Robust Autocalibration for a Surveillance Camera Network

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Abstract

We propose a novel approach for multi-camera autocalibration by observing multiview surveillance video of pedestrians walking through the scene. Unlike existing methods, we do NOT require tracking or explicit correspondences of the same person across time/views. Instead, we take noisy foreground blobs as the only input and rely on a joint optimization framework with robust statistics to achieve accurate calibration under challenging scenarios. First, each individual camera is roughly calibrated into its local World Coordinate System (lWCS) based on analysis of relative 3D pedestrian height distribution. Then, all lWCSs are iteratively registered with respect to a shared global World Coordinate System (gWCS) by incorporating robust matching with a partial Direct Linear Transform (pDLT). As demonstrated by extensive evaluation, our algorithm achieves satisfactory results in various camera settings with up to moderate crowd densities with a large proportion of foreground outliers.

1. Introduction

The main goal of surveillance camera calibration is to find the mapping relating objects in the 3D scene to their projections in the 2D image plane[9]. This helps to infer object locations as well as scales and orientations, and allows for more accurate object detection and tracking. For example, sampling-based pedestrian detection [1, 4] yields better performance when hypotheses are generated in 3D and then projected into one or more image views. Pedestrian/face/object detection based on sliding windows can also benefit from calibration, since the search over orientation and scale can be constrained to a small range, reducing false positives [13].

In this paper, we present an automated calibration method that enables smart sampling of object size and orientation in all views given either a 2D location in one view or 3D location in the scene. The method works directly on noisy foreground observations collected by the surveillance

Figure 1. Example frames for calibration: (top) original frame overlaid with calibration results; (middle) noisy foreground masks with major axes of inlier blobs; (bottom) registered top-down view with the same blob

system, without any further information such as scene geometry or tracklets from tracking.

Most existing work on unsupervised surveillance (pedestrian-based) camera calibration focuses on the single-view case, ([13, 7, 15, 12, 8]) and requires clean pedestrian detections as well as explicit correspondences of the same person at different locations in the scene. For example, [12] proposes to detect leg-crossings for more accurate pedestrian height estimation; [13] requires the extraction of multiple control points on the contour of the pedestrian. [3, 6] and [14] adopt similar ideas and use a walking human to calibrate a camera network. In all the above work, the correspondence of the same person, if not manually labeled, is obtained either by tracking, or under the assumption that there is only one person in the view.

In some cases however, it can be very difficult to accurately detect pedestrians prior to calibration, let alone track them robustly through the scene. [11] takes noisy foreground blobs as input and achieves camera calibration based on the analysis of pedestrian height distribution, with no correspondence information needed. However the estima-

tion of focal length may not be very accurate, and it only applies to single views. To the best of our knowledge, the automatic extraction of cross-view correspondences in noisy environments has not been addressed in the above work.

It is known that once clean correspondences (of points, planes, objects in 2D/3D) are given, calibration is a well-solved problem, *e.g.*, using bundle adjustment[16]. The main contribution of this work is to propose a novel framework for unsupervised surveillance system calibration that efficiently prunes outliers and estimates the calibration based on a subset of inlier foreground correspondences discovered through applying a series of robust statistics.

We address four major challenges that are commonly encountered but not fully considered in the existing literature on surveillance-based calibration: (1) moderately crowded scenes; (2) a large proportion of outliers from foreground extraction; (3) large noise (variance) in foreground detections; (4) no correspondence information across frames/views. Similar to most surveillance work, we assume (1) there is one single flat ground-plane and (2) people are almost vertical, standing/walking on the ground plane.

2. Camera Model and the Coordinate System

Adopting a simplified CCD camera model with focal length being the only intrinsic parameter, we calibrate each view into its *local World Coordinate System* (IWCS), where each camera has zero pan angle and is translated from the local origin O_L by one unit along the Z-axis (thus the relative scale of the coordinate system is proportional to the camera height above the ground). Camera orientation is modeled by a tilt angle θ around the X-axis ($\theta \in (\pi/2, \pi)$ for a downward looking camera) and a roll angle ρ around the Z-axis. The 3D-to-2D projection matrix is thus defined by:

$$P_L = \begin{bmatrix} f & & \\ & f & \\ & & 1 \end{bmatrix} R_Z(\rho) R_X(\theta) \begin{bmatrix} 1 & & 0 \\ & 1 & 0 \\ & & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix}, \quad (1)$$

where, *e.g.*, $R_X(\theta)$ is a 3D rotation around the X-axis by angle θ .

