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DDDAS for Object Tracking in Complex and Dynamic Environments (DOTCODE)

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A dynamic data driven application system prototype applicable to an adaptive multimodal sensor together with a proposed adaptive sampling strategy was demonstrated to greatly reduce the amount of data required to perform target identification. By using an adaptive sampling strategy, while ~10% of the image pixels were selected to collect spectral data to perform feature matching in the prototype examined here. Target identification was shown to be improved using a background data elimination method was designed to remove redundant spectral data and an adaptive forecasting strategy based on the extracted context from OpenStreetMap improved tracking accuracy and target identification. In summary, the vehicle tracking adjusts to the vehicle movement, the background environment, and the road network as derived from the imagery used in the tracking.

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Final Performance Report to Dr. Darema

Anthony Vodacek and John P. Kerekes, RIT Center for Imaging Science
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Summary - Simulations of a dynamic data driven sensor together with an adaptive sampling strategy were created using Dynamic Data Driven Application Systems (DDDAS) principles and demonstrated to reduce the amount of data required to perform robust vehicle tracking. By employing an adaptive sampling strategy (controlling the pixel sampling based on analysis of prior data) for a simulated multimodal sensor for which pixels can be individually addressed, only about 10% of the pixels in a scene were required to collect spectral data to perform feature matching. Further, the method was shown to require as little as approximately 1.5% of the data compared to the case of a full hyperspectral sensor. The method employs a Gaussian Sum Filter for the vehicle-tracking model and an adaptive forecasting strategy to morph the Gaussian Sum Filter based on the extracted context from OpenStreetMap to improve tracking accuracy. Eliminating target spectra contamination with the background by sampling the background at forecasted vehicle locations was shown to improve tracking by improving feature matching results leading to better association of vehicles with specific tracks.

Motivation - The tracking of ground objects via electro-optical imaging from a remote platform is a common Air Force activity. This type of surveillance is often controlled by an operator who devotes attention to a specific previously identified object, with little or no opportunity to understand the wider background context in which the object is maneuvering. In contrast, spectral cameras and algorithms have been developed for wide-area surveillance and tracking of multiple objects autonomously. However, these systems generate large data volumes and often track any moving object, including those that may be of irrelevant. Further, while these systems may reacquire object tracking after moving behind a tall obscuration, the system may not associate the reacquired object as being the same object that was previously tracked and then obscured.

Objective - The objective was to prototype methods for a vehicle tracking system via airborne imaging that would overcome the limitations of previous object tracking methods by applying Dynamic Data Driven Applications Systems principles. By implementing dynamic interactions between tracking models and data information methods appropriate for multi-modal adaptive sensors, the system would allow an operator to mark multiple vehicles for tracking in an image and then tracking of those specific objects would proceed autonomously while maintaining object association despite obscurations and a variety of vehicle maneuvers.

Methods and Outcomes - True to the principles of DDDAS, the methods created for the system all adjust the system to the content of the image data being collected (Figure 1). The work focused on three different components where DDDAS principles were applied. One, the sensor considered is itself multi-modal and controllable at the pixel level, thus forward-looking sampling strategies were demonstrated based on analysis of the current image collection. Two, the background to the moving vehicle naturally changes and the system continuously monitors and updates the changing background to improve separation of the vehicle from the background during feature matching. Three, logical decisions on future vehicle movements based on the geometry of the road network derived from OpenStreetMap are used to morph the Gaussian Sum

Filter to improve efficiency of tracking.

