ can be used to detect residual motion after compensation for optical flow. Large values of $w_{\perp}$ occur near regions of motion. $w_{\perp}$ is thresholded and a 4-connectivity scheme is used to aggregate points into regions of residual motion.

Cohen represents potential tracks using a graph. Nodes in the graph represent blobs detected using the normal to the optical flow. Edges in the graph represent relationships between blobs in coincident frames. Edges are created by measuring grayscale similarity between blobs in a neighborhood. The size of the neighborhood is calculated based on the amplitude of the blob's motion. The eigenvalue of the potential transformation from a blob in I_0 to a blob in I_1 are attached to the associated edge. A set of attributes are also associated with each node. Cohen associates the following attributes: frame number, centroid, principal directions, mean, variance, velocity, parent ID and similarity, children IDs and similarities, and length.

Single objects may be detected as multiple blobs when using the optical flow normal. This situation can be detected in the graph when multiple blobs which are spatially close and have nearly the same direction and velocity. When this occurs, the nodes on the graph are merged to a single node and the edges updated accordingly. Detection accuracy of broken objects is increased by maintaining a dynamic template for each object and matching it to potential broken objects. The blob centroids and orientations are aligned over the last five detected frames and a median filter is applied. Cohen calls this process a *median shape template*. This filter can also detect objects which stop and then resume motion. Each blob which has no connected components in subsequent frames will be propagated some number of frames into the future. The template for this node is matched against nodes in these future frames and a positive match indicates an object which has resumed motion.

Object trajectories can be extracted from the graph by finding an optimum path through the graph. Each edge receives a cost calculated in Equation 15 where C_{ij} is the gray level and shape correlation between regions i and j . d_{ij} is the distance between centroids.

$$c_{ij} = \frac{C_{ij}}{1 + d_{ij}^2} \quad (15)$$

An optimal graph path is then calculated from a node with no successors to a node with no parent to determine an object trajectory.

Cohen's algorithm is not expected to work well with WAAS data as stated. The need to build a sizeable graph using many frames before tracks can be extrapolated lends itself to offline data processing. Using low frame rate WAAS data may create a significant delay between data collection and track determination, independent of processing resource requirements.

3.9 Camera motion compensation

The Columbus Large Image Format (CLIF) and CLIF-II data are used as a basis for motion compensation and tracking. Data from a single camera in the six camera system is used. Since a hierarchical subdivision of the image is used to target specific areas of the image to maximize the throughput, using a spatial subset is equivalent to using the entire data set and setting focus to the spatial subset. Scaling up processing to multiple machines would allow simultaneous processing of these additional areas.

4 Approach

This thesis meets the objectives of increasing tracking efficiency and accuracy by breaking a WAAS scene into hierarchical areas of interest (AOIs) and through the use of hyperspectral cueing. The size of these AOIs and the number of AOIs which are actively processed will provide a measure of control over the accuracy/efficiency ratio.

4.1 WAAS Data Characteristics

The primary datasets from the Air Force Research Labs are the Columbus Large Image Format (CLIF[16] and CLIF-II[17]) datasets. Each are approximately 12000x5000 pixels spatially and were collected with a matrix of commercial digital cameras. The panchromatic frames are 8-bit uncompressed. One dataset contains 50 frames and the other contains 56 frames. The data were collected at approximately 2 fps.

The CLIF dataset has a number of camera registration issues resulting in overlapping areas within the image. The data was acquired with a high off NADIR angle (side looking collection) and contains light industrial and farmland areas. The registration makes accurate tracking difficult as it generates a significant number of false detections and duplicate tracks. It is interesting due to

the unique location, the other data used is primarily urban, so this dataset is used for comparison of execution speed but not for accuracy of object and track detection. A sample frame is show in Figure 2.

Figure 2: Sample frame from the CLIF dataset

Within the CLIF-II dataset, the areas captured by cameras 0 and 1 are used. A single camera is a convenient region to use as it represents a reasonably sized subset of the data for the workstation used for analysis, approximately 4000x2600 pixels.

The camera 0 area is a residential neighborhood with two multi-lane roads meeting at an intersection. A number of vehicles are in motion and there are a small number of pedestrians in motion. Lighting is fairly constant and there are no large buildings showing significant parallax.

The camera 1 area contains the Ohio State University football stadium and the surrounding area. A couple of tall buildings show parallax effects and there are some noticeable reflection, sun glint, and shadow effects in and around the stadium. These effects add noise to the image which may be mistaken for moving objects. A small number of vehicles are in motion but this portion of the scene is mostly static.

Hyperspectral data from a number of sensors including NASA's AVIRIS, RIT's MISI, the US Army's COMPASS, the USGS' HYDICE, and the US Air Force's HyCas. Specific details of these

scenes are shown in Table 2.

No current collection system provides synchronized WAAS video and hyperspectral data required for integrated performance analysis of the complete cueing system. Processing throughputs of the individual compone

4.2 Frame Segmentation

An integral part of the optimizations of the various component algorithms is a hierarchical, spatial breakdown of the WAAS data. A WAAS frame was segmented into smaller sub-images arranged in a quadtree. The extent of the segmentation will vary based on the step in the tracking pipeline.

Breaking an image into smaller areas allows selective processing of a subset of the areas based on expected processing requirements. When the average processing requirements of an AOI exceed a threshold, the AOI can be further divided into four smaller AOIs and processing can be limited to one or more of these.

This independent processing of a subset of the image allows for easy exploitation of parallel computing capabilities. A number of AOIs can be processed independently on multiple computation units. Processing of a greater number of concurrent AOIs could be accomplished by increasing the number of available processing units. This aspect will not be fully explored by this thesis.

The frame segmentation is accomplished using a balanced quadtree whose leaf nodes contain sub-frames of a reasonable (user defined) spatial dimension. When objects are being actively tracked, further decomposition in areas of high object density can reduce processing load. Figure 3 shows a sample quadtree decomposition of a scene.

4.3 Motion Compensation

Motion compensation of a sub-frame is accomplished by calculating the optical flow vectors between points in neighboring frames. A pyramidal implementation of the Lucas-Kanade (LK) optical flow calculation method [10] is employed. The LK method is applied to various levels in an image detail pyramid of each sub-frame. This captures large motions using the LK method which employs a small change detection window.

Sparse tracking is used to speed up calculations. Strong corners are located in an edge image and these points are tracked between sub-frames. Once the optical flow vectors between these points are calculated, RANSAC is used to approximate the motion of the sub-frame while ignoring errors in the optical flow calculations.

The 3-D motion of the aircraft mapped to the 2-D image plane requires a perspective transform to accurately capture the sub-frame transformation but calculating this transform can be slow.

Figure 3: An unbalanced quadtree decomposition has a higher depth in areas of high object density.

An assumption is made that the altitude of the aircraft does not change significantly between neighboring frames which allows for a fairly accurate estimation of the sub-frame motion using an affine transform. This assumption does not always hold particularly in urban environments with many tall buildings. This fails to compensate for some of the parallax effect seen when looking at these buildings. Parallax is the apparent motion of an object (usually rotation about a point) due to differences in observation location. The CLIF-II dataset provides an example of this as seen in Figure 4. The apparent motion of buildings may register as object tracks but these false positives are obvious to an analyst interpreting the data. Tracking extra objects may slow down execution of the algorithm due to the additional data processing. Compensation for parallax may be addressed in future work. Once the affine transform has been estimated, one of the sub-frames can be transformed in order to remove the camera motion.

Figure 4: Apparent motion due to parallax in frames 1 and 10 of CLIF-II dataset. The motion is particularly noticeable with the building in the bottom center of the images.

4.4 Object Detection

Two object detection methods are available depending on availability of hyperspectral data. When hyperspectral data is available for a sub-frame, K-RXD is used to detect anomalous pixels in the sub-frame. K-RXD was chosen instead of NSWTD as it is less sensitive to noise than NSWTD. [18] provides a study of the accuracy and performance characteristics of a number of hyperspectral anomaly detection algorithms including RXD and NSWTD. NSWTD is potentially faster to execute and has a higher correct detection rate for high signal to noise data and is worth further exploration for future work.

When hyperspectral data is not available, frame differencing is used to remove the background. The two sub-frames are thresholded to minimize brightness differences between the two frames. Additional noise is removed by eroding the resulting threshold images. This removes single pixel noise often called salt and pepper noise or speckle. The frames are subtracted from each other to remove the background.

In either case, the resulting foreground or anomaly images are run through a morphological opening to fill in small gaps internal to the object blobs. These blobs are labeled using connected component labeling and each is treated as an object candidate.

4.5 Object Tracking

Object tracking was accomplished using a variation of Wang's tracking algorithm.

Each object is added to a directed graph as a vertex. Objects from the base frame are connected to the objects in the current frame and a number of properties are calculated on the vertices and edges.

The vertices contain a dispersion value, an object blob centroid, and a hyperspectral spectra. The edges contain the absolute difference of the dispersion values of the vertices and a velocity calculated from the object centroids. In addition, each edge compares the velocity of the previous

track edge to the current edge. Both the absolute velocity magnitude difference is calculated and the velocity vector angular difference. Finally, the spectral angle between the two objects is calculated for each edge.

Edges with a velocity magnitude exceeding a threshold are removed. This is based on the assumption that objects being tracked (usually vehicles and people) have an upper limit on their speed. A cost is calculated on the remaining edges as a weighted sum of the edge properties. F

Tracking is performed within a quadtree AOI. As a track approaches the edge of an AOI, the tracking algorithm is applied to the parent AOI in the quadtree. This larger area processing is performed for a small number of frames until the location of the object in an AOI lower in the tree can be determined. The object track information is passed to the new AOI for processing.

4.6 Testing and Verification

The following tests indicates the level of success for the thesis.

1. The efficiency of the hierarchical partitioning and hyperspectral cueing.
2. The accuracy of the tracking algorithm without hyperspectral object detection.
3. The accuracy of the hyperspectral object detection and track property.

Performance of the partitioning is determined by executing the tracking algorithm without any partitioning and comparing this to execution of the algorithm with various quadtree partition depths. Throughput in terms of megapixels per second processed is the primary metric.

Comparison of the hyperspectral cueing performance is measured is megapixels per second processed. This is compared to the collection rate of the hyperspectral sensor and to the processing throughput of the optical flow differencing method.

Accuracy of the tracking algorithm is compared to human derived truth data. Two WAAS analysts manually locate and mark objects and tracks in available data sets using techniques employed by US Air Force intelligence services. These sets of truth data are compared and outliers discarded. This technique may under-represent the number of objects and tracks in a data set but should minimize the number of false positives. The accuracy in terms of number of correctly identified tracks, false positives, false negatives, and incomplete or interrupted tracks are the primary metrics.

Table 1: Properties of hyperspectral test data

Sensor	Rows (along track)	Columns (cross track)	Bands	Data size (mpel)
Cueing System	512	256	256	32
Hydice[19]	181	97	168	2.95
COMPASS[20]	550	256	146	20.56
MISI[21]	2000	3689	16	118.05
AVIRIS[22]	512	614	197	61.93
HyCAS[23]	2664	2495	12	79.76

4.7 Hyperspectral Cueing

No current collection system provides synchronized WAAS video and hyperspectral data required for a complete hyperspectral cueing system as described in the background section. A hypothetical HSI collection system is used as the basis for hyperspectral cueing in the tracking system. The properties of this system are consistent with current HSI imaging system technologies. Performance of the system is characterized and conclusions are drawn about the utility of the system. Future work may analyze integrated WAAS and hyperspectral data collections.

The system is a whiskbroom collector which contains a 256x256 pixel CMOS imaging array which collects spectral information along one axis and spatial information along the other. Light enters the system and is reflected off a rotating mirror, passes through a prism and is directed to the detector array. The mirror slowly rotates which collects data across the second spatial dimension. The speed of the mirror and extent of the rotation for which data is captured define the collection rate and width of the collected swath. The size of the imaging array defines the height and each swath and the number of spectral bands collected, 256 for each. Bands are in the visible and near-IR spectral region; 400nm to 1000nm. A swath with a width of 512 pixels can be collected in approximately 10 seconds including time to reset the mirror to the start position. The collection platform can be moved such that a swath can be collected anywhere in the ground area covered by the panchromatic WAAS imager. The maximum time to move the imager across the entire WAAS field of view is less than or equal to 10 seconds. This means that the worst case collection rate including repositioning of the imager is 20 seconds per swath. This yields a collection rate in megapixels between 1.6mpel/s and 3.3mpel/s .

