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Continuous Multi-View Tracking using Tensor Voting

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Abstract

We present a novel approach for continuous tracking of moving objects observed by multiple fixed cameras. The continuous tracking of moving objects in each view is realized using a Tensor Voting based approach. We infer objects trajectories by performing a perceptual grouping in 2D+t. Gaps are bridged using a multi-scale approach in object trajectories. The trajectories obtained from the multiple cameras are registered in space and time allowing synchronization of the video streams and continuous tracking of objects across multiple views. We demonstrate the performance of the system on several real video surveillance sequences.

1. Introduction

Video surveillance of large facilities usually requires a set of cameras for ensuring a complete coverage of the scene. While visual tracking from a single camera has been extensively studied in computer vision and related fields, very little attention was given to tracking objects across a heterogeneous network of cameras. Tracking objects across multiple heterogeneous cameras is a challenging task, as it requires a space and time registration of the trajectories recovered from each camera.

Several multi-camera tracking algorithms have been developed recently and most of them use "color distribution" as a cue for tracking across the views. Various approaches were proposed such as matching color histogram of the blobs across the views [4], switching to another cameras when the tracked blob is no longer visible from the current view [5], constructing blobs in 3D space using short-base line stereo matching with multiple stereo cameras [6], or using volume intersection [7]. Since the "color" information can be easily biased by several factors such as illumination, shadow, blobs segmentation, or different camera controls, color cue is not very reliable for tracking moving objects across large scenes such as halls or campuses. The use of such methods is limited to the case of synchronized cameras. In [8], author proposed an approach for space and time self-calibration of cameras, but the proposed approach is limited to small moving objects where the observed shape is similar across views.

In this paper, we describe a novel approach to continuously track moving regions across cameras using the graph-based description and the Tensor Voting methodology for enforcing the smoothness constraint and tracks completion. The correspondence of trajectories across views is done using the graph-based description. The camera views and the trajectories are registered using a perspective transformation allowing us to provide space and time registration of objects trajectories across views.

Our proposed method uses the graph-based tracking for obtaining a trajectory description from the detected blobs. The description includes the center positions of moving regions and relationship between two frames. Our method adopts Tensor Voting approach for dealing with these problems. It solves the false detection problem, and fragmentation and ambiguity problems of trajectories at the same time. We also propose a multi-scale approach for merging the fragmented trajectories efficiently and therefore achieving continuous tracking of moving objects. This efficient tracking approach is applied to the problem of tracking objects across a network of heterogeneous cameras. The integration of trajectories across multiple views requires a robust trajectories correspondence and a registration in the 2D+t space. We propose an approach based on the use of perspective registration of the multiple-views and the trajectories in space and time using the graph-based representation of moving objects.

The paper is organized as follows. Section 2 introduces the continuous tracking using Tensor Voting formalism. Section 3 presents the proposed approach for space-time registration of trajectories across a network of heterogeneous cameras. Section 4 presents some result obtained from real sequences. Finally, in section 5 we conclude our paper with future work.

2. Continuous Tracking using Tensor Voting

Tracking using the graph-based representation of moving objects was proposed in 0. It preserves both spatial and temporal information. The tracking result from this approach includes many discontinuous trajectories due to large occlusions and false detection. Furthermore, due to lack of model of object trajectories, these fragmented trajectories cannot be merged to the real object trajecto-

ries. However, the graph-based representation is sufficient enough for initial tracking input and we can pre-group a candidate trajectory for each object by this description. A Tensor Voting based tracking approach was proposed in [2], providing an efficient way for handling discontinuous trajectories. However, it is applicable only to an off-line computation because it can perform the voting procedure after all the frames are available. Also the proposed method has a poor result when the gap between trajectories is greater than the size of voting field.

The graph representation provides an exhaustive description of the regions where a motion was detected and the way these regions evolve in time. However, more edges than necessary are created and the lack of trajectory model prevents us from merging sub-tracks of the same object into a single trajectory.

2.1. Overview of tracking by Tensor Voting

We propose to adapt the Tensor Voting-based tracking proposed in [2] to achieve efficient continuous tracking. We reformulate the tracking problem as a problem of extracting salient curves in 2D+t space.