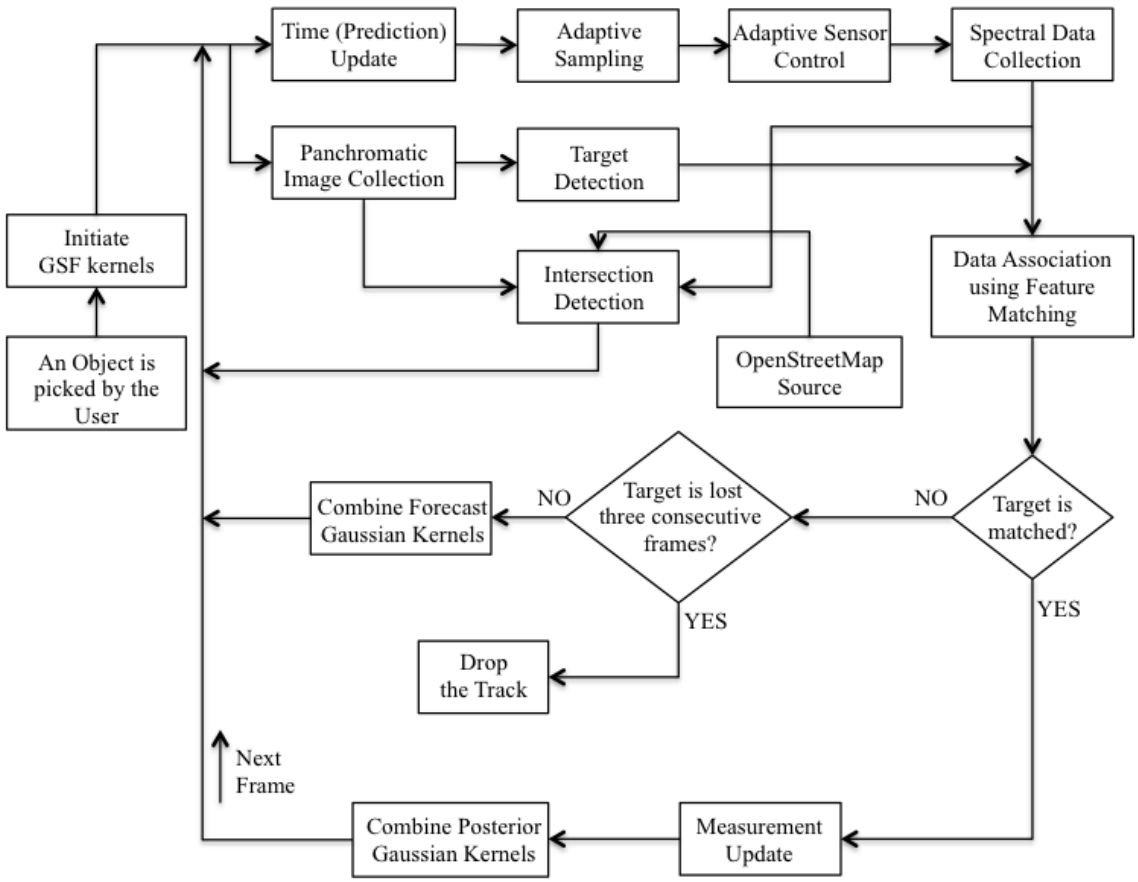

Figure 1. Flow chart of the vehicle tracking system.

In parallel to the DDDAS development a computationally simple method for assessing spectral similarity that could be applied in feature matching was demonstrated. Finally, by using the Digital Imaging and Remote Sensing Image Generation (DIRSIG) model to create surveillance image simulations, the approach was developed without expensive and time-consuming fieldwork, adaptive multimodal sensors that exist only in design studies were tested, and complex obscuration and viewing scenarios were possible. These methods are summarized below.

Adaptive Sampling

To fully exploit the utility of a multimodal adaptive sensor requires implementing sampling strategies. The goal was to pick pixels that most likely contain target values and not background values in order to associate the vehicle detection with the correct track. This strategy addressed the orientation of the vehicle relative to the columns and rows of the image.

The orientation sampling strategy created was based on the orientation angle of a target in the image was made relative to the determination of two thresholds. If the orientation angle of the target was found to be lower than both of the thresholds, the horizontal sampling (image rows) method was assigned since the target was likely to travel horizontally in the image. If the estimated orientation angle is in between the thresholds, then diagonal sampling (diagonal of image rows and columns) was employed to provide a higher number of possible target pixels. If the estimated orientation angle is higher than both of the thresholds (the target is in vertical shape), the horizontal sampling method is assigned again since with rotation of the image horizontal sampling becomes identical to vertical sampling.

Feature matching and background monitoring and elimination

A method to continuously assess and update the background to the vehicle was created since it is inevitable that spectral measurements of the background will be made in addition to the target measurements. The unknown presence of background data in an assumed vehicle spectrum can yield the association of a detected object to a wrong track. A background elimination method was designed to remove background pixel spectra from the spectral measurements of the vehicles. A forecast of the target of interest location for the future time step of the vehicle movement model can be assumed to be background and updated continuously as the background changes. During adaptive sampling, as previously described, simple comparison between target and background spectra is performed using the Spectral Angle Method (SAM) to remove background pixels from the vehicle spectra, which resulted in the improvement in the association of the vehicle with its track.