It has been shown [10] that the local extrinsic parameters (ρ, θ) can be estimated given the vertical vanishing point $v_0 = (v_x, v_y, 1)^T$ together with the focal length f as:

$$v_x x + v_y y + f^2 = 0 \quad (2)$$

$$\rho = \text{atan}(-v_x/v_y) \quad (3)$$

$$\theta = \text{atan2}(\sqrt{v_x^2 + v_y^2}, -f), \quad (4)$$

where Eqn. 2 is the equation of the horizon.

To relate all IWCSs, we choose a *global World Coordinate System* (gWCS) that is aligned to the ground plane so that each IWCS can be registered with the gWCS by a 2D

Figure 2. Illustration of the global WCS (black) and the local WCSs (blue and red), where the local Y-axis is coplanar with the camera optical axis and all XY-planes lie within the ground-plane.

translation and rotation within the ground plane (XY-plane), as well as a relative scaling (proportional to the individual camera height), as illustrated in Fig. 2. The final projection matrix of a camera is defined as

$$P = P_L \cdot P_G, \quad (5)$$

where P_G denotes the ground-plane alignment transformation,

$$P_G = \begin{bmatrix} s & & & \\ & s & & \\ & & s & \\ & & & 1 \end{bmatrix} \begin{bmatrix} \cos \alpha & -\sin \alpha & T_x \\ \sin \alpha & \cos \alpha & T_y \\ & & 1 & 0 \\ & & & 1 \end{bmatrix}. \quad (6)$$

3. Camera Calibration

Our algorithm works on videos captured by multiple cameras with overlapping views. The original frames are preprocessed to generate foreground blobs. From these noisy blobs in each single view, we first estimate the vertical vanishing point and the maximum-likelihood focal length f that recovers 3D blob heights resembling the real world distribution of human heights using [11], thus estimating the individual camera calibration matrix $P_L^{(k)}$ that relates the coordinate system of camera k to its local WCS. We then iteratively and sequentially modify the global registration (P_G) of each camera. The iteration usually converges in a few rounds (2 to 3). During each iteration, we minimize the re-projection error between the 2D blobs in the current view and the joint set of global-world 3D blobs maintained by all cameras, where the correspondence information is implicitly encoded in a robust-statistic error metric. We then efficiently solve for a final estimate of P_G via partial *Direct Linear Transform* (pDLT) in a reduced solution space. The workflow of the algorithm is summarized in Alg. 1.

3.1. Framework

Following adaptive background subtraction on the input video sequences, we merge connected foreground pixels to form foreground blobs. We then fit an ellipse to each blob and represent the blob by the two end points of the major

axis of the ellipse. Assuming each foreground blob corresponds to a person in the 2D image plane, the two end points approximately represent the pixel locations of the foot and head of the person. Denote by $b_n^{(k)}$ the n th 2D blob extracted from the k th view and $B_n^{(k)}$ the corresponding 3D blob in the gWCS. These 2D and 3D blobs can be represented in homogeneous coordinates as:

$$b_n^{(k)} = \begin{bmatrix} x_f & x_h \\ y_f & y_h \\ 1 & 1 \end{bmatrix} \quad B_n^{(k)} = \begin{bmatrix} X & X \\ Y & Y \\ 0 & H \\ 1 & 1 \end{bmatrix}, \quad (7)$$

where x_f, y_f, x_h, y_h are pixel locations of the foot and head, and X, Y, H indicate the pedestrian's location (in the ground plane) and height respectively. The projective matrix $P^{(k)}$ (Eqn. 6) projects a 3D blob into 2D: $b_n^{(k)} \sim P^{(k)} \cdot B_n^{(k)}$. Assuming upright pedestrians walking in the ground-plane, the degree of freedom (DoF) of $\{B_n^{(k)}\}$ is 3. Thus $B_n^{(k)}$ can be linearly solved given $P_{3 \times 4}^{(k)}$ and $b_n^{(k)}$. Specifically, let

$$M = \begin{bmatrix} x_f P_{31} - P_{11} & x_f P_{32} - P_{12} & 0 \\ y_f P_{31} - P_{21} & y_f P_{32} - P_{22} & 0 \\ x_h P_{31} - P_{11} & x_h P_{32} - P_{12} & x_h P_{33} - P_{13} \\ y_h P_{31} - P_{21} & y_h P_{32} - P_{22} & y_h P_{33} - P_{23} \end{bmatrix}, \quad (8)$$