The graph representation provides approximate points from a cloud of regions in 2D+t with an estimate of the motion associated to each moving object. We propose here to perform a perceptual grouping in the 2D+t space using Tensor Voting for extracting trajectory as a salient structure in 2D+t. The two main elements of the Tensor Voting theory are:

(A) Tensor-based data representation: We use tensors to encode simultaneously data and the corresponding uncertainties. In the case of a single point in 2D+t space, no specific orientation is known a priori and therefore we encode this uncertainty uniformly along all directions by considering a ***ball tensor***. If an orientation (or motion) is available, we use the following ***stick tensor*** aligned along the given motion vector $v = (v_x, v_{y,}1)$:

$$v^T v = \begin{bmatrix} v_x^2 & v_x v_y & v_x \\ v_x v_y & v_v^2 & v_y \\ v_x & v_y & 1 \end{bmatrix} \qquad (1)$$

This stick tensor allows the encoding of the orientation and its uncertainty. In Figure 1.a, we illustrate the tensorial description and tensor field in 2D+t space as proposed by [2]. The shape of the ellipsoid encodes the uncertainty. The stick tensor describes the point location and velocity simultaneously.

(B) Data propagation: Based on the uncertainties of a given tensor, the information of each location is propagated to the neighbouring points using a voting scheme. Every point propagates its tensor representation to its neighbouring points. The tensor field depicted in Figure 1.b defines the shape of the neighbourhood. The scale defines its size. Every point collects votes from its neighbouring points by combining their tensors. This data propagation scheme allows collecting local properties and representing the local structure through the combination of the tensors. The resulting tensor is characterized by three positive eigenvalues $\lambda_{\max} \geq \lambda_{mid} \geq \lambda_{\min} \geq 0$. Its "shape" is then the representative of the collected votes. More precisely, the eigenvector associated with $\lambda_{\max}$ is the privileged orientation and $\lambda_{\max} - \lambda_{mid}$, is the saliency; it indicates the confidence in this direction.

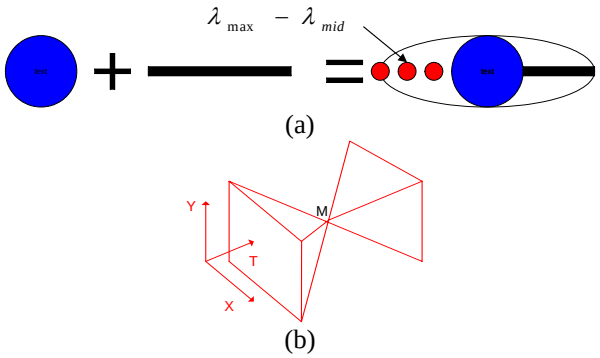


Figure 1. 2D+t Tensorial description and Tensor field; (a) tensorial description, (b) tensor field

The key point in the Tensor Voting formalism is the tensor field. Its role is to enforce the continuity properties desired, such as curvature consistency. The 2D+t case is a neither 2D nor 3D inference system. Since the 2D+t space is not isotropic, the tensor fields are different from the generic ones used in the 3D case [3].

The classical steps of a Tensor Voting approach can be summarized as follow: We first estimate the tangent and saliency at each input token. Then, we densify the information creating a dense tensor distribution by voting everywhere. Finally, curves and junctions are extracted analyzing the saliency map.

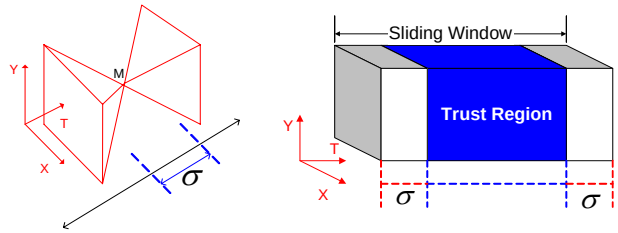
The Tensor Voting framework described in [2] allows us to disambiguate multiple hypotheses, infer direction and velocities of the objects, and bridge gaps in object trajectories using a smoothness constraint. This described approach is based on perceptual grouping in the 2D+t space. We reformulate tracking problem as a problem of extracting salient curves in 2D+t. The output is a set of trajectories with corrected bounding boxes of moving objects. It provides an efficient way for handling discontinuous trajectories. However, the proposed method is only applicable to an off-line computation since the voting procedure can be performed only after processing all available frames. Also, the ability of the proposed method to merge sub-tracks into a single trajectory is dependent on a correct choice of the size of the voting field. The method fails bridge gaps in object trajectories when this parameter is not chosen properly.