Another use of feature matching in complex environments is that tracking will often be lost when vehicles move under trees, behind buildings or near other moving targets, etc. In these cases, it is important to re-establish the track when a new detection occurs, as opposed to treating the re-detected vehicle as a new object. This is accomplished through feature matching, where the spectral features of the new target are compared with those of the past targets. The comparison is performed using spectra data collected at different wavelengths by a sensor. In a real system, the sensor must be tasked to take spectral data without any a priori knowledge of where detections will occur. Therefore, sampling is performed by taking a subset of the pixels from where the forecasting model predicts the target will be. Using the sampled pixels, a spectrum is formed for each prediction component. The spectrum (the prediction component) that matches best with an existing track is used to perform association. After detecting moving objects in the new frame, the closest detected object to the prediction component, which matches best with an existing track, is associated to the corresponding existing track. In other words, the new object is regarded as a re-detection of the old target. If no preexisting target is matched, then a new track is initiated. The Spectral Angle Mapper (SAM) spectral measure was used to compare spectra. It computes the similarity between two spectra by measuring the angular difference of spectral direction. It is insensitive to the magnitude of brightness since it takes only the vector direction into account. This research project included the development of a new spectral similarity measure that does include the magnitude as well as the spectral direction.

A new image spectral similarity algorithm

While SAM was used to test spectral similarity in the prototype development, a more powerful yet simple new spectral similarity measure was developed based on the geometric characteristics of the Mahalanobis distance so as to incorporate both spectral direction and spectral magnitude. With a minimum of a human operator input to define representative pixels, the measure was tested experimentally to demonstrate through the analysis of ROC curves the potential advantages of the novel distance measure when applied to the identification of materials in urban images such as vehicles. Further details on this algorithm can be found in the publication by Chen, Sun, and Vodacek listed in the section below listing publications derived from this research.

Gaussian Sum Filter that adjusts to vehicle movement and intersections

Estimating the state of a target vehicle using data collected by an airborne sensor can be challenging due to possible non-Gaussian distribution of target movement. A nonlinear filter can better approximate a non-Gaussian distribution and evolve the corresponding uncertainty. The previously developed Gaussian Sum Filter (GSF), a nonlinear filter, was employed in this study. It represents a non-Gaussian distribution by a finite mixture of Gaussian distributions. The mean and covariance of these density kernels are updated using the Extended Kalman filter (EKF) was used in this study. There are two advantages of the GSF over a single EKF. A single EKF represents a nonlinear model by linearizing it. Meanwhile, the GSF represents a non-Gaussian problem by a mixture of Gaussian distributions. Besides, GSF, a mixture of different EKF banks, were used to implement a multiple forecasting model set strategy to predict the target vehicle movement. With a single EKF, we would only be able to employ one model at each time step. In this case, the single forecasting model should be well defined to predict the target movement. The weights of the density kernels are kept constant while propagating the uncertainty and updated in the presence of observation.

Tests were made to find an appropriate number of Gaussian components to perform robust tracking in challenging scenarios. More components can improve tracking but also bring undesired complexity. Different numbers of components were tested to represent a target to perform a trade study of complexity versus computational complexity. For example, in a design scenario consisting of a T-type road intersection, where going left and right are the only possibilities a target can take 6 components is the optimum number of components to cover a possible path (going left, right, straight) while keeping the complexity at a desired level. As a result 12 components (6 for left turn and 6 for right turn) are placed in the vicinity of the observation while one component is placed on the observation initially for a total of 13 components while maintaining the required computational speed.

Matching the image and the OpenSteetMap road network

Despite the effectiveness of the background elimination approach described above, there were challenges in maintaining feature matching at intersections where nonlinearities occur. The main reason behind this was the difficulty of forecasting a nonlinear and complex movement. To improve forecasting and analysis performance, additional context was added to the system by using prior knowledge of the road network. In a DDDAS sense the context is changed as the vehicle moves through the environment. Vehicles are more likely to follow road networks, so following identification of a car localizing its placement on a known road reduces the uncertainty for its next location. In other words, using the extracted additional road network context allowed pre-adjusting of the forecasting multiple model set with the result of better target tracking. For instance, probable paths a target may take were based on the type of an intersection (T-type, plus type, etc.) the vehicle was approaching.