$$t = \begin{bmatrix} P_{14} - x_f P_{34} \\ P_{24} - y_f P_{34} \\ P_{14} - x_h P_{34} \\ P_{24} - x_h P_{34} \end{bmatrix}, \quad (9)$$

it can be proven that $[X, Y, H]^T = (M^T M)^{-1} M^T t$. We denote such a backward projection from 2D to 3D as: $B_n^{(k)} = \{P^{(k)}\}^{-1} b_n^{(k)}$. Note that the $\{\cdot\}^{-1}$ operator here does not refer to the conventional matrix inversion.

We formulate the multi-camera calibration as a joint energy minimization problem. Among various choices of the cost function for multi-camera calibration, we select the widely used mean-squared image re-projection error as our optimization goal, which can also be interpreted as maximum likelihood estimation under an assumption of Gaussian noise[5]. The re-projection from view j to view k can be expressed as:

$$\begin{aligned} b_n^{(k|j)} &\sim P^{(k)} \{P^{(j)}\}^{-1} b_n^{(j)} \\ &\sim P^{(k)} B_n^{(j)} \end{aligned} \quad (10)$$

where a 2D blob in view j is first back-projected into the gWCS with operator $\{P^{(j)}\}^{-1}$ and then projected into view k under $P^{(k)}$. The overall re-projection error is defined by

$$\varepsilon = \sum_k \varepsilon^{(k)} = \sum_k \sum_j e(b^{(k)}, b^{(k|j)}) \quad (11)$$

$$= \sum_k e(b^{(k)}, P^{(k)} B) \quad (12)$$

Alg. 1 Unsupervised multi-camera calibration.

input: $\{b^{(k)} | k = 1, \dots, K\}$
output: $\{P^{(k)} | k = 1, \dots, K\}$

individual camera calibration:

estimate $\{P_L^{(k)} | k = 1, \dots, K\}$ via [11]

joint camera network calibration:

initialize 3D blobs:

$B^{(k)} = \emptyset, k = 1, \dots, K - 1$

$B^{(K)} = \{P_L^{(K)}\}^{-1} b^{(K)}$ (i.e., $P^{(K)} = P_L^{(K)}$)

for $m = 1, 2, \dots$

for $k = 1, \dots, K$

1) $B = [B^{(1)}, \dots, B^{(k-1)}, B^{(k+1)}, \dots, B^{(K)}]$

2) update $P^{(k)} = P_L^{(k)} \cdot P_G^{(k)} \leftarrow \arg \min \{\varepsilon_k | b^{(k)}, B\}$

3) update $B^{(k)} \leftarrow (P^{(k)})^{-1} b^{(k)}$

4) compute ε according to Eqn. 12

if $\varepsilon_m > \varepsilon_{m-1}$: **terminate**

where $B = (B^{(1)}, \dots, B^{(K)})$ is the set of 3D blobs contributed by all views. Note that the self back-projection always has $b_n^{k|k} = b_n^{(k)}$. Hence $e(b^{(k)}, P^{(k)} B^{(k)})$ is always 0. $e(\cdot, \cdot)$ is a robust matching error metric, defined in Sec. 3.3 that measures the compatibility between the set of foreground blobs $b^{(k)}$ observed in view k and the set of re-projected blobs from 3D (B), as contributed by all views, where no correspondence information between $b^{(k)}$ and B is given.

Minimizing the above cost function directly is intractable. However, as can be seen from Eqn. 12, we can iteratively optimize the projection matrix for each view. To initiate the IWCS-gWCS matching, we first align the gWCS with one of the IWCSs (here we pick the last view indexed by K) to obtain an initial set of 3D blobs. Then we sequentially calibrate each camera k by (1) inferring the correspondences between $b^{(k)}$ and B under the presence of outliers and noise with a robust matching metric (Sec. 3.3) and (2) optimizing the projective matrix $P^{(k)}$ given the 2D-3D blob correspondences by partial direct linear transformation (Sec. 3.4). Empirically, we observe that our multi-camera calibration usually converges in no more than three iterations, i.e., $m \leq 3$ in Alg. 1.

