Volume 3, Issue 10, October 2013 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Multiview Graphical Models for Tracking Occluded Objects

Bharath
Student,
Dept.of CSE,
Jntuk, Kakinada, India

Smt. D.Neelima
Asst.Professor,
Dept.of CSE,
Jntuk, Kakinada, India

Abstract: ***Graphical models for tracking images are the main representation in space parking for image extraction. Representation of scenes containing relocatable objects that can cause partials occlusions of people in a camera's field of view. This representation is called Graphical model layer. A graphical model layer is used to track partially occluded objects. In this comparing with sprite learning algorithm with pedestrian tracker based on deformable contours and with pedestrian detectors. These results also indicate several areas in need of improvement. But formulation for tracking on the boundary of free space and to activity zones is a challenge on retrieving image specials when body is moving to multi free space in dime national. So in this paper we propose to extend our graphical model in multiview representation for tracking of moving from free space relocations. We are maintaining separate scene in each view and formulate the image evidence across all the views. Our experimental results show the multiview representation of each user image efficiently. Different model can be take ground plane for multiview representation.***

Index Terms: Computer vision, image representation, tracking, graphical models, multiview representation, and connectivity access.

I. Introduction

Tracking is the process of locating a moving object over time using camera. Example for tracking was Human Computer Interaction, security and surveillance, video communication and compression. Video tracking is a time consuming process due to the amount of data that is contained in video. The objective of video tracking is to associate target objects in consecutive video frames. The association can be especially difficult when the objects are moving fast relative to the frame rate. Another situation that increases the complexity of the problem is when the tracked object changes orientation over time. For these situations video tracking systems usually employ a motion model which describes how the image of the target might change for different possible motions of the object.

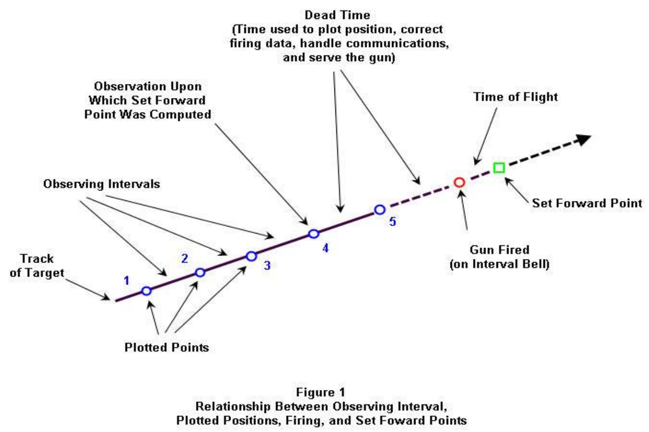

Figure 1: Target tracking system.

The above diagram shows target tracking indifferent models. Tracking of multiple targets using fixed camera's with non overlapping is a challenging problem in present days. Previous introduced concepts like finding the relocatable objects in relocatable occludes. A complementary line of research has focused on learning static occlusion maps using large sets of observations accumulated over time. Relocatable objects tend to cause severe occlusions of people in the scene and, since these objects are movable, learning a single fixed occlusion map is impractical. In many practical applications, relocatable objects are of known classes and tend to be observed repeatedly over time. Because many examples of relocatable occluder's are observed it is possible to learn a function that decides a relocatable occluder's class.

Figure 2: Examples of moving around relocatable occluder's such as cars.

A scene is modeled as a composition of depth-ordered layers of probabilistic graphical models. The number of these models equals the number of relocatable occluder's in the scene at any given time. Each graphical model is comprised of an occlusion mask, a set of image observation regions for observing a person's motion near and around this occlusion mask, and a first-order Markov model for the person's motion around the relocatable object. The person's motion model is defined in the relocatable object's object-centered coordinate system, but this motion model is then mapped into the image plane where observations are obtained. Individual models are then composed to yield a coherent observation and state space. In this paper we are introducing the Multiview representation of moving objects in real time efficiency. Because some objects are moving in nature but previously we are not maintaining datasets representation in each dimension. In our dataset representation we are maintaining each view representation of data accessing of moving objects.