The extraction of the road network in the image involved three aspects: image-based road network extraction, vector road to raster imagery conflation, and a seamless integration of both into a unified framework. The road extraction approach was fairly generic since the OpenStreetMap (OSM) vector road data is globally and readily freely available. The OSM quality improves and coverage grows over time, which made it a valuable source of prior data for image-based road extraction. Due to the persistent mis-registration between image and map data, map conflation (making maps match) is carried out first to adjust the OSM road vectors to align with road centerlines in the image. Junction templates derived from rasterized OSM road segments are then matched with image-derived binary road masks and curvilinear response images to conflate junction points. The non-junction point matching approach effectively conflates the vector road network based on pre-corrected road segments and image curvilinear structures, within which width and orientation estimations are also embedded and can be obtained to recover the piecewise width of road segments. A road label mask is finally created with complete road knowledge - centerline, width, connectivity, and topology. The approach was tested on some large and diverse image data sets and was verified for its effectiveness and robustness and was found to achieve a minimum of 80% conflation correctness and 70% road extraction accuracy on some extremely challenging scenes with dense and irregular road networks with building shadows.

To identify roads and intersections, the OSM road network data were injected into the tracking system. The OSM source data are standardized and rasterized, but lingering misregistration with image data due to image distortions, topographical change, inaccurate map surveys, GPS errors, etc. A method to register the image and map data was developed. This process started with the identification of intersections, end points, and points with high curvature in the OSM data to form templates. Using the map coordinates as a first guess, a search of the extracted image features in the neighborhood of the first guess was used to match the templates. This allowed finding the accurate positions of intersections and curvy roads on the image. To account for different type of roads, different width values are tested during template formation. This process identifies important intersections in the image that the tracked target might approach.

Once the road network is identified in a given scenario, all possible paths a target can travel in a particular time step are available for approximating the prior and posterior probability distribution function of the target. A recently published multiple model set tracking system called an Interactive Multiple Modal (IMM) filter was adopted for the tracking system. In essence, specific models are adaptively avoided using the intersection data in certain situations. For example, in a T-type intersection, the coordinated turn models (CTM) are applied while the constant velocity (CV) model is avoided while in the case of a plus type intersection both the CV and CTM models are allowed. In the DDDAS sense, the models are adjusted as the vehicle moves through the environment.

Leveraging DIRSIG simulations to create the system prototype

To develop and test the system in a controlled environment that allows us a knowable ground truth, we use synthetic imagery generated by the Digital Imaging and Remote Sensing Image Generation (DIRSIG) model. DIRSIG is a first-principles image generation model that computes time and material dependent surface temperature values, incorporates atmospheric contributions using MODTRAN,9 and predicts bi-directional reflectance functions to render realistic image sets. In addition, the Simulation of Urban Mobility (SUMO) traffic simulator has been integrated with DIRSIG to produce dynamic imagery for tracking scenarios. SUMO has the capability to simulate both vehicular and pedestrian movement, but only vehicular traffic is considered for this study. Different paint models are used for different vehicles. The motivation for using synthetic data is that, since we know the true positions and characteristics in a synthetic image, we can accurately compute performance metrics for the tracking system. Furthermore, multiple scenarios and sampling strategies within those scenarios can also be carried out without running multiple experiments. The scenario used in this paper comes from DIRSIG Megascene I, which is built to resemble part of Rochester, NY, USA. The simulation uses hyperspectral imaging from a fixed aerial platform assuming a static sensor mount. To test the algorithm we design a 30-second video sequence formed by these images featuring vehicles motion variations via SUMO. The spectral range is 400 to 1000 nm with a spectral resolution of 5 nm. Thus, generated hyperspectral images have 121 wavelength bands. Since the base image was spectral any sensor adaptive in vis-NIR wavelengths could be simulated.

Conclusion - A dynamic data driven application system prototype applicable to an adaptive multimodal sensor together with a proposed adaptive sampling strategy was demonstrated to greatly reduce the amount of data required to perform target identification. Without an adaptive multimodal sensor, the default would be to collect a full spectral image. By using an adaptive sampling strategy, while ~10% of the image pixels were selected to collect spectral data to perform feature matching in the prototype examined here. The data volume was ~1.5% of the data used by a hyperspectral sensor. Target identification was shown to be improved using a background data elimination method was designed to remove redundant spectral data and an adaptive forecasting strategy based on the extracted context from OpenStreetMap improved tracking accuracy and target identification. In summary, the vehicle tracking adjusts to the vehicle movement, the background environment, and the road network as derived from the imagery used in the tracking.