3.2. Individual Camera Calibration to IWCS

This section explains how we obtain the input matrices $\{P_L^{(k)}\}$ w.r.t. IWCS. As shown in Eqns. 1,3,4, this is equivalent to estimating the focal length f and the vertical vanishing point v_0 . We apply the method of [11] that first uses RANSAC to find the vanishing point and then roughly estimates the focal length based on prior knowledge of the 3D-height distribution of inlier blobs. Note that we do not need to assume a constant person height for calibration, as is often done in algorithms for foot-head homography esti-

Figure 3. Vanishing point detection under different camera angles, foreground blob sizes, and crowd densities. Green lines indicate the major axes of inlier blobs. Outliers are marked with red lines. Yellow dashed lines indicate the vanishing points.

mation.

The vanishing point estimation is carried out in homogeneous coordinates, and is robust in cases when a vanishing point is close to infinity. Fig. 3 demonstrates a few examples of RANSAC-based vanishing point voting under different camera settings as well as varying foreground sizes and densities. It is worth mentioning that many blobs corresponding to real pedestrians are classified as outliers because of region deformation due to partial detection or being merged with other people, especially in crowded scenes. However our goal is not to detect all pedestrian foreground blobs but to extract enough inlier blobs for the following analysis.

Focal length estimation follows a hypothesize-and-test process. Given a hypothesized focal length f , together with the vanishing point v_0 , we can recover the relative 3D heights H_i of each inlier blob b_i (w.r.t. the camera height)¹. This process leverages the fact that the distribution of human heights in 3D forms a very strong cluster with $|H_i - \mu|/\mu < \lambda$, where μ is the average inlier pedestrian height and $\lambda = 0.1$ [11]. Different hypotheses are evaluated against a robust log likelihood function defined as:

$$\mathcal{L}(f) = \frac{1}{\mu^2} \sum_{i \in I} \max\{\lambda\mu - |H_i - \mu|, 0\}^2, \quad (13)$$

where I represents the set of RANSAC inliers, and outlier candidates H_i that fall out of the height range of the majority of the inlier blobs, e.g., $H_i > (1 + \lambda)\mu$, are ignored. As we sample the camera field of view (FoV) angle at a resolution of 1° , which is about the state-of-the-art accuracy for pedestrian-based surveillance camera calibration [8], the focal length f that produces the highest likelihood score according to Eqn. 13 is selected as our initial estimate for the multi-view calibration.

3.3. Robust Distance Metric for Blob Matching

This section explains the cost function (Eqn. 11) for cross-view IWCS matching. Recall that $b^{(i)}$ denotes the set

¹A more efficient method would use the cross-ratio invariance trick [11].

of 2D blobs in view i for the entire sequence, $B^{(i)}$ denotes the set of 3D blobs back-projected from view i to gWCS, and $b^{(i|j)}$ is the set of re-projected 2D blobs from view j to i . The cost function is defined as the sum of the re-projection errors of all pairs of 2D-3D blobs (denoted as set l) extracted at the same time stamp.

Since the foreground blobs are noisy in the sense of both false alarms and missed detections, the proportion of ‘good’ pairs (two ‘good’ blobs extracted from different views corresponding to the same person) is even smaller, especially under crowded scenarios. We thus adopt truncated quadratic[2], which belongs to the robust statistics of truncated least squares, defined as:

$$e(b^{(i)}, b^{(i|j)}) = \sum_{(b_{n_1}^{(i)}, b_{n_2}^{(j)}) \in l} \min\{d(b_{n_1}^{(i)}, b_{n_2}^{(i|j)})^2, \tau^2\}, \quad (14)$$

where $d(\cdot)$ is the 4D Euclidian distance, (x, y) coordinates of feet and head, between 2 blobs in pixels, and the error tolerance is set to be $\tau^2 = \frac{1}{100}W \cdot H$, where W and H are the width and height of the image. We find this setting yields satisfactorily consistent results for video sequences with very different camera settings, as demonstrated in the experiments section. We iteratively use the error tolerance as a threshold to discover ‘good’ blob correspondences from all possible pairs in l and re-estimate calibration parameters based on these inliers.

3.4. Multiview Calibration to gWCS by Partial DLT

This section describes the sequential registration of multiple IWCS in Alg. 1. The goal is to estimate the camera projection matrix P from an initial set of noisy inlier 2D-3D blob correspondences (l_{in}) and the results of the single-view calibration (P_L). We propose an iterative process based on a variant of direct linear transform (DLT). The algorithm iteratively estimates the global projection matrix and refines the inlier correspondences l_{in} and P_L once P_G has been updated. The overall optimization is summarized in Alg. 2.