II. Related Work

We first review related representations for dynamic scene analysis, and then discuss related approaches to tracking persons and vehicles. Many approaches, even to this date, are based on silhouettes (e.g.) and perform tracking using stochastic search in high dimensional spaces. While using silhouettes may be appropriate for tracking a single person, silhouette extraction becomes unreliable because of complex backgrounds, occlusions, and moving cameras. Moreover, stochastic search in these high-dimensional spaces is notoriously difficult. To work around these problems, a number of recent tracking approaches turned to feature-based detectors for matching tracking hypotheses, discriminative components, strong dynamical models, or alternative methods for exploring the search space.

Relation to the Existing Approach:

Although the scene representations mentioned earlier have been successfully used in practical applications, these representations are not immediately applicable to relocatable occluder's. When there is no overlap between multiple camera views and when occlusions in each non overlapping view are severe, maintaining an accurate 3D scene model may become a challenge. In such cases, it might still be possible to maintain a 2D layered representation of the scene. However, previous works on layered representations did not model the motion of a person around these layers. An additional shortcoming of the layered representations mentioned in this section is the unique challenge posed by relocatable objects.

Figure 3: Rectangular observation regions, three of which are shown, are depth-ordered with respect to the vehicle's occlusion mask.

A graphical model represents encapsulates the knowledge of person moves around the relocatable object. Because occlusion masks of relocatable objects are acquired offline and stored into a database, a global scene model is assembled on-the-fly rather than learned from scratch every time a relocatable object enters the field of view. These objects are accessed in multi view representation of every user, that user details are stored in separate datasets. In that we are maintaining each view representation.

III. Existing Approach

The key concept behind the approach is an occluder centered representation. This representation encapsulates prior knowledge of a person's motion around a relocatable object in the ground plane and where this motion would be observed in the image plane. a separate graphical model layer is instantiated for every parked vehicle. Input video frames feed into a module that tracks vehicles as they arrive, park, or depart. When a vehicle parks, a pre computed object-centric graphical model is retrieved from the database of such models and instantiated as a layer in our global scene representation.

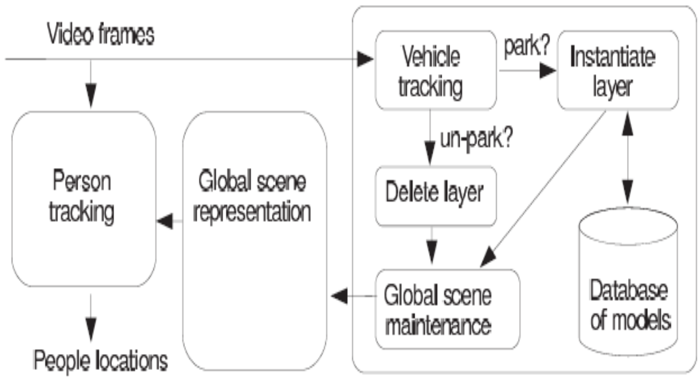

Figure 4: Data representation enables tracking of pedestrians despite prolonged.

We are ultimately interested in person-tracking on activity zones. A person standing in approximated in the image plane by a bounding rectangle r, called an observation region. In previous implementation, observation regions correspond to a height of 1.8 meters to fully cover people of likely heights. Projection of the relocatable object yields an occlusion mask M. To accommodate people entering or leaving the scene within the temporal window, we augment our global scene representation with an additional virtual activity zone. For vehicle tracking it is common to track the position of a vehicle's center within the state variable Xt. However, there is an interesting dependence between our belief about the vehicle's shape and position.

IV. Proposed System

Probabilistic model and notation:

Our goal for this work is to track multiple vehicles in an urban environment. Our ego vehicles have been out fitted with applanix navigation system.