A number of existing hyperspectral sensor images have been used for experimental testing. These sensors share some properties with the hypothetical system so they can be used to extrapolate performance characteristics of the hypothetical system. All datasets contain data in the visible and near-IR spectral regions providing complete or nearly complete overlap with the proposed system. The datasets used have the following characteristics.

5 Results and Discussion

5.1 Hyperspectral Anomaly Detection

The K-RXD implementation was tested on 5 hyperspectral data cubes and information on performance was calculated. The resulting anomalous regions were reviewed by 2 hyperspectral data analysts to ensure the results are reasonable and correct. Validation is purely subjective and the experience of the analysts is used to lend credibility to the opinions. The analysts visually inspected the spectra of a sample of flagged pixels to surrounding pixels. Inspection took approximately 10 minutes per data set per analyst. In all cases, the analysts felt the indicated anomalous regions are reasonable and correct. A visual comparison of the results with results from a similar anomaly detection algorithm in the ENVI tool indicates nearly identical anomalous pixels. The exact details of the ENVI detector are not known as that information is not made available in the documentation for the tool. ENVI is a frequently used tool for hyperspectral analysis so it is reasonable to assume that it generates valid results.

Figure 5: MISI K-RXD Results (in yellow)

The five data sets used have the following properties. Band counts do not include "bad bands" which contain invalid data. This invalid data is usually due to atmospheric absorption spectral regions which yield very low signal to noise values. In most cases data does not represent a single swath either because the sensor is not a whiskbroom sensor or multiple whisks had already been combined into a single image. All tests were run on a Windows XP 64-bit workstation with 4GB of RAM and an Intel Core2 E8500 dual-core CPU running at 3.17GHz.

Table 3 shows timing information for the K-RXD implementation. The values indicate the average of five executions of the algorithm for each data set. Absolute times are shown for the entire algorithm execution minus the overhead introduced by unrelated processes such as graphical display of the results and for the execution of the covariance matrix calculations. The data is also presented as a throughput in terms of megapixels per second. The covariance matrix calculations are performed by a separate plug-in which prevented certain optimizations such as calculation of the covariance matrix and sample mean in the same loop. Therefore, the execution time of

Table 2: Properties of datasets used for K-RXD timing

Sensor	Rows (along track)	Columns (cross track)	Bands	Data size (mpel)
Hydice	181	97	168	2.95
COMPASS	550	256	146	20.56
MISI	2000	3689	16	118.05
AVIRIS	512	614	197	61.93
HyCAS	2664	2495	12	79.76

Table 3: Execution times and throughput for K-RXD

Sensor	Execution Time (ms)	Throughput ($mpel/s$)	Optimized Throughput ($mpel/s$)
Hydice	3132	0.9417	1.310
COMPASS	20402	1.008	1.441
MISI	77315	1.527	2.737
AVIRIS	66685	0.9287	1.261
HyCAS	52016	1.533	2.762

the loop which calculate the sample mean has been removed and the throughput recalculated to estimate the throughput of an implementation with this optimization.

This yields an average throughput across all the data set of $1.188\text{ }mpel/s$ and a standard deviation of 0.3140 . Applying the stated optimization, the average throughput is $1.902\text{ }mpel/s$ and a standard deviation of 0.7763 . This is between 57% and 75% of the estimated collection rate of the hypothetical hyperspectral sensor. It is clear that further optimization would be necessary to maintain the hardware collection throughput. A faster processor or more highly optimized implementation seems within reach especially if the anomaly detection is performed on the collection hardware using a highly optimized DSP implementation. The correlation matrix variant R-RXD may also provide a more efficient implementation. Finally, the number of spectral bands in the data strongly effects the calculation throughput. The number of bands increases the size of the matrices and vectors in the RXD calculations which the spatial resolution effects the number of times the RXD calculations are made. The higher order complexity of the RXD calculation (due to three matrix multiplications) accounts for this effect. Minimizing the number of spectral bands needed for adequate anomaly detection can also increase the throughput of the algorithm.

5.2 Motion Compensation

Table 4 shows timing information for the optical flow motion compensation implementation. The values indicate the average of five executions of the algorithm for each data set. Absolute times are shown for the entire algorithm execution for a single frame. Times include overhead introduced by informational display processes. The data is also presented as a throughput in terms of megapixels per second.

This yields an average throughput across all the data set of $6.6614\text{ }mpel/s$ and a standard

Table 4: Execution time and throughput for motion compensation

Sensor	Size (mpel)	Execution Time (ms)	Throughput ($mpel/s$)
CLIF	61.28	6690.00	9.1645
CLIF-II camera 0 (vehicle traffic)	10.23	1769.64	5.8119
CLIF-II camera 1 (noise from sun glint)	10.23	2045.13	5.0079

deviation of 2.2047. These values suggest that processing has a noticeable per frame constant overhead. Much of this can likely be attributed to informational data visualization which would not be needed in a production implementation. Even though the current implementation does not meet the expected 1fps data rate of the sensor, it is reasonable to assume additional optimizations and a faster CPU can achieve the desired processing rate at the single camera resolution. This sensor has six cameras which can be processed on multiple compute cores.

Figure 6: CLIF-II Motion Correction

from top left CLIF-II frame 0, frame 1 with optical flow vectors, frame 0 corrected for sensor motion

5.3 Object Detection

Figure 7 shows two frames from the CLIF-II dataset. Optical flow camera motion correction has been applied to the frames. Objects detected from residual motion are shown and color coded to indicate distinct objects. All moving objects have been at least partially identified although in

Table 5: Execution time and throughput for residual motion object detection

Sensor	Size (mpel)	Execution Time (ms)	Throughput (<i>mpel/s</i>)
CLIF-II full scene	61.40	3285.6	19.187
CLIF-II camera 0	10.23	476.68	21.476
CLIF-II camera 1	10.23	483.28	21.228

some cases only part of the object have been flagged. In another case, two cars passing each other are flagged as the same object in frame 1.

Timing information for object detection for two sub-sets of the CLIF-II dataset are shown below. Camera 0 contains an intersection with a number of moving vehicles. Camera 1 has fewer moving vehicles and a significant amount of noise due to shadows and sun glint. The results are averaged over 5 frame transitions. The standard deviation for the camera 0 data is 0.6146 and for camera 1 is 0.4872. Full scene data is also included so that some information on scaling can be inferred. The standard deviation for the full scene data is 1.629.

Figure 7: CLIF-II Object Detection

left to right from top CLIF-II frame 0, frame 1, frame 0 with detected object, frame 1 with detected objects

5.4 Object Tracking

A WAAS analyst was asked to locate moving objects and assign tracks over 5 frames of data. A mission objective is always provided when WAAS analysis is performed. This allows the analyst to limit evaluation to relevant data. The situation presented was a need to divert a VIP motorcade through a residential neighborhood. The analyst was asked to provide a situational awareness report within a short suspense of 10 minutes. Figure 8 shows identified tracks in the CLIF-II

camera 0 scene. The blue tracks represent objects located in the raw data stream and the green tracks represents objects located after camera motion was removed. The importance of camera motion compensation can be seen by the number of additional tracks found after motion compensation. Figure 9 shows a similar image comparing the analyst tracks to objects located using the automated method. Detail of the intersection is show in Figure 10 as this area of the data has a significant amount of activity. These images show that the analyst was able to locate 7 additional tracks, some of them indicating very little motion. These slower objects are people which the algorithm has difficulty detecting. This is likely due to the various blurring operations and morphological erosions which remove small detected object candidates. There are also a number of tracks which the algorithm located but it required an additional frame of data. Looking more closely at these locations indicates that the objects are obscured by shadows in all cases. This results in dark areas a low signal to noise ratio which are likely removed during the threshold portion of the object detection algorithm.

Figure 8: Tracks found in raw data (blue) and in data with camera motion removed (orange)

Another problem can be seen in Figure 10 near the center of the image on the upper right road. Two cars are passing each other but the algorithm detects a single, multi-lobed object instead of two distinct objects. Hyperspectral data for this scene is not available but if it were, the different spectra of the two vehicles, due to different paint colors, would be used to distinguish the two vehicles. Figure 11 compares the spectra of two vehicles with different paint colors.

Tracking objects which leave a sub-frame can be non-optimal in some circumstances as shown in Figure 12. An object moving outside of a sub-frame, represented by locations 1, 2, and 3, will reach the edge of sub-frame A at location 2. Tracking this object to location 3 requires processing of a larger sub-frame. The next larger sub-frame is B but the edge of A is also the edge of B. Therefore the entire frame must be processed in order to locate position 3 in sub-frame C. This

Figure 9: Tracks found in data with camera motion removed (orange lines) and objects found using the automated method. The two colored blobs indicate object locations in different frames.

Figure 10: Intersection detail with analyst tracks and automated object detection.

could be resolved by allowing arbitrary sub-frames but this increases the number of possible sub-frames. Another way to address this problem is to locate the adjacent sub-frame instead of using the next larger sub-frame in the quadtree.

Figure 11: Spectral comparison of two car paint colors.

6 Conclusions

The algorithms presented in this thesis are effective at compensating for camera motion in WAAS data, locating objects of interest in hyperspectral and panchromatic WAAS data, and identifying tracks between interconnected objects. The execution speed and throughput for these algorithms is not sufficient to match the framerate of the WAAS data at full spatial resolution. Processing a portion of the image using a quadtree decomposition on the frames maintains the framerate of the data. The size of the processing area can be adjusted to match the processing capability of the workstation.

The K-RXD hyperspectral anomaly detection algorithm is effective at locating spectrally distinct areas in images with varying signal to noise. However, other anomaly detection algorithms may be more efficient in terms of processing requirements. Further exploration of other anomaly detection algorithms, especially NSWTD may decrease the processing requirements for hyperspectral cueing without serious effect on the quality of the results.

The lack of availability of coordinated hyperspectral and WAAS data collections prevents an integrated test of the proposed tracking system. While this thesis provides arguments that the integrated system will prove efficient and effective in production situations, coordinated data collections of both types of imagery are required to continue research on this topic. The increased interest in WAAS by commercial and government entities suggests that these data collects may

Figure 12: An object at locations 1, 2, and 3 in subsequent frames requires processing of the entire image.

occur in the coming years. Testing the integrated system on operational data is of prime interest for future research.