To solve the global transformation of the k th view $P^k = P_L^k \cdot P_G^k$ (Eqn. 6) from a linear system constructed from inlier blob correspondences between the 2D blobs and 3D blobs

$$[x, y, z]^T \sim P_L^k \cdot P_G^k \cdot [X, Y, Z, 1]^T, \quad (15)$$

a straightforward approach would treat P as a general matrix with 12 DoF, and solve it using DLT. However, the DLT solution is known to be overdetermined, as the real perspective matrix only has 11 DoF (up to a scale). More importantly, when the 2D-3D correspondences are noisy, DLT can easily overfit the free-form solution, making it harder to distinguish inlier correspondences from outliers during the iterative process, which would further degrade the estimation accuracy. Therefore, we limit the DoF of the solution space

Alg. 2 Calibration to gWCS by Partial DLT

input: $\{P_L^{(k)}\}_{init}, b^{(k)}, B, l$
output: $P^{(k)}, \{P_L^{(k)}\}_{updated}, \{l_{in}\}_{updated}$
initialization:
 randomly sample the initial correspondences: $l_{in} \subset l$
for $m = 1, \dots, M$
 1) optimize α in $P_G^{(k)}$, given $l_{in}, P_L^{(k)}$
 2) optimize s, t_x, t_y in $P_G^{(k)}$, given $l_{in}, P_L^{(k)}, \alpha$
 3) optimize: $f, P_L^{(k)}$, given $l_{in}, P_G^{(k)}$
 4) compute $\varepsilon^{(k)}$ and update l_{in} (Eqn. 14)
 if $\varepsilon_m^{(k)} > \varepsilon_{m-1}^{(k)}$: **terminate**

by estimating the five variables in Eqns. 1, 6: α, s, t_x, t_y, f sequentially, while fixing the vanishing point. The motivation is that (1) we assume the initial estimation for vanishing point v_0 is accurate enough; (2) by reducing the DoF of the projection matrix, we introduce a partial DLT here to solve for subsets of parameters efficiently without suffering from the ‘over-determinant’ problem of DLT.

To estimate the ground-plane rotation angle α , we fix f and P_L^k so that P_G^k has 7 DoF:

$$P_G^k \sim P_{G|7}^k = \begin{bmatrix} m_{11} & m_{12} & m_{14} \\ m_{21} & m_{22} & m_{24} \\ & & m_{33} \\ & & & 1 \end{bmatrix}. \quad (16)$$

$P_{G|7}$ can be directly optimized by linearizing Eqn. 15 similar to the DLT (thus referred to as partial DLT) and the rotation angle can be approximated as $\alpha = \text{atan2}(m_{21} - m_{12}, m_{11} + m_{22})$. We then fix α and f , so that s, t_x, t_y together can be directly linearly solved in the same way (see Appendix for detailed derivation). Although the initial estimation of focal length f may not be very accurate, it constrains the search space to a small region for refining the estimates. To optimize f , we fix the current estimates of the other parameters and adopt pDLT again on the linear system of:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} \sim \begin{bmatrix} a_f & & \\ & a_f & \\ & & 1 \end{bmatrix} \cdot P_L^k \cdot P_G^k \cdot \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}, \quad (17)$$

with a_f being the only parameter. This suggests the optimal focal length should be updated as: $f^* \leftarrow a_f \cdot f$. We then update θ in P_L with f^* according to Eqn. 4 (thus the vanishing point remains the same) and re-evaluate the matching error of Eqn. 14. We only accept f^* if it reduces the matching error.

4. Experiments

We have conducted extensive evaluation on a synthesized dataset for stress testing, and on four different pub-

lic sequences with various camera settings, crowd densities, and background subtraction qualities: (a) indoor 4-person sequence with three views of resolution 288×360 [1], (b) outdoor campus sequence with two views of 960×1280 [14], (c) PETS09 sparse crowd sequence with 4 views (1,5,6,8), where view#1 is 576×768 and the rest are 576×720 , and (d) PETS09 medium density crowd sequence with two views (#1 and #2) of resolution 576×768 ².

We also provide quantitative comparison against [11] in terms of focal length estimation, since to our best knowledge, no other existing work estimates surveillance network calibration without correspondence information.