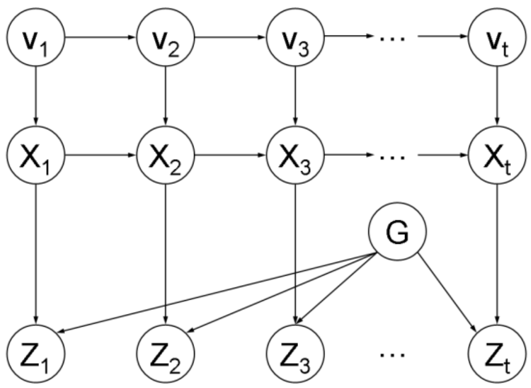

Figure 5: Dynamic Bayesian network model.

Multiple vehicle tracking entails a single joint probability distribution over the state parameters of all of the vehicles.

Vehicle Geometry:

The exact geometric shape of a vehicle can be complex and difficult to model precisely. As we observe the object from a different vantage point, we change not only our belief of its shape, but also our belief of the position of its center point.

Vehicle dynamics model:

The pose evolves via linear motion - a motion law that is often utilized when exact dynamics of the object are unknown. The motion consists of perturbing orientation by $\Delta\varphi 1$, then moving forward according to the current velocity by $V_t\ \Delta t$, and making a final adjustment to orientation by $\Delta\varphi\ 2$.

Sensor Data Representation:

As the sensor rotates to collect the data, each new reading is made from a new vantage point due to ego-motion. Ignoring this effect leads to significant sensor noise. Taking this effect into account makes it difficult to quickly access data that pertains to a specific region of space. Much of the data comes from surfaces uninteresting for the purpose of vehicle tracking, e.g. ground readings, curbs and tree tops. Finally, the raw 3D data wastes a lot of resources as vehicle tracking is a 2D application where the cars are restricted to move on the ground surface. Therefore it is desirable to pre-process the data to produce a representation tailored for vehicle tracking.

V. Performance Results

The most challenging traffic situation at the Urban Grand Challenge was presented on course A during the qualifying event In these conditions accurate estimates of positions and velocities of the cars are very useful for determining a gap in traffic large enough to perform the merge safely. Cars passed in close proximity to each other and to stationary obstacles (e.g. signs and guard rails) providing plenty of opportunity for false associations. Partial and complete occlusions happened frequently due to the traffic density. Moreover these occlusions often happened near merge points which complicated decision making. For each frame of data we counted how many vehicles a human is able to identify in the laser range data. The vehicles had to be within 50m of the ego-vehicle, on or near the road, and moving with a speed of at least 5mph.

Table 1: Represents datasets and overall process in between vehicle detection.

Datasets	Total Frames	Total Vehicles	Currently Detected
Area A	1577	5911	5676
Stanford	2140	3581	3530
Alameda	1531	901	879
Overall	5248	10393	10085

Note that the maximum theoretically possible true positive rate is lower than 100% because three frames are required to detect a new vehicle. On all three data sets the tracker performed very close to the theoretical bound. We have presented the vehicle detection and tracking module developed for Stanford's autonomous driving robot Junior. Tracking is performed from a high-speed moving platform and relies on laser range finders for sensing. Our approach models both dynamic and geometric properties of the tracked vehicles and estimates them with a single Bayes filter per vehicle.

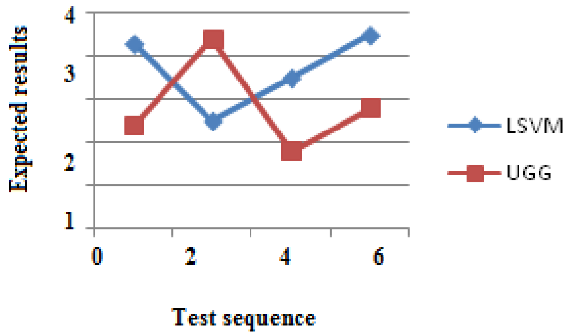

Figure 6: Vehicle detection results with each test presented in our proposed work.