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A Source Code Listing

The following pages contain source code listings for the test application. This source code builds a plug-in for the Opticks analysis workbench which can be obtained from <http://www.opticks.org>

```
1  /*
2  * The information in this file is
3  * Copyright(c) 2010 Ball Aerospace & Technologies Corporation
4  * and is subject to the terms and conditions of the
5  * GNU Lesser General Public License Version 2.1
6  * The license text is available from
7  * http://www.gnu.org/licenses/lgpl.html
8  */
9
10 #include "AoiElement.h"
11 #include "AppVerify.h"
12 #include "BitMaskIterator.h"
13 #include "DataAccessorImpl.h"
14 #include "DataRequest.h"
15 #include "DesktopServices.h"
16 #include "ObjectResource.h"
17 #include "PlugInArgList.h"
18 #include "PlugInManagerServices.h"
19 #include "PlugInRegistration.h"
20 #include "PlugInResource.h"
21 #include "ProgressTracker.h"
22 #include "RasterDataDescriptor.h"
23 #include "RasterElement.h"
24 #include "RasterUtilities.h"
25 #include "SpatialDataView.h"
26 #include "Rx.h"
27 #include "ThresholdLayer.h"
28 #include <gsl/gsl_blas.h>
29 #include <gsl/gsl_matrix.h>
30
31 REGISTER_PLUGIN_BASIC(Tracking, Rx);
32
33 Rx::Rx()
34 {
35     setName("Rx");
36     setDescriptorId("{55f85fb3-1a65-4686-9fdf-2c759383fbcf}");
37     setSubtype("Anomaly Detection");
38     setMenuLocation("[Tracking]/RX");
39 }
40
41 Rx::~Rx()
42 {
43 }
44
45 bool Rx::getInputSpecification(PlugInArgList*& pArgList)
46 {
47     VERIFY(pArgList = Service<PlugInManagerServices>()->getPlugInArgList());
48     VERIFY(pArgList->addArg<Progress>(ProgressArg(), NULL));
49     VERIFY(pArgList->addArg<RasterElement>(DataElementArg()));
50     VERIFY(pArgList->addArg<SpatialDataView>(ViewArg()));
51     VERIFY(pArgList->addArg<AoiElement>("AOI", NULL));
52     return true;
53 }
54
55 bool Rx::getOutputSpecification(PlugInArgList*& pArgList)
56 {
57     VERIFY(pArgList = Service<PlugInManagerServices>()->getPlugInArgList());
58     VERIFY(pArgList->addArg<RasterElement>("Results"));
59     return true;
60 }
61
62 bool Rx::execute(PlugInArgList *pInArgList, PlugInArgList *pOutArgList)
63 {
64     VERIFY(pInArgList);
65     ProgressTracker progress(pInArgList->getPlugInArgValue<Progress>(ProgressArg()),  
        "Executing RX.", "COAN", "{f5a21b68-013b-4d32-9923-b266e5311752}");
```

```

66
67   RasterElement* pElement = pInArgList->getPlugInArgValue<RasterElement>
    (DataElementArg());
68   SpatialDataView* pView = pInArgList->getPlugInArgValue<SpatialDataView>(ViewArg());
69   AoiElement* pAoi = pInArgList->getPlugInArgValue<AoiElement>("AOI");
70
71   if (pElement == NULL)
72   {
73       progress.report("No element specified.", 0, ERRORS, true);
74       return false;
75   }
76   RasterElement* pCov = NULL;
77   { // scope
78       bool success = true;
79       ExecutableResource covar("Covariance", std::string(), progress.getCurrentProgress
    (, isBatch()));
80       success &= covar->getInArgList().setPlugInArgValue(DataElementArg(), pElement);
81       if (isBatch())
82       {
83           success &= covar->getInArgList().setPlugInArgValue("AOI", pAoi);
84       }
85       success &= covar->execute();
86       pCov = static_cast<RasterElement*>(
87           Service<ModelServices>()->getElement("Inverse Covariance Matrix",
    TypeConverter::toString<RasterElement>(), pElement));
88       success &= pCov != NULL;
89       if (!success)
90       {
91           progress.report("Unable to calculate covariance.", 0, ERRORS, true);
92           return false;
93       }
94   }
95   const RasterDataDescriptor* pDesc = static_cast<const RasterDataDescriptor*>
    (pElement->getDataDescriptor());
96   const BitMask* pBitmask = (pAoi == NULL) ? NULL : pAoi->getSelectedPoints();
97   BitMaskIterator iter(pBitmask, pElement);
98   FactoryResource<DataRequest> pReq;
99   pReq->setInterleaveFormat(BIP);
100  pReq->setRows(pDesc->getActiveRow(iter.getBoundingBoxStartRow()), pDesc->
    getActiveRow(iter.getBoundingBoxEndRow()));
101  pReq->setColumns(pDesc->getActiveColumn(iter.getBoundingBoxStartColumn()), pDesc->
    getActiveColumn(iter.getBoundingBoxEndColumn()));
102  DataAccessor acc(pElement->getDataAccessor(pReq.release()));
103
104  ModelResource<RasterElement> pResult(static_cast<RasterElement*>(
105      Service<ModelServices>()->getElement("RX Results", TypeConverter::toString
    <RasterElement>(), pElement)));
106  if (pResult.get() != NULL && !isBatch())
107  {
108      Service<DesktopServices>()->showSuppressibleMsgDlg("RX Results Exists",
109          "The results data element already exists and will be replaced.",
110          MESSAGE_WARNING, "Rx/ReplaceResults");
111      Service<ModelServices>()->destroyElement(pResult.release());
112  }
113  pResult = ModelResource<RasterElement>(
114      RasterUtilities::createRasterElement("RX Results", iter.getNumSelectedRows(),
    iter.getNumSelectedColumns(), FLT8BYTES, true, pElement));
115  if (pResult.get() == NULL)
116  {
117      progress.report("Unable to create results.", 0, ERRORS, true);
118      return false;
119  }
120  FactoryResource<DataRequest> pResReq;
121  pResReq->setWritable(true);
122  DataAccessor resacc(pResult->getDataAccessor(pResReq.release()));
123  if (!acc.isValid() || !resacc.isValid())

```

```

124 {
125     progress.report("Unable to access data.", 0, ERRORS, true);
126     return false;
127 }
128 { // scope temp matrices
129     int bands = pDesc->getBandCount();
130     EncodingType encoding = pDesc->getDataType();
131     gsl_matrix covMat = {bands, bands, bands, reinterpret_cast<double*>(pCov->
132     getRawData()), NULL, 0};
133     gsl_matrix* pPixelMat = gsl_matrix_alloc(bands, 1);
134     gsl_matrix* pTemp = gsl_matrix_alloc(1, bands);
135     gsl_matrix* pMuMat = gsl_matrix_calloc(bands, 1);
136     for (int row = iter.getBoundingBoxStartRow(); iter != iter.end(); ++iter)
137     {
138         LocationType loc;
139         iter.getPixelLocation(loc);
140         if (loc.mY > iter.getBoundingBoxEndRow()) // work around a bug
141         {
142             break;
143         }
144         if (loc.mY > row)
145         {
146             row = static_cast<int>(loc.mY);
147             progress.report("Calculating means", row * 50 / iter.getNumSelectedRows(),
148             NORMAL);
149             acc->toPixel(static_cast<int>(loc.mY), static_cast<int>(loc.mX));
150             VERIFY(acc.isValid());
151             for (int band = 0; band < bands; ++band)
152             {
153                 double val = Service<ModelServices>()->getDataValue(encoding, acc->
154                 getColumn(), band);
155                 gsl_matrix_set(pPixelMat, band, 0, val);
156             }
157             gsl_matrix_add(pMuMat, pPixelMat);
158         }
159         gsl_matrix_scale(pMuMat, 1.0 / iter.getCount());
160         iter.firstPixel();
161     }
162     for (int row = iter.getBoundingBoxStartRow(); iter != iter.end(); ++iter)
163     {
164         LocationType loc;
165         iter.getPixelLocation(loc);
166         if (loc.mY > iter.getBoundingBoxEndRow()) // work around a bug
167         {
168             break;
169         }
170         if (loc.mY > row)
171         {
172             row = static_cast<int>(loc.mY);
173             progress.report("Calculating RX", row * 49 / iter.getNumSelectedRows() + 50,
174             NORMAL);
175             acc->toPixel(static_cast<int>(loc.mY), static_cast<int>(loc.mX));
176             resacc->toPixel(static_cast<int>(loc.mY) - iter.getBoundingBoxStartRow(),
177             static_cast<int>(loc.mX) - iter.getBoundingBoxStartColumn());
178             VERIFY(acc.isValid() && resacc.isValid());
179             for (int band = 0; band < bands; ++band)
180             {
181                 double val = Service<ModelServices>()->getDataValue(encoding, acc->
182                 getColumn(), band);
183                 gsl_matrix_set(pPixelMat, band, 0, val);
184             }
185             gsl_matrix_sub(pPixelMat, pMuMat);

```

```
184     gsl_matrix resMat = {1, 1, 1, reinterpret_cast<double*>(resacc->getColumn()),  
    NULL, 0};  
185     gsl_matrix_set_zero(pTemp);  
186     gsl_blas_dgemm(CblasTrans, CblasNoTrans, 1.0, pPixelMat, &covMat, 0.0, pTemp);  
187     gsl_blas_dgemm(CblasNoTrans, CblasNoTrans, 1.0, pTemp, pPixelMat, 0.0, &  
    resMat);  
188     }  
189     gsl_matrix_free(pTemp);  
190     gsl_matrix_free(pPixelMat);  
191     }  
192     if (!isBatch())  
193     {  
194         ThresholdLayer* pLayer = static_cast<ThresholdLayer*>(pView->createLayer  
    (THRESHOLD, pResult.get()));  
195         pLayer->setXOffset(iter.getBoundingBoxStartColumn());  
196         pLayer->setYOffset(iter.getBoundingBoxStartRow());  
197         pLayer->setPassArea(UPPER);  
198         pLayer->setRegionUnits(STD_DEV);  
199         pLayer->setFirstThreshold(pLayer->convertThreshold(STD_DEV, 2.0, RAW_VALUE));  
200     }  
201     if (pOutArgList != NULL)  
202     {  
203         pOutArgList->setPlugInArgValue<RasterElement>("Results", pResult.get());  
204     }  
205     pResult.release();  
206  
207     progress.report("Complete", 100, NORMAL);  
208     progress.upAlevel();  
209     return true;  
210 }
```



```
1 /*
2  * The information in this file is
3  * Copyright(c) 2010 Trevor R.H. Clarke
4  * and is subject to the terms and conditions of the
5  * GNU Lesser General Public License Version 2.1
6  * The license text is available from
7  * http://www.gnu.org/licenses/lgpl.html
8  */
9
10 #ifndef RX_H__
11 #define RX_H__
12
13 #include "AlgorithmShell.h"
14
15 class Rx : public AlgorithmShell
16 {
17 public:
18     Rx();
19     virtual ~Rx();
20
21     virtual bool getInputSpecification(PlugInArgList*& pArgList);
22     virtual bool getOutputSpecification(PlugInArgList*& pArgList);
23     virtual bool execute(PlugInArgList* pInArgList, PlugInArgList* pOutArgList);
24 };
25
26 #endif
```

```
1 /*
2  * The information in this file is
3  * Copyright(c) 2010 Trevor R.H. Clarke
4  * and is subject to the terms and conditions of the
5  * GNU Lesser General Public License Version 2.1
6  * The license text is available from
7  * http://www.gnu.org/licenses/lgpl.html
8  */
9
10 #include "AnnotationElement.h"
11 #include "AoiElement.h"
12 #include "AoiLayer.h"
13 #include "ApiUtilities.h"
14 #include "ColorMap.h"
15 #include "ColorType.h"
16 #include "DataAccessor.h"
17 #include "DataAccessorImpl.h"
18 #include "DataRequest.h"
19 #include "DesktopServices.h"
20 #include "GraphicGroup.h"
21 #include "GraphicObject.h"
22 #include "LayerList.h"
23 #include "MessageLogResource.h"
24 #include "PlugInRegistration.h"
25 #include "PseudocolorLayer.h"
26 #include "RasterDataDescriptor.h"
27 #include "RasterData.h"
28 #include "RasterElement.h"
29 #include "RasterLayer.h"
30 #include "SpatialDataView.h"
31 #include "Statistics.h"
32 #include "StringUtilities.h"
33 #include "ThresholdLayer.h"
34 #include "TrackingManager.h"
35 #include "TrackingUtils.h"
36 #include <opencv/cv.h>
37 #include <BlobResult.h>
38 #include <map>
39 #include <set>
40 #include <time.h>
41 #include <vector>
42 #include <QtCore/QtDebug>
43 #include <opencv/highgui.h>
44
45 REGISTER_PLUGIN_BASIC(Tracking, TrackingManager);
46
47 #define SQR(x) ((x) * (x))
48
49 // Define this to generate an annotation layer showing the optical flow vectors
50 // This will slow down processing quite a bit.
51 // #define SHOW_FLOW_VECTORS
52
53 // Define this to calculate connected components on the object results
54 #define CONNECTED
55
56 // Define the threshold for locating objects
57 #define OBJECT_THRESHOLD 15
58
59 // Maximum number of corners to use when calculating optical flow.
60 // Higher numbers may result in more accurate calculations but may also slow down
61 // calculations.
62 // There's a point where increasing this number does nothing as there are only so many
63 // strong corners in a frame.
64 #define MAX_CORNERS 500
65
66 // Maximum change in location allowed before a track is considered...lower values
```

```
        shrink the possible search space for matching objects
65 #define MAX_SPEED 150
66
67 namespace
68 {
69 static const int CodeDeltas[8][2] =
70 { {1, 0}, {1, -1}, {0, -1}, {-1, -1}, {-1, 0}, {-1, 1}, {0, 1}, {1, 1} };
71 }
72
73 const char* TrackingManager::spPlugInName("TrackingManager");
74
75 TrackingManager::TrackingManager() :
76     mCalcBaseObjects(true),
77     mPaused(false),
78     mpDesc(NULL),
79     mpElement(NULL),
80     mBaseFrameNum(-1),
81     mBaseAcc(NULL, NULL),
82     mpBaseCorners(new CvPoint2D32f[MAX_CORNERS]),
83     mCurrentFrameNum(-1),
84     mpGroup(NULL),
85     mpTracks(NULL),
86     mCornerCount(MAX_CORNERS),
87     mpRes(NULL),
88     mpRes2(NULL)
89 {
90     mpAnimation.addSignal(SIGNAL_NAME(Animation, FrameChanged), Slot(this, &
91                                     TrackingManager::processFrame));
92     mpLayer.addSignal(SIGNAL_NAME(Subject, Deleted), Slot(this, &TrackingManager::
93                                     clearData));
94     setName(spPlugInName);
95     setDescriptorId("{c5f096e1-1584-4d7c-aa6f-29c4e422aad1}");
96     setType("Manager");
97     setSubtype("Video");
98     setAbortSupported(false);
99     allowMultipleInstances(false);
100     executeOnStartup(true);
101     destroyAfterExecute(false);
102     setWizardSupported(false);
103     setHandle(ModuleManager::instance()->getService());
104 }
105
106 TrackingManager::~TrackingManager()
107 {
108     mpBaseFrame.reset(NULL);
109 }
110
111 bool TrackingManager::getInputSpecification(PlugInArgList*& pArgList)
112 {
113     pArgList = NULL;
114     return true;
115 }
116
117 bool TrackingManager::getOutputSpecification(PlugInArgList*& pArgList)
118 {
119     pArgList = NULL;
120     return true;
121 }
122
123 bool TrackingManager::execute(PlugInArgList*, PlugInArgList*)
124 {
125     return true;
126 }
127
128 void TrackingManager::setTrackedLayer(RasterLayer* pLayer)
129 {
```

```

128     mpLayer.reset(pLayer);
129     mpAnimation.reset((pLayer == NULL) ? NULL : pLayer->getAnimation());
130     mpBasePyramid.reset(NULL);
131     mpBaseCorners.reset(NULL);
132     mpBaseFrame.reset(NULL);
133     mBaseAcc = DataAccessor(NULL, NULL);
134     initializeDataset();
135 }
136
137 void TrackingManager::setPauseState(bool state)
138 {
139     mPaused = state;
140 }
141
142 void TrackingManager::setFocus(LocationType loc, int maxSize)
143 {
144     if (mpDesc == NULL)
145     {
146         return;
147     }
148     LocationType dloc;
149     mpLayer->translateScreenToData(loc.mX, loc.mY, dloc.mX, dloc.mY);
150     Opticks::PixelLocation minBb(0,0);
151     Opticks::PixelLocation maxBb(mpDesc->getColumnCount(), mpDesc->getRowCount());
152     uint8_t level = TrackingUtils::calculateNeededLevels(maxSize, maxBb, minBb);
153     TrackingUtils::subcubeid_t id = TrackingUtils::calculateSubcubeId(dloc, level, maxBb, minBb);
154     TrackingUtils::calculateSubcubeBounds(id, level, maxBb, minBb);
155     mpFocus->clearPoints();
156     GraphicObject* pRect = mpFocus->getGroup()->addObject(RECTANGLE_OBJECT);
157     pRect->setBoundingBox(LocationType(minBb.mX, minBb.mY), LocationType(maxBb.mX, maxBb.mY));
158     pRect->setFillState(false);
159     mMinBb = minBb;
160     mMaxBb = maxBb;
161     mMaxBb.mX--;
162     mMaxBb.mY--;
163     initializeFrame0();
164 }
165
166 void TrackingManager::processFrame(Subject& subject, const std::string& signal, const boost::any& val)
167 {
168     if (mPaused)
169     {
170         return;
171     }
172     VERIFYNRV(mpLayer.get());
173     try
174     {
175         unsigned int curFrame = mpAnimation->getCurrentFrame()->mFrameNumber;
176         mCurrentFrameNum = curFrame;
177         int width = (*mpBaseFrame).width;
178         int height = (*mpBaseFrame).height;
179         bool fullScene = (width == mpDesc->getColumnCount() && height == mpDesc->getRowCount());
180
181         FactoryResource<DataRequest> req;
182         if (!fullScene)
183         {
184             req->setRows(mpDesc->getActiveRow(mMinBb.mY), mpDesc->getActiveRow(mMaxBb.mY), height);
185             req->setColumns(mpDesc->getActiveColumn(mMinBb.mX), mpDesc->getActiveColumn(mMaxBb.mX), width);
186         }
187         req->setBands(mpDesc->getActiveBand(curFrame), mpDesc->getActiveBand(curFrame),