In the following we address these issues and provide an approach for continuous object tracking.

2.2. Merging tracks using a multi-scale approach

In order to perform a continuous tracking from a live input we use a sliding window method and multi-scale approach to achieve both continuous tracking and Tensor Voting processing simultaneously. The difference between using batch and sliding batch mode is the correction and normalization of the bounding boxes. In batch mode case, bounding boxes are adjusted by the size of the most salient feature in the batch. On the other hand in sliding window mode case, the search region is limited to only the sliding window, and therefore, the most salient feature in the sliding window adjusts the boxes size.

Tensor Voting is dependent on the size of the field used for propagating the local information. Given a domain size, neighbouring tensors are selected for voting. Therefore, the influence of the voting process is limited by the size of voting field (σ). As a result, the centre region of a processing sliding window is selected as trust region since boundary regions do not collect all the votes in the domain (see Figure 2).

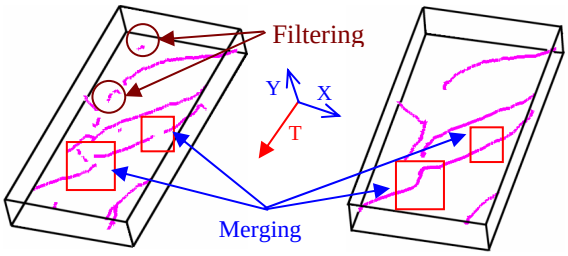


(a) (b)

Figure 2. Domain of influence and trust region; (a) Limitation of domain influence by σ (b) Trust region in one sliding window

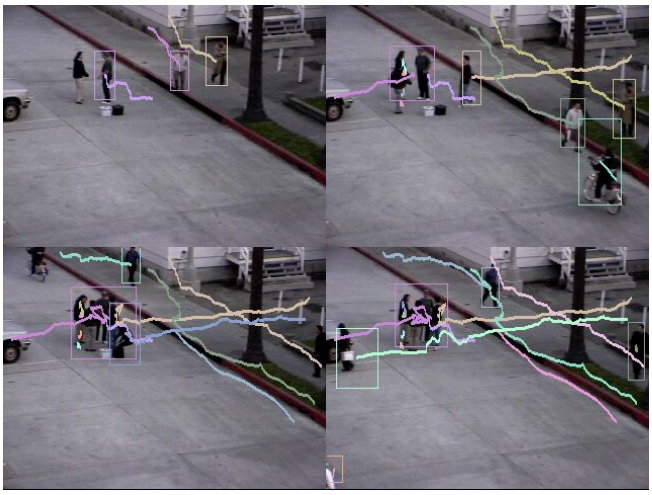
The ability to merge detected tracks depends on σ since it characterizes the influence domain. However, a large σ implies a small trust region for a fixed size sliding window and a higher computational complexity. We propose a multi-scale approach, which uses multi-scale voting fields for merging sub-tracks into the global trajectory. We search for an ending point of each trajectory segment and possible fragmented trajectories based on the Euclidean distance in 2D+t space. Given a set of tracks and isolated points, provided by the graph-based representation, we apply the Tensor Voting with a small σ for extracting salient curves in the 2D+t space. This local Tensor Voting does not allow merging sub-trajectories. It however generates smooth fragments of the tracks. Our approach consists in merging these sub-tracks by performing a perceptual grouping at various scales in the 2D+t space. The process focuses on searching for potential completion for each ending/starting points of the computed sub-tracks.

Given a set of trajectories in the 2D+t space, we characterize the potential locations for curves merging as being the ending/starting points within a specified neighbourhood and apply the Tensor Voting with a large σ (see Figure 3).