The comparison of both detectors is done on a sequence with multiple full and partial occlusions. Note that in such cluttered sequences ground truth annotation is difficult as it is unclear how to decide when a partially or fully occluded person should be included. Those tracklets are then used to enable people tracking in complex scenes with many people and long-term occlusions.

VI. Conclusion

A direct extension of our approach is to maintain a separate scene model in each view and fuse the image evidence across all the views. Our approach simultaneously processes video streams from stationary and pan-tilt-zoom cameras. The detection of moving objects from moving camera streams is performed by defining an adaptive background model that takes into account the camera motion approximated by an affine transformation. We address the tracking problem by separately modeling motion and appearance of the moving objects using two probabilistic models. For the appearance model, multiple color distribution components are proposed for ensuring a more detailed description of the object being tracked.

References

[1] J. Kang, I. Cohen, and G. Medioni, "Continuous Tracking within and across Camera Streams," Proc. IEEE Int'l Conf. Computer Vision and Pattern Recognition, 2003.

[2] S.M. Khan and M. Shah, "A Multiview Approach to Tracking People in Crowded Scenes Using a Planar Homography Constraint," Proc. European Conf. Computer Vision, 2006.

[3] S.M. Khan and M. Shah, "Tracking Multiple Occluding People by Localizing on Multiple Scene Planes," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 31, no. 3, pp. 505-519, Mar. 2009.

[4] K. Smith, D. Gatica-Perez, J.-M. Odobez, and S. Ba, "Evaluating Multi-Object Tracking," Proc. IEEE CS Conf. Computer Vision and Pattern Recognition Workshop Empirical, Evaluation Methods in Computer Vision, 2005.

[5] V. Takala and M. Pietikainen, "Multi-Object Tracking Using Color, Texture and Motion," Proc. IEEE Int'l Conf. Computer Vision and Pattern Recognition, 2007.

[6] Anna Petrovskaya and Sebastian Thrun," Model Based Vehicle Tracking for Autonomous Driving in Urban Environments", *The International Journal of Robotics Research, Sep 2007; vol. 26: pp. 89- 916*, 2007.

[7] Mykhaylo Andriluka Stefan Roth Bernt Schiele," People-Tracking-by-Detection and People-Detection-by-Tracking", IJCV, 75:247–266, 2007.

[8] B. Wu and R. Nevatia. Detection and tracking of multiple, partially occluded humans by Bayesian combination of edgelet based part detectors. IJCV, 75:247–266, 2007.

[9] Dikpal Reddy, Aswin C. Sankaranarayanan, Volkan Cevher, Rama Chellappa†," Compressed Sensing For Multi-View Tracking And 3-D Voxel Reconstruction ", IEEE Transactions On Information Theory, Vol. 52, No. 2, Pp. 489–509, 2006.

[10] Jinman Kang," Continuous tracking within and across camera streams", Computer Vision and Pattern Recognition, 2003. Proceedings. 2003 IEEE Computer Society Conference on (Volume: 1).

About Authors:

I am bharath pursuing final Mtech.My interesting research in data mining and cloud computing.

Mrs. D. Neelima received B.Tech and M.Tech in computer science and engineering from Jawaharlal Nehru Technological University of Hyderabad And currently pursuing Ph.D. in JNTU Kakinada, Andhra Pradesh, India. She is presently working as Assistant professor in Computer Science & Engineering department in Jawaharlal Nehru Technological University Kakinada. Andhra Pradesh, India. She has 13 years of experience in teaching Computer Science and Engineering related subjects. She is a research scholar and her area of interest and research includes Video Image Processing. She has published several research papers out of which 12 are international Journals and 2 papers in various international conferences. She has guided more than 70 students of Bachelor degree, 30 Students of Master degree in Computer Science and Engineering in their major projects.