



Dynamic Subspace-Based Coordinated Multicamera Tracking

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Abstract

We consider the problem of sustained multicamera tracking. The key insight of the proposed method is the fact that the 2D trajectories of a target in the image planes of each of the cameras are constrained to evolve in the same dynamic subspace. Then, when the target is occluded on some of the cameras, the missing measurements can be estimated using the newly proposed dynamical constraint along with the classical epipolar constraints. The proposed method can handle substantial occlusion, without the need of performing 3D reconstruction, calibrated cameras or constraints on sensor separation. Besides these benefits, the computational demands of the proposed method are minimal, making this approach very suitable for real-time surveillance applications of large areas.

Relevance

A key problem in surveillance applications is to maintain tracking on a target, in spite of temporarily occlusions. *Dynamics based tracking* allows to fuse information from multiple video streams of a surveillance system and successfully handle target occlusions to achieve persistent tracking.

Existing approaches:

- Only use geometric constraints
- Need to assume fixed dynamics
- Need calibrated cameras

Our Approach:

- Defines and incorporates dynamic constraints
- Can handle time varying dynamics
- Does **NOT** need prior assumptions on the dynamics of the targets
- Does **NOT** require camera calibration

Technical Approach

BACKGROUND:

n 'th order Autoregressive model

$$y_k = \alpha_1 y_{k-1} + \alpha_2 y_{k-2} + \dots + \alpha_n y_{k-n}$$

It's associated Hankel matrix

$$H_p^{(n)} \triangleq \begin{bmatrix} y_0 & y_1 & \dots & y_p \\ y_1 & y_2 & \dots & y_{p+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_n & y_{n+1} & \dots & y_{n+p} \end{bmatrix} \text{ holds } H_p^{(n)} \begin{bmatrix} \alpha \\ -1 \end{bmatrix} = 0$$

An estimate for α can be found as

$$\hat{\alpha} = (H_p^{(n-1)T} H_p^{(n-1)})^{-1} H_p^{(n-1)T} \begin{bmatrix} y_n \\ \vdots \\ y_{n+p} \end{bmatrix}$$

α can be updated with the new measurement and an estimate for $y(k+1)$ can be found as

$$y_{k+1} = [y_{k+1} \dots y_{k+n}] \hat{\alpha}$$

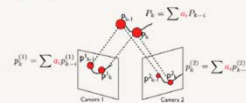
MODIFIED PARTICLE FILTER:

1. Obtain the measurement for $y(k+1)$ estimate
2. Compute the **instantaneous drift**
3. $v(k+1) = y(k+1) - w(k)$
4. **Drift the particles using the deterministic drift $v(k+1)$**
5. Re-sample the particles
6. Diffuse the samples
7. Recompute the weights for the particles
8. Output the particle with the highest confidence value
9. as the output of the tracker

MAIN RESULT:

In the absence of noise, all the 2D affine projections of the 3D trajectory of a target, captured simultaneously by a set of affine cameras, lie on a single subspace orthogonal to a vector that can be estimated using data from a single camera.

$$H_p^{(n)} \begin{bmatrix} \alpha \\ -1 \end{bmatrix} = 0 \quad i = 1, \dots, M \quad i \text{ is the camera number}$$



OCCLUSION HANDLING:

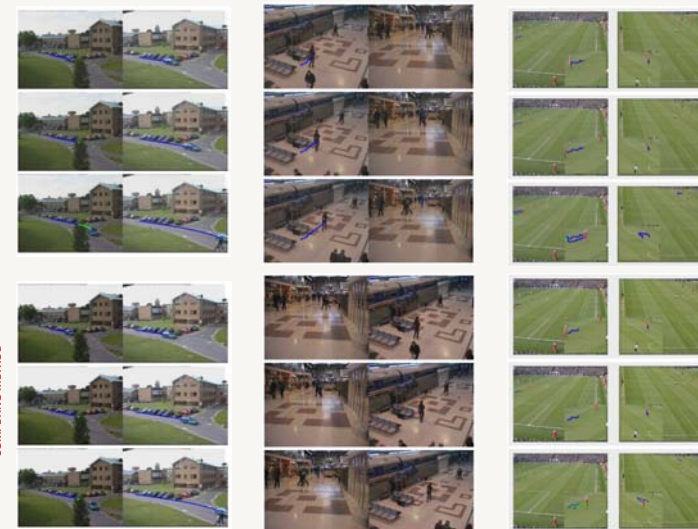
When the target is occluded in a view, it is possible to use a combination of dynamic and epipolar geometry constraints to estimate the current location of the target in the occluded view and use this estimate to predict the location of the target in the next frame in all views

$$A = \begin{bmatrix} H_p^{(n)} & 0 & 0 & \text{vect} \begin{bmatrix} y_{k+1}^{(1)} \\ \vdots \\ y_{k+n+1}^{(1)} \end{bmatrix} \\ H_p^{(n)} & 0 & 0 & \text{vect} \begin{bmatrix} y_{k+1}^{(2)} \\ \vdots \\ y_{k+n+1}^{(2)} \end{bmatrix} \\ \vdots & \vdots & \vdots & \vdots \\ y_{k-1-n}^{(2)} & -I_{2 \times 2} & 0 & 0_{2 \times 1} \\ \vdots & \vdots & \vdots & \vdots \\ 0_{2 \times n} & e_1 & e_2 & -e_3 \end{bmatrix} \begin{matrix} \text{DYNAMIC CONSTRAINTS} \\ \text{Estimation} \\ \text{Epipolar constraints} \end{matrix}$$

$$x = \begin{bmatrix} \alpha \\ y_k^{(1)} \\ y_k^{(2)} \end{bmatrix}; Y_k^{(i)} = [y_k^{(i)T} \quad y_{k+1}^{(i)T} \quad \dots \quad y_{k+n}^{(i)T}]^T$$

$$[e_1 \quad e_2 \quad e_3] = [y_k^{(1)T} \quad 1 \quad 0]^T \Rightarrow Ax = b$$

RESULTS:



Accomplishments Through Current Year

- Algorithm Development
- Efficient Implementation of the method
- Early testing of the algorithm and comparison with existing methods

Future Work

Research is currently underway seeking to extend these results to perspective cameras.

Opportunities for Transition to Customer

There are security cameras almost every where. Our algorithm can be used for increasing robustness of tracking algorithms, especially in crowded and cluttered spaces where occlusion occurs frequently, without need of additional calibration requirements.

Patent Submissions

Not Available

Publications Acknowledging DHS Support

• Ayazoglu M., Li B., Dicle C., Camps O. and Sznaier M.: Dynamic Subspace-Based Coordinated Multicamera Tracking In IEEE ICCV, (2011)

Other References

• Z. Wu, N. I. Hristov, T. L. Hedrick, T. H. Kunz, and M. Betke. Tracking a large number of objects from multiple views. In ICCV, 2009.