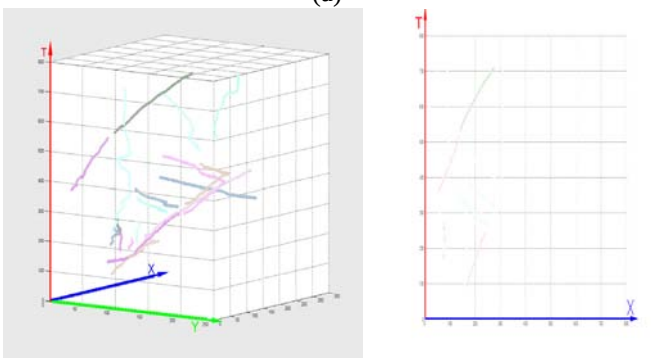


(a) (b)

Figure 3. Using multi-scale σ (a) σ = 10, (b) σ = 20



(a)



(b)

Figure 4. Tracking example (800 frames) (a) Real Image with trajectory overlap. (b) 2D+t representation of the trajectories from 2 different view

This approach performs trajectory completion in the 2D+t space and provides an efficient solution for merging fragmented tracks due to occlusions or bad detections. The variation of the scales and the range of σ are depending on the size of the sliding window. The choice of σ should be smaller than the half size of the given sliding

window in order to ensure a large data propagation for the Tensor Voting formalism. However, the minimum value depends on the temporal distribution of the input data. In Figure 4 we show an example of objects tracking and trajectory completion using the presented approach. We have used two scales, σ = 10 and σ = 20 for a window size of 40 frames.

When we move the sliding window for the next process, it can be moved more than one frame because Tensor Voting preserves global optimality. By experiment, it is allowed to move the sliding window up to 2σ. By moving the window up to 2σ, the computation time is reduced comparing to the case of moving the sliding window frame by frame. The processing time is 5-7 frame/sec for 640 by 480 resolution image.

3. Multiple cameras-based Continuous Tracking

Multiple cameras are usually required for monitoring large scenes such as halls or campuses. The set of cameras provide a good coverage of the scene but the integration of the information extracted from each camera still requires to address issues such as: tracking the same object from multiple cameras or tracking an object across different cameras. While geometric registration is performed offline and allows to map the relative position of the cameras with regard to the scene, object trajectories cannot usually be mapped across the views. Indeed, object's trajectory is characterized by the centroid's space-time evolution of the detected moving object. The locations of the centroid across multiple cameras do not correspond to the same physical 3D points, and therefore cannot be registered using the same perspective transform registering the cameras locations. On the other hand, even with the same 3D feature points that are the centriods of the detected moving object, the correspondence problem between trajectories across views is still remaining. Furthermore, the cameras are not necessarily synchronized, and may have different shutter speed, requiring a synchronization of the computed trajectories prior to their integration.

The integration of trajectories across multiple views requires a registration step in 2D+t space. We propose an approach based on the use of perspective registration of the multiple-views, and the trajectories in 2D+t space using prior knowledge of moving regions based on the graph-representation of each view.

3.1. Geometric Registration

The geometric registration of cameras viewpoint is performed using a perspective transform from a set of 4 matching points. The perspective parameters correspond to a null space of the matrix A (given in equation (2)) and are estimated using SVD decomposition of A. In Figure 5, we show the registration of two views. Each view has an occluding region represented as a red region, which is not occluded from the other view. By the geometric registration of cameras viewpoint, one can get fully available geometric description from either view and the improved part of each view is represented as a blue region.

$$AH = \begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 & -x'_1x_1 & -x'_1y_1 & -x'_1 \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -y'_1x_1 & -y'_1y_1 & -y'_1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 & -x'_2x_2 & -x'_2y_2 & -x'_2 \\ 0 & 0 & 0 & x_2 & y_2 & 1 & -y'_2x_2 & -y'_2y_2 & -y'_2 \\ x_3 & y_3 & 1 & 0 & 0 & 0 & -x'_3x_3 & -x'_3y_3 & -x'_3 \\ 0 & 0 & 0 & x_3 & y_3 & 1 & -y'_3x_3 & -y'_3y_3 & -y'_3 \\ x_4 & y_4 & 1 & 0 & 0 & 0 & -x'_4x_4 & -x'_4y_4 & -x'_4 \\ 0 & 0 & 0 & x_4 & y_4 & 1 & -y'_4x_4 & -y'_4y_4 & -y'_4 \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \\ h_{33} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (2)$$