```

```

1);
188     req->setInterleaveFormat(BSQ);
189     DataAccessor curAcc = mpElement->getDataAccessor(req.release());
190
191     if (!curAcc.isValid())
192     {
193         return;
194     }
195     IplImageResource pCurFrame(NULL);
196     if (fullScene)
197     {
198         pCurFrame = IplImageResource(width, height, 8, 1, reinterpret_cast<char*>
199         (curAcc->getColumn()));
200     }
201     else
202     {
203         pCurFrame = IplImageResource(width, height, 8, 1);
204         for (int row = 0; row < height; ++row)
205         {
206             if (row > 0)
207             {
208                 curAcc->nextRow();
209                 VERIFYNRV(curAcc.isValid());
210             }
211             memcpy((*pCurFrame).imageData + (row * width), curAcc->getRow(), (*
212             pCurFrame).width);
213         }
214         CvSize pyr_sz = cvSize((*mpBaseFrame).width + 8, (*mpBaseFrame).height / 3);
215         IplImageResource pCurPyramid(pyr_sz.width, pyr_sz.height, IPL_DEPTH_32F, 1);
216         std::auto_ptr<CvPoint2D32f> pCurCorners(new CvPoint2D32f[MAX_CORNERS]);
217         cvCalcOpticalFlowPyrLK(mpBaseFrame, pCurFrame, mpBasePyramid, pCurPyramid,
218         mpBaseCorners.get(), pCurCorners.get(), mCornerCount,
219         cvSize(10,10), 5, mpFeaturesFound, mpFeatureErrors, cvTermCriteria
220         (CV_TERMCRIT_ITER|CV_TERMCRIT_EPS, 20, 0.3), 0);
221
222         // display flow vectors in an annotation layer
223         std::vector<std::pair<CvPoint2D32f, CvPoint2D32f> > corr;
224
225         if (mpGroup != NULL)
226         {
227             mpGroup->removeAllObjects(true);
228         }
229         for (int i = 0; i < mCornerCount; ++i)
230         {
231             if (mpFeaturesFound[i] == 0 || mpFeatureErrors[i] > 550)
232             {
233                 continue;
234             }
235             if (mpGroup != NULL)
236             {
237                 GraphicObject* pObj = mpGroup->addObject(ARROW_OBJECT);
238                 pObj->setBoundingBox(LocationType(mpBaseCorners.get()[i].x, mpBaseCorners.
239                 get()[i].y),
240                 LocationType(pCurCorners.get()[i].x, pCurCorners.get()[i].y));
241             }
242             corr.push_back(std::make_pair(mpBaseCorners.get()[i], pCurCorners.get()[i]));
243         }
244         srand((unsigned int)time(NULL));
245         CvMat* pMapMatrix = TrackingUtils::ransac_affine(corr, 15, 5.0f, 5);
246         if (pMapMatrix != NULL)
247         {
248             IplImageResource pXform(width, height, 8, 1);
249             IplImageResource pTemp(width, height, 8, 1);
250             IplImageResource pRes(width, height, 8, 1, reinterpret_cast<char*>(mpRes->
251             getRawData()));

```

```

247     IplImageResource pRes2(width, height, 8, 1, reinterpret_cast<char*>(mpRes2->
getRawData()));
248     cvCopy(pCurFrame, pXform); // initialize to the current frame so any "offsets"
have a consistent background
249     cvWarpAffine(mpBaseFrame, pXform, pMapMatrix, CV_INTER_LINEAR); // warp the
base frame to the current camera position
250     cvCopy(pXform, mpBaseFrame); // copy the transformed base frame back to the
raster element
251     cvSmooth(pXform, pRes, CV_MEDIAN, 5, 5); // smooth the base frame to remove
high frequency noise
252     cvSmooth(pCurFrame, pTemp, CV_MEDIAN, 5, 5); // smooth the current frame to
remove high frequency noise
253
254     // threshold the results
255     cvThreshold(pCurFrame, pTemp, OBJECT_THRESHOLD, 255, CV_THRESH_BINARY); //
threshold the current frame
256     cvThreshold(pXform, pRes, OBJECT_THRESHOLD, 255, CV_THRESH_BINARY); //
threshold the base frame
257     // erode to remove some noise
258     cvErode(pTemp, pTemp); // erode the current frame
259     cvErode(pRes, pRes); // erode the base frame
260     // difference the frames
261     cvSub(pTemp, pRes, pRes2); // subtract the base from the current and store in
res2
262     cvSub(pRes, pTemp, pRes); // subtract the current from the base and store in
res
263     // remove final small differences with an open
264     cvErode(pRes, pRes, NULL, 3); // open the current frame
265     cvDilate(pRes, pRes, NULL, 3);
266
267     cvErode(pRes2, pRes2, NULL, 3); // open the base frame
268     cvDilate(pRes2, pRes2, NULL, 3);
269
270     std::vector<TrackVertex> curObjs;
271     { // scope blobs
272         CBlobResult blobs(pRes, NULL, 0);
273 #ifdef CONNECTED
274         for (int bidx = 0; bidx < blobs.GetNumBlobs(); ++bidx)
275         {
276             CBlob blob(blobs.GetBlob(bidx));
277             blob.FillBlob(pRes, CV_RGB(bidx+1, bidx+1, bidx+1));
278         }
279 #endif
280         curObjs = updateTrackObjects(blobs, pCurFrame, true);
281     } // scope blobs
282     { // scope blobs
283         CBlobResult blobs(pRes2, NULL, 0);
284 #ifdef CONNECTED
285         for (int bidx = 0; bidx < blobs.GetNumBlobs(); ++bidx)
286         {
287             CBlob blob(blobs.GetBlob(bidx));
288             blob.FillBlob(pRes2, CV_RGB(bidx+1, bidx+1, bidx+1));
289         }
290 #endif
291         if (mCalcBaseObjects)
292         {
293             mBaseObjects = updateTrackObjects(blobs, mpBaseFrame, false);
294         }
295         else
296         {
297             // apply affine transform to the coords
298             for (size_t idx = 0; idx < mBaseObjects.size(); ++idx)
299             {
300                 mTracks[mBaseObjects[idx]].mCentroidB.mX =
301                     (mTracks[mBaseObjects[idx]].mCentroidA.mX * cvGetReal2D(pMapMatrix,
, 0, 0)) +

```

```

302         (mTracks[mBaseObjects[idx]].mCentroidA.mY * cvGetReal2D(pMapMatrix,
303         , 0, 1)) +
304         cvGetReal2D(pMapMatrix, 0, 2);
305         mTracks[mBaseObjects[idx]].mCentroidB.mY =
306         (mTracks[mBaseObjects[idx]].mCentroidA.mX * cvGetReal2D(pMapMatrix,
307         , 1, 0)) +
308         (mTracks[mBaseObjects[idx]].mCentroidA.mY * cvGetReal2D(pMapMatrix,
309         , 1, 1)) +
310         cvGetReal2D(pMapMatrix, 1, 2);
311     }
312     } // scope blobs
313     matchTracks(curObjs);
314     if (!fullScene)
315     {
316         mBaseAcc->toPixel(mMinBb.mY, mMinBb.mX);
317         VERIFYNRV(mBaseAcc.isValid());
318         for (int row = 0; row < height; ++row)
319         {
320             if (row > 0)
321             {
322                 mBaseAcc->nextRow();
323                 VERIFYNRV(mBaseAcc.isValid());
324             }
325             memcpy(mBaseAcc->getRow(), (*mpBaseFrame).imageData + (row * width), (*
326             mpBaseFrame).width);
327         }
328         mpElement->updateData();
329         if (mpRes != NULL)
330         {
331             mpRes->updateData();
332         }
333         if (mpRes2 != NULL)
334         {
335             mpRes2->updateData();
336         }
337         cvReleaseMat(&pMapMatrix);
338         mBaseObjects = curObjs;
339     }
340     // prep for next frame
341     mpBasePyramid = pCurPyramid;
342     mpBaseCorners.reset(pCurCorners.release());
343     mpBaseFrame = pCurFrame;
344     mBaseAcc = curAcc;
345     mBaseFrameNum = mCurrentFrameNum;
346     mCornerCount = MAX_CORNERS;
347     cvGoodFeaturesToTrack(mpBaseFrame, mpEigImage, mpTmpImage, mpBaseCorners.get(), &
348     mCornerCount, 0.01, 5.0);
349     cvFindCornerSubPix(mpBaseFrame, mpBaseCorners.get(), mCornerCount, cvSize(10, 10)
350     , cvSize(-1, -1), cvTermCriteria(CV_TERMCRIT_ITER|CV_TERMCRIT_EPS, 20, 0.03));
351     mCalcBaseObjects = false;
352 }
353 catch (cv::Exception& err)
354 {
355     Service<DesktopServices>()->showMessageBox("OpenCV Error", err.err + "\n" + err.
356     file + ":" + StringUtilities::toDisplayString(err.line) + "\n" + err.func);
357 }
358 }
359
360 void TrackingManager::clearData(Subject& subject, const std::string& signal, const