Theses to be published

The major part of the actual vehicle tracking code including the implementation of the GSF and the adaptive sensing strategies using DDDAS principles is the work of Ph.D. student Burak Uzkent. Mr. Uzkent is expected to defend his dissertation in winter 2014-15. Tentative dissertation title: Persistent Ground Target Tracking using Dynamic Data Driven Adaptive Optical Sensor.

The spectral similarity measure and the OpenStreetMap technique is the work of Ph.D. student Bin Chen. Mr. Chen is expected to defend his dissertation in August 2014. Tentative dissertation title: Scene Content Understanding of High-resolution Remote Sensing Imagery.

These two dissertations, like all RIT theses and dissertations will be made available online at the RIT Digital Media Library in pdf format as a degree requirement <https://ritdml.rit.edu/>.

Cumulative list of people involved in the research effort:

Anthony Vodacek
Matthew J. Hoffman
John P. Kerekes
Bin Chen
Burak Uzkent

Cumulative list of publications stemming from the research effort:

1. Uzkent, B.; Hoffman, M.J.; Vodacek, A.; Chen, B., In review. Feature Matching with an Adaptive Optical Sensor in a Ground Target Tracking System. IEEE Sensors Journal.
2. Chen, B., W. Sun, and A. Vodacek. In press. Proc. IEEE 2014 Geoscience and Remote Sensing Symposium (IGARSS), Quebec, Canada.
3. Chen, B., A. Vodacek, and N. D. Cahill. 2013. A Novel Adaptive Scheme for Evaluating Spectral Similarity in High-resolution Urban Scenes. IEEE J. Selected Topics Appl. Earth

Obs. Remote Sens. (JSTARS). 6:1376-1385. doi:10.1109/JSTARS.2013.2254702
4. Uzkent, B.; Hoffman, M.J.; Vodacek, A.; Kerekes, J.P.; Chen, B., 2013. Feature Matching and Adaptive Prediction Models in an Object Tracking DDDAS, Procedia Computer Science, 18, pp. 1939-1948. doi:10.1016/j.procs.2013.05.363
5. Chen, B., A. Vodacek, and N.D. Cahill. 2012. Novel spectral similarity measure for high resolution urban scenes. Proc. IEEE 2012 Geoscience and Remote Sensing Symposium (IGARSS). pp. 6637-6640. DOI: 10.1109/IGARSS.2012.6352077
6. Vodacek, A., J.P. Kerekes, M.J. Hoffman. 2012. Adaptive Optical Sensing in an Object Tracking DDDAS, Procedia Computer Science, 9, pp. 1159-1166. doi:10.1016/j.procs.2012.04.125

Appendix A - Pseudo code for the image and OpenStreetMap conflation operation

The pseudo code for the image and OpenStreetMap conflation operation is listed below. For a detailed description of the algorithm, please refer to the IGARSS 2014 paper: Bin Chen, Weihua Sun, Anthony Vodacek, "Improving Image-Based Characterization of Road Intersections, Widths, and Connectivity by Leveraging OpenStreetMap Vector Map", 2014 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 2014.

```
Given a geo-referenced multispectral image MSI

// Generate Binary Road Mask BRM
Foreach reference spectrum REF representing road-like pixels
     Foreach pixel X in MSI
          SSM = Spectral similarity measurement (X, REF)
          Threshold SSM -> binary SSM (BSM)
     End
     BRM = OR(BRM, BSM)
End

// Generate Curvilinear Response Image CRI
Foreach filter width w
     Foreach filter orientation theta
          Create filter bank FB(w,theta)
          CRI(w,theta) = conv(FB(w,theta), MSI)
     End
End

// Generate Vector Road Network VEC
Import ShapeFile from OpenStreetMap
Standardize ShapeFile -> VEC

// Road Junction Matching
Foreach road junction JCT
     Foreach junction branch width option
          Create junction template TEMP from localized VEC
          Generate Correlation Map (CM)
          CM1 = conv(TEMP, BRM)
          CM2 = conv(TEMP, CRI)
     End
     Max(CM1, CM2) -> (Max Location, Corresponding Filter Bank)
End

// Pre-Correction of Road Network
Foreach junction point pair within the same SEG
     2D_Intepolation(Max Location) -> Pre-corrected SEG
End

// Non-Junction Point Matching
Foreach pre-corrected SEG
     Transverse_Search(SEG) -> (Conflated SEG, SEG_width)
End

// Road Pixel Extraction
Foreach SEG
      Expand SEG with width SEG_width
END
```