If we denote a homography from view 2 to 1, we can register multiple cameras by series of concatenated homography as in (3).

$$H_m^n = H_{n+1}^n H_{n+2}^{n+1} \cdots H_{m-1}^{m-2} H_m^{m-1} \quad (3)$$

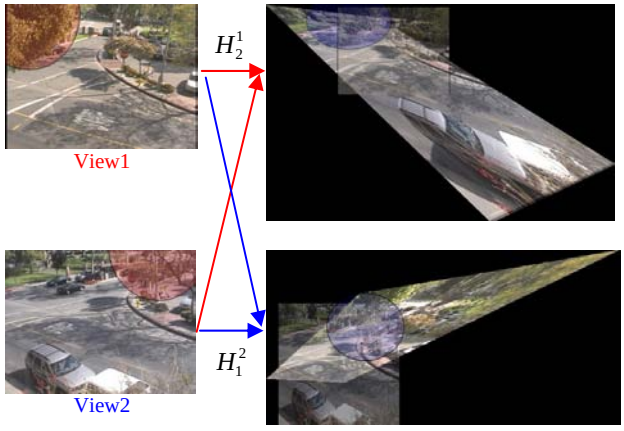
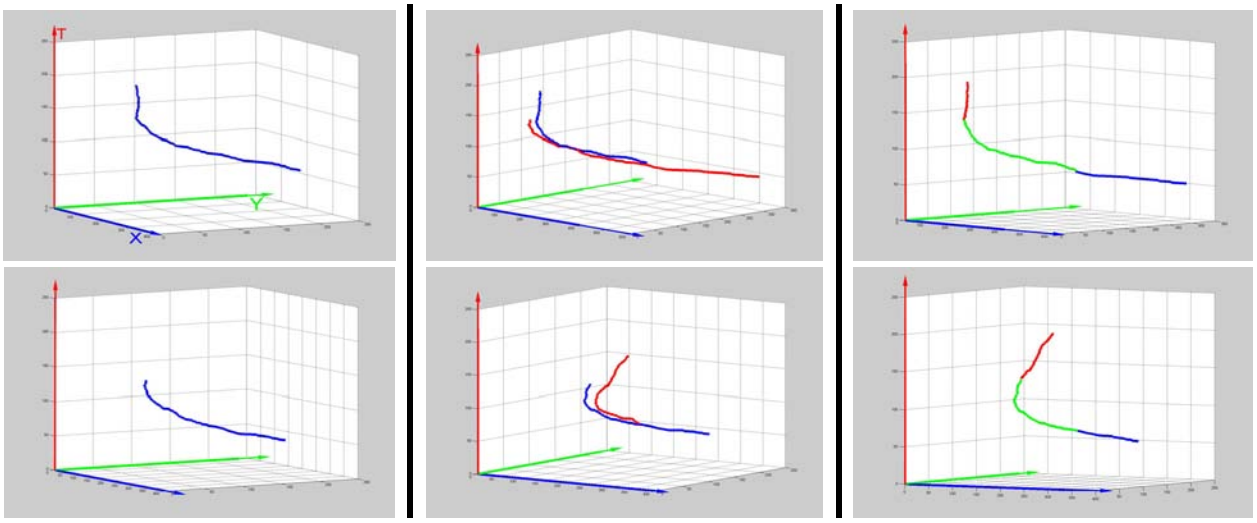


Figure 5. Camera registration using two views

3.2. Trajectories Correspondence

If we assume that a color distribution of each moving region is not much changed by the time and view difference, the correspondence problem between trajectories across views can be solved by the pre-calculated description of moving regions from the tracking step, which is the graph representation of them.