```

```

        boost::any& val)
361 {
362     setTrackedLayer(NULL);
363 }
364
365 void TrackingManager::initializeDataset()
366 {
367     if (mpLayer.get() == NULL)
368     {
369         mpElement = NULL;
370         mpDesc = NULL;
371         return;
372     }
373     VERIFYNRV(mpElement = static_cast<RasterElement*>(mpLayer->getDataElement()));
374     VERIFYNRV(mpDesc = static_cast<RasterDataDescriptor*>(mpElement->getDataDescriptor
375     if (mpDesc->getBytesPerElement() != 1)
376     {
377         // only 8-bit supported right now
378         mpElement = NULL;
379         mpDesc = NULL;
380         return;
381     }
382
383     mpGroup = NULL;
384     mpTracks = NULL;
385 #ifdef SHOW_FLOW_VECTORS
386     {
387         // Create elements and views to show the optical flow vectors
388         ModelResource<AnnotationElement> pAnno(static_cast<AnnotationElement*>(
389             Service<ModelServices>()->getElement("Flow Vectors", TypeConverter::toString
390         bool created = pAnno.get() == NULL;
391         if (created)
392         {
393             pAnno = ModelResource<AnnotationElement>("Flow Vectors", mpElement);
394             static_cast<SpatialDataView*>(mpLayer->getView())->createLayer(ANNOTATION, pAnno.
395         }
396         mpGroup = pAnno->getGroup();
397         pAnno.release();
398     }
399 #endif
400     {
401         // Create elements and views to show the optical flow vectors
402         ModelResource<AnnotationElement> pTrackAnno(static_cast<AnnotationElement*>(
403             Service<ModelServices>()->getElement("Object Tracks", TypeConverter::toString
404         bool created = pTrackAnno.get() == NULL;
405         if (created)
406         {
407             pTrackAnno = ModelResource<AnnotationElement>("Object Tracks", mpElement);
408             static_cast<SpatialDataView*>(mpLayer->getView())->createLayer(ANNOTATION,
409         }
410         mpTracks = pTrackAnno->getGroup();
411         pTrackAnno.release();
412     }
413
414     // Create an AOI to define a sub-area for processing.
415     mpFocus = static_cast<AoiElement*>(
416         Service<ModelServices>()->getElement("Focus", TypeConverter::toString<AoiElement>
417     if (mpFocus == NULL)
418     {
419         mpFocus = static_cast<AoiElement*>(

```



```
420     Service<ModelServices>()->createElement("Focus", TypeConverter::toString
    <AoiElement>(), mpElement));
421     AoiLayer* pLayer = static_cast<AoiLayer*>(
422     static_cast<SpatialDataView*>(mpLayer->getView())->createLayer(AOI_LAYER,
    mpFocus));
423     pLayer->setSymbol(BOX);
424     pLayer->setColor(ColorType(0, 0, 128));
425 }
426 mMinBb = Opticks::PixelLocation(0, 0);
427 mMaxBb = Opticks::PixelLocation(mpDesc->getColumnCount()-1, mpDesc->getRowCount()-1);
428
429 initializeFrame0();
430 }
431
432 void TrackingManager::initializeFrame0()
433 {
434     if (mpLayer.get() == NULL)
435     {
436         mpElement = NULL;
437         mpDesc = NULL;
438         return;
439     }
440     try
441     {
442         unsigned int baseFrame = mpLayer->getDisplayedBand(GRAY).getActiveNumber();
443         mBaseFrameNum = baseFrame;
444         mCurrentFrameNum = -1;
445
446         int width = mMaxBb.mX - mMinBb.mX + 1;
447         int height = mMaxBb.mY - mMinBb.mY + 1;
448         bool fullScene = (width == mpDesc->getColumnCount() && height == mpDesc->
    getRowCount());
449
450         FactoryResource<DataRequest> baseRequest;
451         if (!fullScene)
452         {
453             baseRequest->setRows(mpDesc->getActiveRow(mMinBb.mY), mpDesc->getActiveRow
    (mMaxBb.mY), height);
454             baseRequest->setColumns(mpDesc->getActiveColumn(mMinBb.mX), mpDesc->
    getActiveColumn(mMaxBb.mX), width);
455         }
456         baseRequest->setBands(mpDesc->getActiveBand(baseFrame), mpDesc->getActiveBand
    (baseFrame), 1);
457         baseRequest->setInterleaveFormat(BSQ);
458         mBaseAcc = mpElement->getDataAccessor(baseRequest.release());
459
460         if (!mBaseAcc.isValid())
461         {
462             return;
463         }
464         // Wrap the accessors with OpenCV data structures and create some temporary
    arrays.
465         if (fullScene)
466         {
467             mpBaseFrame = IplImageResource(width, height, 8, 1, reinterpret_cast<char*>
    (mBaseAcc->getColumn()));
468         }
469         else
470         {
471             mpBaseFrame = IplImageResource(width, height, 8, 1);
472             for (int row = 0; row < height; ++row)
473             {
474                 if (row > 0)
475                 {
476                     mBaseAcc->nextRow();
```

```

477         VERIFYNRV(mBaseAcc.isValid());
478     }
479     memcpy((*mpBaseFrame).imageData + (row * width), mBaseAcc->getRow(), (*
mpBaseFrame).width);
480 }
481 }
482
483     mpEigImage = IplImageResource(width, height, IPL_DEPTH_32F, 1);
484     mpTmpImage = IplImageResource(width, height, IPL_DEPTH_32F, 1);
485     mCornerCount = MAX_CORNERS;
486     mpBaseCorners.reset(new CvPoint2D32f[MAX_CORNERS]);
487     cvGoodFeaturesToTrack(mpBaseFrame, mpEigImage, mpTmpImage, mpBaseCorners.get(), &
mCornerCount, 0.01, 5.0);
488     cvFindCornerSubPix(mpBaseFrame, mpBaseCorners.get(), mCornerCount, cvSize(10, 10)
, cvSize(-1, -1), cvTermCriteria(CV_TERMCRIT_ITER|CV_TERMCRIT_EPS, 20, 0.03));
489
490     CvSize pyr_sz = cvSize((*mpBaseFrame).width + 8, (*mpBaseFrame).height / 3);
491     mpBasePyramid = IplImageResource(pyr_sz.width, pyr_sz.height, IPL_DEPTH_32F, 1);
492
493     // Create elements and views to show identified objects
494     mpRes = NULL;
495     mpRes2 = NULL;
496
497     RasterElementArgs args={height, width, 1, 0, 1, 1, mpElement, 0, NULL}; // BSQ,
uchar (ushort)
498     DataElement* pTmp = Service<ModelServices>()->getElement("Current Objects",
TypeConverter::toString<RasterElement>(), mpElement);
499     if (pTmp != NULL)
500     {
501         Service<ModelServices>()->destroyElement(pTmp);
502     }
503     mpRes = static_cast<RasterElement*>(createRasterElement("Current Objects", args));
504 #pragma message(__FILE__ "(" STRING(__LINE__) ") : warning : Work around for OPTICKS-
932 (tclarke)")
505     std::vector<int> badValues(1, 0);
506     mpRes->getStatistics()->setBadValues(badValues);
507 #ifdef CONNECTED
508     RasterLayer* pPseudo = static_cast<RasterLayer*>(
509         static_cast<SpatialDataView*>(mpLayer->getView())->createLayer(RASTER, mpRes));
510     pPseudo->setXOffset(mMinBb.mX);
511     pPseudo->setYOffset(mMinBb.mY);
512     pTmp = Service<ModelServices>()->getElement("Base Objects", TypeConverter::
toString<RasterElement>(), mpElement);
513     if (pTmp != NULL)
514     {
515         Service<ModelServices>()->destroyElement(pTmp);
516     }
517     mpRes2 = static_cast<RasterElement*>(createRasterElement("Base Objects", args));
518     mpRes2->getStatistics()->setBadValues(badValues);
519     RasterLayer* pPseudo2 = static_cast<RasterLayer*>(
520         static_cast<SpatialDataView*>(mpLayer->getView())->createLayer(RASTER,
mpRes2));
521     pPseudo2->setXOffset(mMinBb.mX);
522     pPseudo2->setYOffset(mMinBb.mY);
523     pPseudo->setStretchUnits(GRAYSCALE_MODE, RAW_VALUE);
524     pPseudo->setStretchValues(GRAY, 0, 47);
525     pPseudo2->setStretchUnits(GRAYSCALE_MODE, RAW_VALUE);
526     pPseudo2->setStretchValues(GRAY, 0, 47);
527     ColorMap cmap("C:/Opticks/COAN/Tracking/Release/SupportFiles/ColorTables/
pseudocolor.clu");
528     pPseudo->setColorMap(cmap.getName(), cmap.getTable());
529     pPseudo2->setColorMap(cmap.getName(), cmap.getTable());
530 #endif
531

```

```

532     mCalcBaseObjects = true;
533 }
534 catch (const cv::Exception& exc)
535 {
536     MessageResource msg("OpenCV error occurred.", "tracking", "{b16ae5e9-ef7e-474f-
9c45-8a061aa3cda2}");
537     msg->addProperty("Code", exc.code);
538     msg->addProperty("Error", exc.err);
539     msg->addProperty("Function", exc.func);
540     msg->addProperty("File", exc.file);
541     msg->addProperty("Line", exc.line);
542     msg->finalize(Message::Failure);
543 }
544 }
545
546 std::vector<TrackingManager::TrackVertex> TrackingManager::updateTrackObjects
    (CBlobResult& blobs, IplImage* pFrame, bool current)
547 {
548     // Get contour points for each blob
549     std::vector<TrackVertex> objects;
550     for (int blobi = 0; blobi < blobs.GetNumBlobs(); ++blobi)
551     {
552         std::map<int, std::set<int> > pts;
553         CBlob blob = blobs.GetBlob(blobi);
554         CBlobContour* pCon = blob.GetExternalContour();
555         CvTreeNodeIterator iter;
556         cvInitTreeNodeIterator(&iter, pCon->GetContourPoints(), 0);
557         CvSeq* pContour;
558         while((pContour = reinterpret_cast<CvSeq*>(cvNextTreeNode(&iter))) != 0 )
559         {
560             CvSeqReader reader;
561             int count = pContour->total;
562             int elem_type = CV_MAT_TYPE(pContour->flags);
563             cvStartReadSeq(pContour, &reader, 0);
564             if (CV_IS_SEQ_CHAIN_CONTOUR(pContour))
565             {
566                 cv::Point pt = ((CvChain*)pContour)->origin;
567                 char prev_code = reader.ptr ? reader.ptr[0] : '\0';
568
569                 for (int i = 0; i < count; i++)
570                 {
571                     char code;
572                     CV_READ_SEQ_ELEM(code, reader);
573
574                     if (code != prev_code)
575                     {
576                         prev_code = code;
577                         pts[pt.y].insert(pt.x);
578                     }
579
580                     pt.x += CodeDeltas[(int)code][0];
581                     pt.y += CodeDeltas[(int)code][1];
582                 }
583             }
584             else if (CV_IS_SEQ_POLYLINE(pContour) && elem_type == CV_32SC2)
585             {
586                 cv::Point pt1, pt2;
587                 int shift = 0;
588
589                 count -= !CV_IS_SEQ_CLOSED(pContour);
590                 CV_READ_SEQ_ELEM(pt1, reader);
591                 pts[pt1.y].insert(pt1.x);
592
593                 for(int i = 0; i < count; i++)
594                 {
595                     CV_READ_SEQ_ELEM(pt2, reader);