In each view, each moving region is described and pre-grouped by the graph representation, and the color distribution of moving regions is described in nodes elements (see Figure 6). The correspondence problem of trajectories across views can be characterized as a similarity measurement based on color information between pre-grouped nodes across views. For an arbitrary time stamp of a moving region, the corresponded trajectories from other views are a trajectory, which has maximum likelihood color distribution in each view. The proposed approach has two advantages. First of all, for each moving region, it only requires one time processing when the moving region is



(a) (b) (c)

Figure 7. Example of trajectory registration (blue : original trajectory, red : registered trajectory, green : overlapping trajectory between two views) (a) Tracking result by Tensor Voting. (b) Trajectory registration using the ground plane homography. (c) Refinement by the homography obtaining from the trajectories correspondence.

available at least between two views. Once a correspondence is set up for a moving region, it can be used until the updated connected component for the moving region is available because each path for the moving regions in the graph representation has been optimized. Second, the trajectory correspondence step can be done simultaneously with tracking step since the graph representation is used for both of them. Finally, due to the advantage of the Tensor Voting methodology for the tracking, the grouping problem such as an exchange of objects is solved when the overlapping period of the exchanging objects are short enough to extract each trajectory using Tensor Voting methodology. Once the trajectory correspondences of the moving regions are available, input streams can be synchronized.

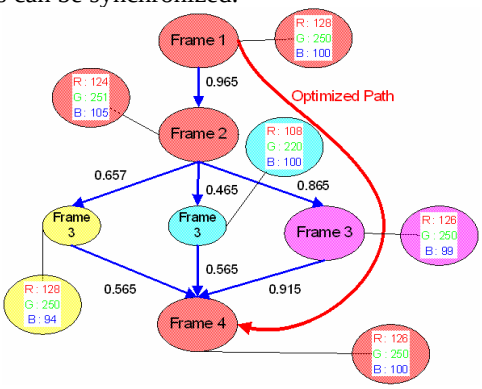
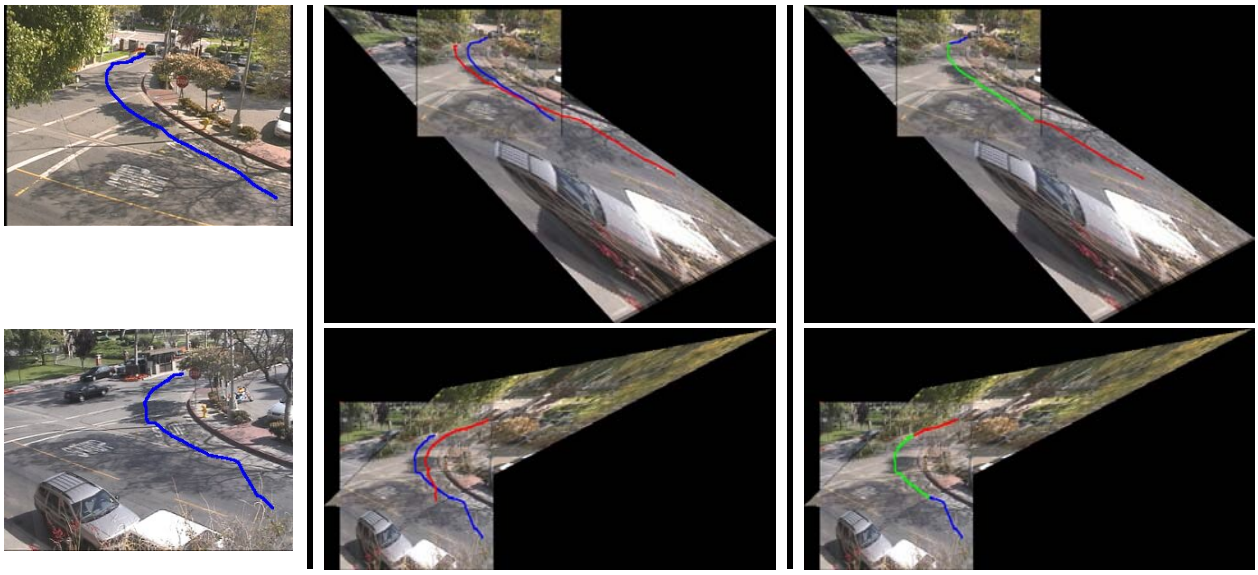


Figure 6. Example of the pre-grouped nodes

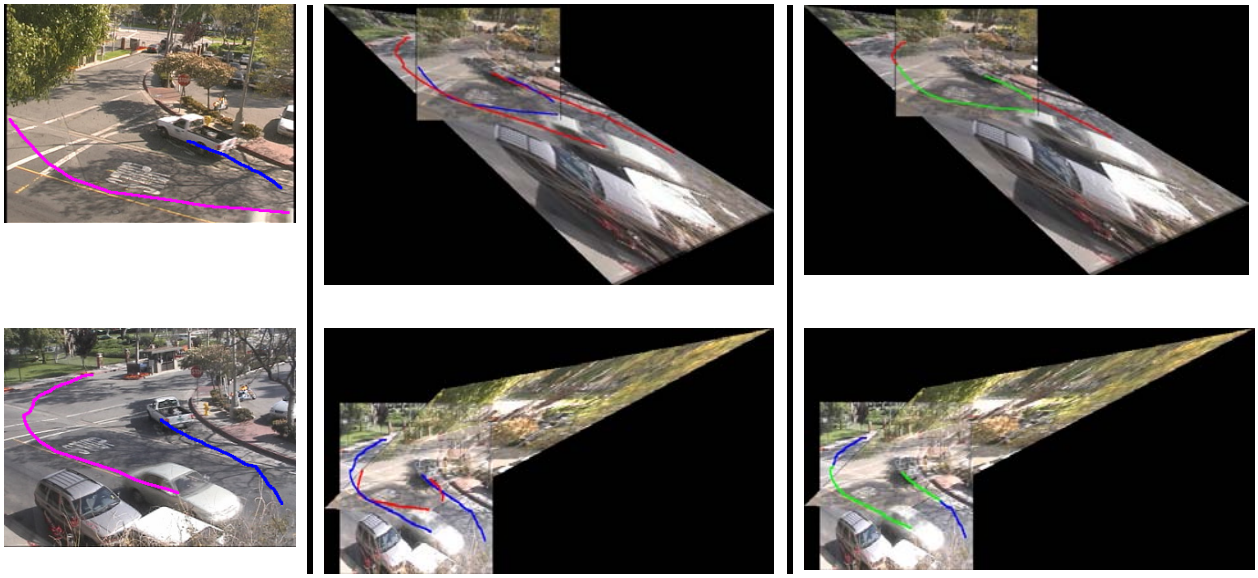
3.3. Stream Synchronization

Synchronization of input streams can be solved by a registration of observed trajectories in 2D+t space. There are several ways for the registration of observed trajectories. If we assume that each trajectory corresponds the same 3D physical points through all views and the moving object moves above the ground plane with same height, the homography using the ground plane is sufficient for registering trajectories. In this case, synchronization can be done using minimization of the distance between trajectories for each frame by shifting the trajectory along the time axis. If the trajectories correspond to the same 3D physical points, but the 3D physical points change through the sequence, the homography obtained from the ground plane is not sufficient enough for the registration. In this case, we need calibration information for each camera and a fundamental matrix between any two views. With the fundamental matrix between any two views, the synchronization can be done by finding the intersection of the trajectory point of one view and epipolar line calculated by the fundamental matrix from the other view since these points correspond to the same 3D points. Once synchronization is done, we can correct the height by calculating 3D position of matched trajectory points using the calibration information. Then, the homography from the ground plane is sufficient for the registration since the trajectories are already synchronized. However, in most cases, these centroids do not correspond to the same 3D points. Here we propose a simple approach to solve space and time registration by using the homography obtained from ground plane and trajectories.



(a) (b) (c)

Figure 8. Multiple View Registration (a single moving object) (a) Tracking result by Tensor Voting. (b) Ground plane registration. (c) Trajectory registration.



(a) (b) (c)

Figure 9. Multiple View Registration (multiple moving object) (a) Tracking result by Tensor Voting. (b) Ground plane registration. (c) Trajectory registration.