```

```

596         pts[pt2.y].insert(pt2.x);
597         pt1 = pt2;
598     }
599 }
600 }
601 // Fill the contour and calculate some properties
602 Opticks::PixelLocation centroid(0,0);
603 std::vector<cv::Point> filledPoints;
604 for (std::map<int, std::set<int> >::iterator ptiter = pts.begin(); ptiter != pts.
end(); ++ptiter)
605 {
606     int startCol = -1;
607     for (std::set<int>::iterator coliter = ptiter->second.begin(); coliter !=
ptiter->second.end(); ++coliter)
608     {
609         if (startCol == -1)
610         {
611             startCol = *coliter;
612         }
613         else
614         {
615             for (int col = startCol; col <= *coliter; ++col)
616             {
617                 filledPoints.push_back(cv::Point(col, ptiter->first));
618                 centroid.mX += col;
619                 centroid.mY += ptiter->first;
620             }
621             startCol = -1;
622         }
623     }
624 }
625 centroid.mX /= filledPoints.size();
626 centroid.mY /= filledPoints.size();
627 double tmpNum = 0.0, tmpDen = 0.0;
628 for (std::vector<cv::Point>::iterator ptiter = filledPoints.begin(); ptiter !=
filledPoints.end(); ++ptiter)
629 {
630     double val = cvGetReal2D(pFrame, ptiter->y, ptiter->x);
631     tmpNum += sqrt((double)SQR(ptiter->x - centroid.mX) +
632                 SQR(ptiter->y - centroid.mY)) * val;
633     tmpDen += val;
634 }
635 TrackVertex obj;
636 if (current || mCalcBaseObjects)
637 {
638     obj = boost::add_vertex(mTracks);
639     mTracks[obj].mFrameNum = current ? mCurrentFrameNum : mBaseFrameNum;
640     mTracks[obj].mDispersion = static_cast<float>(tmpNum / tmpDen);
641 }
642 else
643 {
644     // locate the correct item.
645 }
646 if (current)
647 {
648     mTracks[obj].mCentroidA = centroid;
649 }
650 else
651 {
652     mTracks[obj].mCentroidB = centroid;
653 }
654 objects.push_back(obj);
655 }
656 return objects;
657 }
658

```

```

659 void TrackingManager::matchTracks(const std::vector<TrackVertex>& curObjs)
660 {
661     if (mpTracks != NULL)
662     {
663         mpTracks->removeAllObjects(true);
664     }
665     for (std::vector<TrackVertex>::const_iterator base = mBaseObjects.begin(); base !=
        mBaseObjects.end(); ++base)
666     {
667         std::pair<TrackTraits::in_edge_iterator, TrackTraits::in_edge_iterator> edges =
        boost::in_edges(*base, mTracks);
668         bool hasInVel = false;
669         Opticks::Location<int, 2> inVel(0, 0);
670         double inVelAng = 0.0;
671         if (edges.first != edges.second)
672         {
673             inVel = mTracks[*edges.first].mVelocity;
674             inVelAng = atan((double)inVel.mY / inVel.mX);
675             hasInVel = true;
676         }
677         // add connections which meet certain minimum criteria
678         TrackEdge minE;
679         float minCost = 9999999999999999;
680         for (std::vector<TrackVertex>::const_iterator cur = curObjs.begin(); cur !=
        curObjs.end(); ++cur)
681         {
682             Opticks::Location<int, 2> vel(mTracks[*cur].mCentroidA.mX - mTracks[*base].
        mCentroidB.mX,
683                                     mTracks[*cur].mCentroidA.mY - mTracks[*base].
        mCentroidB.mY);
684             double velDiff = 0.0;
685             if (hasInVel)
686             {
687                 velDiff = fabs(inVelAng - atan((double)vel.mY / vel.mX));
688             }
689             if (vel.length() < MAX_SPEED)
690             {
691                 TrackEdge e = boost::add_edge(*base, *cur, mTracks).first;
692                 mTracks[e].mVelocity = vel;
693                 mTracks[e].mVelDiff = velDiff;
694                 mTracks[e].mSpeedDiff = fabs(vel.length() - inVel.length());
695                 mTracks[e].mDiffDispersion = fabs(mTracks[*base].mDispersion - mTracks[*
        cur].mDispersion);
696                 mTracks[e].mCost = mTracks[e].mDiffDispersion * 0.2
697                                     + mTracks[e].mVelDiff * 0.5
698                                     + mTracks[e].mSpeedDiff * 0.3;
699                 if (mTracks[e].mCost < minCost)
700                 {
701                     minCost = mTracks[e].mCost;
702                     minE = e;
703                 }
704             }
705         }
706         TrackTraits::edge_iterator ei, eitmp, ei_end;
707         for (boost::tie(ei, ei_end) = boost::edges(mTracks); ei != ei_end;)
708         {
709             eitmp = ei;
710             ++eitmp;
711             if (*ei != minE)
712             {
713                 boost::remove_edge(*ei, mTracks);
714             }
715             else
716             {
717                 LocationType start(mTracks[boost::source(*ei, mTracks)].mCentroidB.mX,
        mTracks[boost::source(*ei, mTracks)].mCentroidB.mY);

```

```
718         LocationType stop(mTracks[boost::target(*ei, mTracks)].mCentroidA.mX,
719         mTracks[boost::target(*ei, mTracks)].mCentroidA.mY);
720         mpTracks->addObject(LINE_OBJECT)->setBoundingBox(start, stop);
721         ei = eitmp;
722     }
723 }
724 // diff in velocity
725 // ang = atan(A.y/A.x) - atan(B.y/B.x); if (ang > 180) ang = 360 - ang
726 // mag = fabs(A.distance() - B.distance())
727 }
```

```
1 /*
2  * The information in this file is
3  * Copyright(c) 2010 Trevor R.H. Clarke
4  * and is subject to the terms and conditions of the
5  * GNU Lesser General Public License Version 2.1
6  * The license text is available from
7  * http://www.gnu.org/licenses/lgpl.html
8  */
9
10 #ifndef TRACKINGMANAGER_H__
11 #define TRACKINGMANAGER_H__
12
13 #include "Animation.h"
14 #include "AttachmentPtr.h"
15 #include "ConfigurationSettings.h"
16 #include "DataAccessor.h"
17 #include "ExecutableShell.h"
18 #include "RasterData.h"
19 #include "RasterLayer.h"
20 #include "TrackingUtils.h"
21 #include <boost/any.hpp>
22 #include <boost/graph/graph_traits.hpp>
23 #include <boost/graph/adjacency_list.hpp>
24
25 class AoElement;
26 class CBlobResult;
27 class GraphicGroup;
28 class RasterDataDescriptor;
29 class RasterElement;
30
31 class TrackingManager : public ExecutableShell
32 {
33 public:
34     SETTING(InitialSubcubeSize, TrackingManager, unsigned int, 0);
35
36     static const char* spPlugInName;
37
38     TrackingManager();
39     virtual ~TrackingManager();
40
41     virtual bool getInputSpecification(PlugInArgList*& pArgList);
42     virtual bool getOutputSpecification(PlugInArgList*& pArgList);
43     virtual bool execute(PlugInArgList* pInArgList, PlugInArgList* pOutArgList);
44
45     void setTrackedLayer(RasterLayer* pLayer);
46     void setPauseState(bool state);
47     void setFocus(LocationType loc, int maxSize);
48
49     struct TrackVertexProps
50     {
51         TrackVertexProps() : mFrameNum(-1), mCentroidA(0,0), mCentroidB(0,0), mTexture(0.0,
52             0), mDispersion(0.0) {}
53
54         int mFrameNum; // frame number where this objects was found
55         Opticks::PixelLocation mCentroidA; // position when this is the "current" frame (pre-transform)
56         Opticks::PixelLocation mCentroidB; // position when this is the "base" frame (post-transform)
57         float mTexture; // grayscale texture
58         float mDispersion; // grayscale dispersion
59         // optional HSI sig goes here
60     };
61
62     struct TrackEdgeProps
63     {
64         TrackEdgeProps() : mVelocity(0,0), mVelDiff(0.0), mSpeedDiff(0.0),
65             mDiffDispersion(0.0) {}
66     };
67 }
```

```
63
64     Opticks::Location<int, 2> mVelocity; // previous frame's centroid B to this frame ✓
        's centroid A
65     float mVelDiff; // angular difference between this velocity ✓
        vector and the previous location's
66     float mSpeedDiff; // magnitude difference between this ✓
        velocity vector and the previous location's
67     float mDiffDispersion; // difference in dispersion values
68     float mCost; // total "cost" of this track
69 };
70 typedef boost::adjacency_list<boost::vecS, boost::vecS, boost::bidirectionalS, ✓
        TrackVertexProps, TrackEdgeProps> TrackGraph;
71 typedef boost::graph_traits<TrackGraph> TrackTraits;
72 typedef boost::graph_traits<TrackGraph>::vertex_descriptor TrackVertex;
73 typedef boost::graph_traits<TrackGraph>::edge_descriptor TrackEdge;
74
75 protected:
76     void processFrame(Subject& subject, const std::string& signal, const boost::any& ✓
        val);
77     void clearData(Subject& subject, const std::string& signal, const boost::any& val);
78     std::vector<TrackVertex> updateTrackObjects(CBlobResult& blobs, IplImage* pFrame, ✓
        bool current);
79     void matchTracks(const std::vector<TrackVertex>& curObjs);
80
81 private:
82     void initializeDataset();
83     void initializeFrame0();
84
85     TrackGraph mTracks;
86
87     bool mCalcBaseObjects; // should the base objects be calculated or results from the ✓
        previous iteration used?
88     std::vector<TrackVertex> mBaseObjects;
89     bool mPaused;
90     AttachmentPtr<RasterLayer> mpLayer; // tracked layer
91     AttachmentPtr<Animation> mpAnimation; // tracked animation
92     const RasterDataDescriptor* mpDesc; // tracked element descriptor
93     RasterElement* mpElement; // tracked element
94
95     // base frame information, passed to the next iteration
96     int mBaseFrameNum;
97     DataAccessor mBaseAcc;
98     IplImageResource mpBaseFrame;
99     IplImageResource mpEigImage;
100    IplImageResource mpTmpImage;
101    std::auto_ptr<CvPoint2D32f> mpBaseCorners;
102    IplImageResource mpBasePyramid;
103
104    // pass feature state to the next iteration
105    char mpFeaturesFound[500];
106    float mpFeatureErrors[500];
107
108    int mCurrentFrameNum;
109    GraphicGroup* mpGroup; // draw flow vectors
110    GraphicGroup* mpTracks; // draw tracks
111
112    int mCornerCount;
113
114    RasterElement* mpRes; // base frame object blobs
115    RasterElement* mpRes2; // current frame object blobs
116
117    // sub-frame AOI and bounding box information
118    AoiElement* mpFocus;
119    Opticks::PixelLocation mMinBb;
120    Opticks::PixelLocation mMaxBb;
121 };
```