First, we register each view and trajectories using the homography obtain from ground plane by (2). Since the trajectories do not correspond the same 3D point and they are not synchronized, the misalignment of the registered trajectories can be observed (see Figure 7.b). These misalignments are reduced using another homography obtaining from the trajectories correspondences. Here we propose to use a MLE approach. We obtain a homography by arbitrary selecting 4 points of each trajectory, then calculate the errors between base trajectory and transferred trajectory. We select the homography, which is minimizing the errors for the trajectory registration (see Figure 7.c). The registration of the trajectories allows us to synchronize the multiple streams collected by the set of cameras.

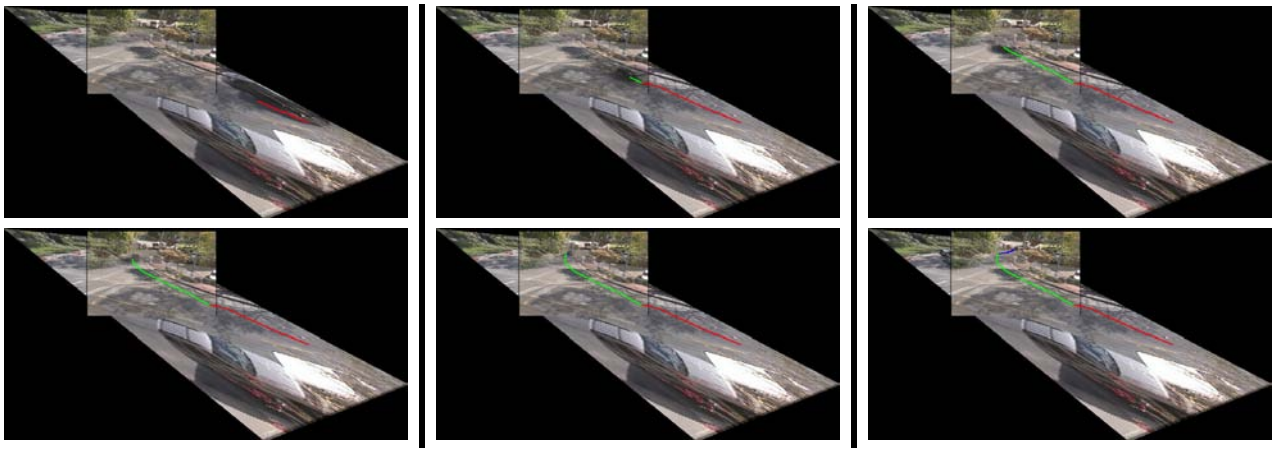


Figure 10. Example of continous tracking of moving objects across views.

4. Experimental Results

We present in this section some results obtained on real sequences to show how we can register multi-views and trajectories.

In Figure 8.a and 9.a, we show the tracking result of each view by using Tensor Voting technique addressed in Section 2. In this examples, one can observe that trajectory of each moving object is very smooth and continuous. However, the discontinuity of trajectories is observed due to the existence of occluding regions. In Figure 8.b and 9.b, we present the result of view registration using ground plane. In this geometric registered view, the occluded regions become available across views. Then, we represent space and time registered trajectories for each view in Figure 8.c and 9.c. A blue line represents an original trajectory belonging to the reference view. A red line represents a registered trajectory transferred from other view and a green line represents an overlapping trajectory between two views. Finally, in Figure 10, we show the continuous tracking of a moving object across views by representing several intermediate frames.

5. Conclusion

We have presented a novel approach for continuous tracking of moving regions with multiple views. Using homography transformations, multiple views and trajectories can be registered and tracked across views. For each view, the combination of the sliding batch window approach and multi-scale approach permits to track efficiently the moving objects continuously in each view. The multi-scale approach with sliding window method provides an efficient way to solve the continuity problem in Tensor Voting methodology. This multi-scale approach can be used not only for merging trajectories, but also for other temporal related Tensor Voting problems such as feature inference in 3D from video streams. Another contribution is the efficient way to solve the synchronization problem by registering trajectories obtained from various streams. The graph-based moving objects representation allows setting up the correspondence of trajectories across views. Several unsolved issues are still remaining such as variably changing frame rate of different cameras and the ambiguity of the corresponding points in image space.

Acknowledgements

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