122

123 #endif

```
1 /*
2  * The information in this file is
3  * Copyright(c) 2010 Trevor R.H. Clarke
4  * and is subject to the terms and conditions of the
5  * GNU Lesser General Public License Version 2.1
6  * The license text is available from
7  * http://www.gnu.org/licenses/lgpl.html
8  */
9
10 #include "AppConfig.h"
11 #include "LocationType.h"
12 #include "RasterData.h"
13 #include "TrackingUtils.h"
14 #include <stdlib.h>
15 #include <opencv/cv.h>
16
17 #if defined(WIN_API)
18 #include <boost/cstdint.hpp>
19 using boost::uint8_t;
20 #endif
21
22 namespace TrackingUtils
23 {
24 subcubeid_t calculateSubcubeId(LocationType location, uint8_t levels,
25                               Opticks::PixelLocation maxBb,
26                               Opticks::PixelLocation minBb)
27 {
28     subcubeid_t id(levels);
29     for (uint8_t level = 0; level < levels; ++level)
30     {
31         Opticks::PixelLocation center(static_cast<int>((maxBb.mX - minBb.mX + 1) / 2.0 +
32 minBb.mX),
33                                       static_cast<int>((maxBb.mY - minBb.mY + 1) / 2.0 +
34 minBb.mY));
35         if (location.mX >= center.mX && location.mY <= center.mY) // quadrant 0
36         {
37             minBb.mX = center.mX;
38             maxBb.mY = center.mY;
39         }
40         else if (location.mX < center.mX && location.mY <= center.mY) // quadrant 1
41         {
42             id |= 1 << (level * 2 + 4);
43             maxBb = center;
44         }
45         else if (location.mX < center.mX && location.mY > center.mY) // quadrant 2
46         {
47             id |= 2 << (level * 2 + 4);
48             maxBb.mX = center.mX;
49             minBb.mY = center.mY;
50         }
51         else // quadrant 3
52         {
53             id |= 3 << (level * 2 + 4);
54             minBb = center;
55         }
56     }
57     return id;
58 }
59
60 bool calculateSubcubeBounds(subcubeid_t subcubeId, uint8_t& levels, Opticks::
61 PixelLocation& maxBb, Opticks::PixelLocation& minBb)
62 {
63     levels = subcubeId & 0x0f;
64     subcubeId >>= 4;
65     for (uint8_t level = 0; level < levels; ++level)
66     {
```

```
64     Opticks::PixelLocation center(static_cast<int>((maxBb.mX - minBb.mX + 1) / 2.0 +  
minBb.mX),  
65                                     static_cast<int>((maxBb.mY - minBb.mY + 1) / 2.0 +  
minBb.mY));  
66     switch (subcubeId & 0x03) // quadrant number  
67     {  
68     case 0:  
69         minBb.mX = center.mX;  
70         maxBb.mY = center.mY;  
71         break;  
72     case 1:  
73         maxBb = center;  
74         break;  
75     case 2:  
76         maxBb.mX = center.mX;  
77         minBb.mY = center.mY;  
78         break;  
79     case 3:  
80         minBb = center;  
81         break;  
82     default:  
83         break; // unreachable  
84     }  
85     subcubeId >>= 2;  
86 }  
87 return subcubeId == 0;  
88 }  
89  
90 uint8_t calculateNeededLevels(uint32_t maxSubcubeSize,  
91                               Opticks::PixelLocation maxBb,  
92                               Opticks::PixelLocation minBb)  
93 {  
94     maxBb = (maxBb - minBb) + 1;  
95     for (uint8_t level = 0; level <= 12; ++level) // maximum number of levels which can  
be represented  
96     {  
97         uint32_t curSize = maxBb.mX * maxBb.mY;  
98         if (curSize <= maxSubcubeSize)  
99         {  
100             return level;  
101         }  
102         maxBb.mX /= 2;  
103         maxBb.mY /= 2;  
104     }  
105     return 0xff; // Invalid return  
106 }  
107  
108 CvMat* ransac_affine(std::vector<std::pair<CvPoint2D32f, CvPoint2D32f> >& corr, int  
maxIter, float thresh, unsigned int numNeeded)  
109 {  
110     if (corr.empty())  
111     {  
112         return NULL;  
113     }  
114     thresh = thresh * thresh; // calculating sqrt for each test is expensive, so we  
square the check value to change from RMS to MSE  
115     unsigned int bestCount = 0;  
116     CvMat* pBest = NULL;  
117     CvMat* pTest = cvCreateMat(2, 3, CV_32F);  
118     CvMat* pVer = cvCreateMat(3, 1, CV_32F);  
119     CvMat* pVerRes = cvCreateMat(2, 1, CV_32F);  
120     pVer->data.fl[2] = 1.0;  
121     for (int it = 0; it < maxIter; ++it)  
122     {  
123         // build mss  
124         int pMss[3];
```

```

125     pMss[0] = rand() % corr.size();
126     do
127     {
128         pMss[1] = rand() % corr.size();
129     }
130     while (pMss[1] == pMss[0]);
131     do
132     {
133         pMss[2] = rand() % corr.size();
134     }
135     while (pMss[2] == pMss[0] || pMss[2] == pMss[1]);
136     CvPoint2D32f pSrc[3] = {corr[pMss[0]].first, corr[pMss[1]].first, corr[pMss[2]].first};
137     CvPoint2D32f pDst[3] = {corr[pMss[0]].second, corr[pMss[1]].second, corr[pMss[2]].second};
138
139     cvGetAffineTransform(pSrc, pDst, pTest);
140
141     // test the mss
142     unsigned int fitCount = 0;
143     for (unsigned int j = 0; j < corr.size(); ++j)
144     {
145         if (j == pMss[0] || j == pMss[1] || j == pMss[2])
146         {
147             continue;
148         }
149         pVer->data.fl[0] = corr[j].first.x;
150         pVer->data.fl[1] = corr[j].first.y;
151         cvGEMM(pTest, pVer, 1.0, NULL, 0.0, pVerRes);
152         float tmpX = pVerRes->data.fl[0] - corr[j].second.x;
153         float tmpY = pVerRes->data.fl[1] - corr[j].second.y;
154         float mse = (tmpX * tmpX + tmpY * tmpY) / 2.0f;
155         if (mse < thresh)
156         {
157             // fits the affine transform
158             fitCount++;
159         }
160     }
161     if (fitCount >= numNeeded && fitCount > bestCount)
162     {
163         if (pBest == NULL)
164         {
165             pBest = pTest;
166             pTest = cvCreateMat(2, 3, CV_32F);
167         }
168         else
169         {
170             std::swap(pBest, pTest);
171         }
172         bestCount = fitCount;
173     }
174 }
175 cvReleaseMat(&pTest);
176 cvReleaseMat(&pVer);
177 cvReleaseMat(&pVerRes);
178 return pBest;
179 }
180 }
181
182 IplImageResource::IplImageResource() : mpImage(NULL), mShallow(false)
183 {
184 }
185
186 IplImageResource::IplImageResource(IplImage* pImage) : mpImage(pImage), mShallow(false)
187 {
188 }

```

```
189
190 IplImageResource::IplImageResource(IplImageResource& other)
191 {
192     reset(other.get());
193     if (other.isShallow())
194     {
195         release();
196     }
197     else
198     {
199         take();
200     }
201     other.mpImage = NULL;
202 }
203
204 IplImageResource::IplImageResource(int width, int height, int depth, int channels) :  ✓
    mShallow(false)
205 {
206     mpImage = cvCreateImage(cvSize(width, height), depth, channels);
207 }
208
209 IplImageResource::IplImageResource(int width, int height, int depth, int channels, char ✓
    * pData) : mShallow(true)
210 {
211     mpImage = cvCreateImageHeader(cvSize(width, height), depth, channels);
212     mpImage->imageData = pData;
213 }
214
215 IplImageResource::~IplImageResource()
216 {
217     reset(NULL);
218 }
219
220 bool IplImageResource::isShallow()
221 {
222     return mShallow;
223 }
224
225 void IplImageResource::reset(IplImage* pImage)
226 {
227     if (mpImage != NULL)
228     {
229         if (mShallow)
230         {
231             mpImage->imageData = NULL;
232         }
233         cvReleaseImage(&mpImage);
234     }
235     mpImage = pImage;
236     mShallow = false;
237 }
238
239 IplImage* IplImageResource::get()
240 {
241     return mpImage;
242 }
243
244 IplImage* IplImageResource::release()
245 {
246     mShallow = true;
247     return mpImage;
248 }
249
250 IplImage* IplImageResource::take()
251 {
252     mShallow = false;
```

```
253     return mpImage;
254 }
255
256 IplImageResource::operator IplImage*()
257 {
258     return get();
259 }
260
261 IplImage& IplImageResource::operator*()
262 {
263     return *get();
264 }
265
266 IplImageResource& IplImageResource::operator=(IplImageResource& other)
267 {
268     mShallow = other.mShallow;
269     mpImage = other.mpImage;
270     other.mShallow = true;
271     other.mpImage = NULL;
272     return *this;
273 }
274
275 dataptr::dataptr(DataElement* pElement, DataPointerArgs args)
276 {
277     int own(0);
278     mpData = createDataPointer(pElement, &args, &own);
279     mOwns = (own != 0);
280 }
281
282 dataptr::~dataptr()
283 {
284     if (mOwns)
285     {
286         destroyDataPointer(mpData);
287     }
288 }
289
290 dataptr::operator void*()
291 {
292     return mpData;
293 }
294
295 dataptr::operator char*()
296 {
297     return reinterpret_cast<char*>(mpData);
298 }
299
300 void* dataptr::get()
301 {
302     return mpData;
303 }
```

```
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8  */
9
10 #ifndef TRACKINGUTILS_H__
11 #define TRACKINGUTILS_H__
12
13 #include "AppConfig.h"
14 #include "LocationType.h"
15 #include "RasterData.h"
16
17 #include <opencv/cv.h>
18 #if defined(WIN_API)
19 #include <boost/cstdint.hpp>
20 using boost::uint8_t;
21 #endif
22
23 namespace TrackingUtils
24 {
25 typedef uint32_t subcubeid_t;
26
27 /**
28  * Calculate a sub-cube ID for a given point.
29  *
30  * A sub-cube ID uses a quadtree to encode a sub-cube of an image.
31  * It is a 32-bit unsigned value. The least significant 4 bits encode the number of
32  * the remaining bit pairs which are significant. The remaining bits encode the child
33  * ID at each level of a quad tree, least significant to most. The quadrants are 0-3
34  * where
35  * 0 is the upper right quadrant (smallest y, largest x) and the remaining follow anti-
36  * clockwise.
37  * The id 0x00000000 indicates the entire image. The id 0x00000902 (0b10010010)
38  * indicates
39  * there are 2 significant bit pairs. Those 4 bits point to the 1 quadrant (upper-left)
40  * and the
41  * 2 sub-quadrant (lower-left). The id 0xffffffff is an invalid ID and can be used for
42  * initialization
43  * of variables, default error values, etc.
44  *
45  * @param location
46  *       The point to encode.
47  * @param levels
48  *       The number of levels deep to calculate.
49  * @param maxBb
50  *       The largest x, y values (inclusive) of the bounding box used for calculations
51  *
52  * @param minBb
53  *       The smallest x, y values (inclusive) of the bounding box used for
54  *       calculations.
55  * @return The sub-cube ID.
56  */
57 subcubeid_t calculateSubcubeId(LocationType location, uint8_t levels, Opticks::
58     PixelLocation maxBb,
59     Opticks::PixelLocation minBb = Opticks::PixelLocation(0,
60     0));
61
62 /**
63  * Calculate the extents in the sub-cube for a sub-cube ID.
64  *
65  * @param subcubeId
66  *       The ID.
67  */
68 }
```

```

58 * @param levels
59 *     Output param containing the number of levels deep.
60 * @param maxBb
61 *     Input/output parameter.
62 *     Initially The largest x, y values (inclusive) of the bounding box used for
    calculations. ✓
63 *     On return, contains the largest x, y values of the specified sub-cube.
64 * @param minBb
65 *     Input/output parameter.
66 *     Initially The smallest x, y values (inclusive) of the bounding box used for
    calculations. ✓
67 *     On return, contains the smallest x, y values of the specified sub-cube.
68 * @return True on success, false otherwise. If false, the output parameters are
    undefined. False usually ✓
69 *     indicates an invalid subcubeId
70 */
71 bool calculateSubcubeBounds(subcubeid_t subcubeId, uint8_t& levels, Opticks::
    PixelLocation& maxBb, Opticks::PixelLocation& minBb); ✓
72
73 /**
74 * Calculate the quadtree level needed to get a sub-cube of at most the specified size.
75 *
76 * @param maxSubcubeSize
77 *     Maximum size of the subcube in pixels^2.
78 * @param maxBb
79 *     The largest x, y values (inclusive) of the bounding box used for calculations. ✓
80 *
81 * @param minBb
82 *     The smallest x, y values (inclusive) of the bounding box used for
    calculations. ✓
83 * @return The level needed. If it can't be represented, 0xff will be returned.
84 */
85 uint8_t calculateNeededLevels(uint32_t maxSubcubeSize, Opticks::PixelLocation maxBb,
    Opticks::PixelLocation minBb = Opticks::PixelLocation(0, 0)); ✓
86
87 /**
88 * Determines the affine transform between a set of correspondances using RANSAC.
89 */
90 CvMat* ransac_affine(std::vector<std::pair<CvPoint2D32f, CvPoint2D32f> >& corr, int
    maxIter, float thresh, unsigned int numNeeded); ✓
91
92 /**
93 * C allocation memory resource.
94 *
95 * Functions like an std::auto_ptr but for memory allocated with malloc() and friends.
96 */
97 template<typename T>
98 class ca_ptr
99 {
100 public:
101     ca_ptr() : mpData(NULL) {}
102
103     ca_ptr(T* pData) : mpData(pData) {}
104
105     ~ca_ptr()
106     {
107         if (mpData != NULL)
108         {
109             free(mpData);
110         }
111     }
112
113     T* get()
114     {
115         return mpData;

```



```
116     }
117
118     T* release()
119     {
120         T* pData = mpData;
121         mpData = NULL;
122         return pData;
123     }
124
125     void reset(T* pData)
126     {
127         if (mpData != NULL)
128         {
129             free(mpData);
130         }
131         mpData = pData;
132     }
133
134     operator T*()
135     {
136         return get();
137     }
138
139     T** operator&()
140     {
141         return &mpData;
142     }
143
144 private:
145     T* mpData;
146 };
147
148 /**
149  * Resource to manage an OpenCV IplImage.
150  *
151  * Can wrap existing memory (shared) or alloc its own memory.
152  */
153 class IplImageResource
154 {
155 public:
156     IplImageResource();
157     IplImageResource(IplImage* pImage);
158     IplImageResource(IplImageResource& other);
159     IplImageResource(int width, int height, int depth, int channels);
160     IplImageResource(int width, int height, int depth, int channels, char* pData);
161     ~IplImageResource();
162     bool isShallow();
163     void reset(IplImage* pImage);
164     IplImage* get();
165     IplImage* release();
166     IplImage* take();
167     operator IplImage*();
168     IplImage& operator*();
169     IplImageResource& operator=(IplImageResource& other);
170
171 private:
172     IplImage* mpImage;
173     bool mShallow;
174 };
175
176 class dataptr
177 {
178 public:
179     dataptr(DataElement* pElement, DataPointerArgs args);
180     ~dataptr();
181     operator void*();
```

```
182     operator char*();
183     void* get();
184
185 private:
186     void* mpData;
187     bool mOwns;
188 };
189
190 #endif
191
```

```
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7  * http://www.gnu.org/licenses/lgpl.html
8  */
9
10 #include "AnimationController.h"
11 #include "AnimationServices.h"
12 #include "AnimationToolBar.h"
13 #include "AttachmentPtr.h"
14 #include "DesktopServices.h"
15 #include "ModelServices.h"
16 #include "LabeledSection.h"
17 #include "LayerList.h"
18 #include "MouseMode.h"
19 #include "OpticalFlowWidget.h"
20 #include "PlugInManagerServices.h"
21 #include "RasterLayer.h"
22 #include "SessionManager.h"
23 #include "Slot.h"
24 #include "SpatialDataView.h"
25 #include "SpatialDataWindow.h"
26 #include "TrackingManager.h"
27 #include <QtGui/QAction>
28 #include <QtGui/QCheckBox>
29 #include <QtGui/QCursor>
30 #include <QtGui/QHBoxLayout>
31 #include <QtGui/QMouseEvent>
32 #include <QtGui/QPushButton>
33 #include <QtGui/QSpinBox>
34 #include <vector>
35
36 OpticalFlowWidget::OpticalFlowWidget(QWidget* pParent) :
37     LabeledSectionGroup(pParent),
38     mpToolBar(SIGNAL_NAME(AnimationToolBar, ControllerChanged), Slot(this, &
39         OpticalFlowWidget::updateAnimation)),
40     mpActiveMode(NULL)
41 {
42     mpToolBar.reset(static_cast<AnimationToolBar*>(Service<DesktopServices>()->getWindow(
43         "Animation", TOOLBAR)));
44     QWidget* pSelectWidget = new QWidget(this);
45     QHBoxLayout* pSelectLayout = new QHBoxLayout(pSelectWidget);
46
47     mpMaxSize = new QSpinBox(pSelectWidget);
48     mpMaxSize->setRange(16, 8192);
49     mpMaxSize->setSingleStep(16);
50     mpMaxSize->setValue(1024);
51     mpMaxSize->setSuffix(" pel^2");
52     pSelectLayout->addWidget(mpMaxSize);
53     QPushButton* pSelectButton = new QPushButton("Select Area", pSelectWidget);
54     pSelectLayout->addWidget(pSelectButton);
55     VERIFYNR(connect(pSelectButton, SIGNAL(clicked()), this, SLOT(activateSelectMode
56         ()))));
57
58     QCheckBox* pPause = new QCheckBox("Pause", pSelectWidget);
59     pSelectLayout->addWidget(pPause);
60     VERIFYNR(connect(pPause, SIGNAL(toggled(bool)), this, SLOT(updatePause(bool))));
61
62     pSelectLayout->addStretch(10);
63     LabeledSection* pDataSelectSection = new LabeledSection("Data Set", this);
64     pDataSelectSection->setSectionWidget(pSelectWidget);
65     addSection(pDataSelectSection);
66 }
```

```

64     addStretch(100);
65
66     mpSelectMode = Service<DesktopServices>()->createMouseMode("OpticalFlowCenterSelect"
        , Qt::CrossCursor);
67 }
68
69 OpticalFlowWidget::~OpticalFlowWidget()
70 {
71 }
72
73 void OpticalFlowWidget::updateAnimation(Subject& subject, const std::string& signal,
        const boost::any& val)
74 {
75     AnimationController* pController = boost::any_cast<AnimationController*>(val);
76     if (pController == NULL || pController->getAnimations().empty())
77     {
78         return;
79     }
80     Animation* pAnimation = pController->getAnimations().front();
81     std::vector<Window*> windows;
82     Service<DesktopServices>()->getWindows(windows);
83     for (std::vector<Window*>::iterator window = windows.begin(); window != windows.end()
        (); ++window)
84     {
85         SpatialDataWindow* pWindow = dynamic_cast<SpatialDataWindow*>(*window);
86         SpatialDataView* pView = pWindow == NULL ? NULL : pWindow->getSpatialDataView();
87         if (pView != NULL)
88         {
89             std::vector<Layer*> layers;
90             pView->getLayerList()->getLayers(RASTER, layers);
91             for (std::vector<Layer*>::iterator layer = layers.begin(); layer != layers.end()
                (); ++layer)
92             {
93                 RasterLayer* pLayer = static_cast<RasterLayer*>(*layer);
94                 if (pLayer != NULL && pLayer->getAnimation() == pAnimation)
95                 {
96                     std::vector<PlugIn*> manager =
97                         Service<PlugInManagerServices>()->getPlugInInstances(TrackingManager:
:spPlugInName);
98                     if (!manager.empty())
99                     {
100                         static_cast<TrackingManager*>(manager.front())->setTrackedLayer
                            (pLayer);
101                     }
102                     return;
103                 }
104             }
105         }
106     }
107 }
108
109 void OpticalFlowWidget::updatePause(bool state)
110 {
111     std::vector<PlugIn*> manager = Service<PlugInManagerServices>()->getPlugInInstances
        (TrackingManager::spPlugInName);
112     if (!manager.empty())
113     {
114         static_cast<TrackingManager*>(manager.front())->setPauseState(state);
115     }
116 }
117
118 void OpticalFlowWidget::activateSelectMode()
119 {
120     View* pView = Service<DesktopServices>()->getCurrentWorkspaceWindowView();
121     if (pView != NULL)
122     {

```

```
123     mpActiveMode = pView->getCurrentMouseMode();
124     if (mpActiveMode == mpSelectMode)
125     {
126         mpActiveMode = NULL;
127     }
128     pView->addMouseMode(mpSelectMode);
129     pView->setMouseMode(mpSelectMode);
130     pView->getWidget()->installEventFilter(this);
131 }
132 }
133
134 bool OpticalFlowWidget::eventFilter(QObject* pObj, QEvent* pEvent)
135 {
136     if (pEvent != NULL && pEvent->type() == QEvent::MouseButtonRelease)
137     {
138         View* pView = Service<DesktopServices>()->getCurrentWorkspaceWindowView();
139         if (pView != NULL)
140         {
141             QPointF loc = static_cast<QMouseEvent*>(pEvent)->posF();
142             loc.setY(pView->getWidget()->height() - loc.y());
143             std::vector<PlugIn*> manager = Service<PlugInManagerServices>()->getPlugInInstances(TrackingManager::spPlugInName);
144             if (!manager.empty())
145             {
146                 int maxSz = mpMaxSize->value();
147                 static_cast<TrackingManager*>(manager.front())->setFocus(LocationType(loc.x(), loc.y()), maxSz*maxSz);
148             }
149
150             pView->setMouseMode(mpActiveMode);
151             mpActiveMode = NULL;
152             pView->getWidget()->removeEventFilter(this);
153             return true;
154         }
155     }
156     return false;
157 }
```

```
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8  */
9
10 #ifndef OPTICALFLOWWIDGET_H__
11 #define OPTICALFLOWWIDGET_H__
12
13 #include "AnimationToolBar.h"
14 #include "AttachmentPtr.h"
15 #include "LabeledSectionGroup.h"
16 #include <boost/any.hpp>
17
18 class MouseMode;
19 class QComboBox;
20 class QSpinBox;
21
22 class OpticalFlowWidget : public LabeledSectionGroup
23 {
24     Q_OBJECT
25
26 public:
27     OpticalFlowWidget(QWidget* pParent = NULL);
28     virtual ~OpticalFlowWidget();
29
30 protected slots:
31     void updatePause(bool state);
32     void activateSelectMode();
33
34 protected:
35     bool eventFilter(QObject* pObj, QEvent* pEvent);
36
37 private:
38     void updateAnimation(Subject& subject, const std::string& signal, const boost::any& val);
39
40     AttachmentPtr<AnimationToolBar> mpToolbar;
41     MouseMode* mpSelectMode;
42     MouseMode* mpActiveMode;
43     QSpinBox* mpMaxSize;
44 };
45
46 #endif
```

```
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8  */
9
10 #include "AppVerify.h"
11 #include "DesktopServices.h"
12 #include "MenuBar.h"
13 #include "OpticalFlow.h"
14 #include "OpticalFlowWidget.h"
15 #include "PlugInRegistration.h"
16 #include "ToolBar.h"
17
18 REGISTER_PLUGIN_BASIC(Tracking, OpticalFlow);
19
20 OpticalFlow::OpticalFlow()
21 {
22     setName("OpticalFlow");
23     setDescription("Calculate optical flow field.");
24     setDescriptorId("{38c907e0-1a57-11df-8a39-0800200c9a66}");
25     setSubtype("Video");
26 }
27
28 OpticalFlow::~OpticalFlow()
29 {
30 }
31
32 QAction* OpticalFlow::createAction()
33 {
34     // Add a menu command to invoke the window
35     MenuBar* pMenuBar = Service<DesktopServices>()->getMainMenuBar();
36     VERIFYRV(pMenuBar, NULL);
37     QAction* pAction = pMenuBar->addCommand("&View/&Optical Flow");
38
39     ToolBar* pToolBar = static_cast<ToolBar*>(Service<DesktopServices>()->getWindow(
40         "Tracking", TOOLBAR));
41     if (pToolBar == NULL)
42     {
43         pToolBar = static_cast<ToolBar*>(Service<DesktopServices>()->createWindow(
44             "Tracking", TOOLBAR));
45     }
46     VERIFYRV(pToolBar, NULL);
47     pToolBar->addButton(pAction);
48     return pAction;
49 }
50
51 QWidget* OpticalFlow::createWidget()
52 {
53     return new OpticalFlowWidget();
54 }
```

```
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8  */
9
10 #ifndef OPTICALFLOW_H__
11 #define OPTICALFLOW_H__
12
13 #include "DockWindowShell.h"
14
15 class OpticalFlow : public DockWindowShell
16 {
17 public:
18     OpticalFlow();
19     virtual ~OpticalFlow();
20
21 protected:
22     virtual QAction* createAction();
23     virtual QWidget* createWidget();
24
25 };
26
27 #endif
```



```
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8  */
9
10 #include "PlugInRegistration.h"
11
12 REGISTER_MODULE(Tracking);
```

```
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8  */
9
10 #ifndef TRACKINGVERSION_H
11 #define TRACKINGVERSION_H
12
13 #define TRACKING_NAME "Tracking"
14 #define TRACKING_NAME_LONG "Object trackgin"
15 #define TRACKING_COPYRIGHT "Copyright © 2010, Trevor R.H. Clarke"
16 #define TRACKING_VERSION_NUMBER "1.0.0Unofficial"
17 #define TRACKING_IS_PRODUCTION_RELEASE false
18
19 #endif
20
```

```
1 <?xml version="1.0" encoding="UTF-8" standalone="no" ?>
2 <ConfigurationSettings xmlns="https://comet.balldayton.com/standards/namespaces/2005/v1/
  comet.xsd">
3
4   <opticks build_revision="9296" release_date="09 June 2009" version="4.3.3rc1"/>
5
6   <group name="settings" version="3">
7     <attribute name="TrackingManager" type="DynamicObject" version="3">
8       <attribute name="InitialSubcubeSize" type="unsigned int">
9         <value>262144</value> <!-- 512x512 -->
10       </attribute>
11     </attribute>
12   </group>
13 </ConfigurationSettings>
14
```