4.1. Synthesized Dataset for Stress-Testing

We synthesize a dataset with three cameras of different focal lengths ($f_1 = 1000, f_2 = 1200, f_3 = 1000$), viewing angles, ground plane locations, and heights. Multiple pedestrians were synthesized in 3D as feet-head pairs with a height variance of $\pm 10\%$, and then projected into individual views. In the stress test, we consider three sources of input noise: location noise σ_0 , foreground blob recall r and precision p rate. The location noise is produced as zero-mean Gaussian noise added onto the original feet-head pixel locations. The blob-recall and precision indicate false negatives and false positives and are simulated by randomly removing inlier blobs and adding outlier blobs. The default

Figure 4. Synthesized 3-camera dataset with calibration results.

stress parameters are set as $\sigma_0 = 5$ (the standard deviation of Gaussian noise in pixels), $r = 70\%$ and $p = 70\%$. We then vary σ_0 from 1 to 10 and r, p from 1 to 0 respectively with the other two parameters fixed at the default level.

Fig. 4 visualizes the calibration results. We also quantitatively evaluate the performance of our algorithm by measuring the average RMSE re-projection error in pixels as well as the average relative focal length estimation error $e = |f - f_{GT}|/f_{GT}$. The performance of our approach under different stress levels is plotted in Fig. 5.

It can be seen the re-projection error increases with increasing feet-head location noise, but is relatively stable w.r.t. missing inliers and against outliers, which well

²<http://www.cvg.rdg.ac.uk/PETS2009/a.html>

Figure 5. Performance under different levels of (a) location noise; (b) foreground recall rate; (c) foreground precision rate. Top: average re-projection error. Bottom: focal length error of our approach (red) and [11]

demonstrates the effectiveness of our robust estimation metric. When the precision increases from $p = 0.2$ to $p = 0.1$ in Fig. 5(bottom), the proportion of outliers increases from 50% to 90% and results in a big performance drop. In all other cases, our focal length estimation remains accurate and performs better than a single-view based approach [11].

4.2. Real Sequences

As can be seen from the calibration results in Fig. 6, our ground plane estimations are accurate in general (a black grid mask overlaid on the original frame). For quantitative evaluation, we manually labeled corresponding pedestrians across views on 50 frames for each sequence. Fig. 7 compares the algorithm re-projections with the groundtruth labels. The view-specific re-projection error is summarized in Tab. 1, where E^{in} column indicates the matching error when pedestrians from other views are mapped into the current view, and the E^{out} column indicates the matching error when pedestrians from the current view are mapped into other views. We show the RMSE in both pixels and in terms of normalized distance as $E_r = E/\sqrt{W \cdot H}$. Note that some labeling error exists on feet/head positions of the groundtruth labels.

The focal length estimation for sequences with ground truth f_{GT} and relative error e are summarized in Tab. 2. Again, compared with the baseline method using single view calibration, our method achieves better accuracy in most cases. The second view of the campus sequence reported the largest error; however, the cross-view re-projection estimation and groundplane estimation are still acceptable. This can be explained as a case when inaccurate focal length estimation cancels out the inaccurate van-

ishing point estimation, resulting in a small re-projection error, which is the primary goal for surveillance calibration.

	View	E^{in}	E^{out}	E_r^{in}	E_r^{out}
indoor	1	13	16	4.0%	5.0%
	2	23	12	7.1%	3.6%
	3	14	22	4.3%	6.8%
campus	1	36	24	3.3%	2.2%
	2	24	36	2.2%	3.3%
PETS09 (sparse)	1	10	34	1.6%	5.1%
	2	29	12	4.7%	2.0%
	3	13	11	2.0%	1.8%
	4	16	12	2.5%	1.8%
PETS09 (dense)	1	18	8	2.6%	1.2%
	2	8	18	1.2%	2.6%

Table 1. View specific re-projection error on real sequences.

	View	f_{GT}	f_{base}	e_{base}	f	e
Campus	1	1057	1044	1%	1034	2%
	2	1198	1545	29%	1427	19%
PETS09 (sparse)	1	1170	1084	7%	1218	4%
	5	830	828	.2%	828	.2%
	6	877	891	2%	869	1%
	8	737	772	5%	772	5%
PETS09 (dense)	1	1170	950	19%	1067	9%
	2	659	624	5%	634	4%

Table 2. Focal length estimation, where f_{GT} is the groundtruth focal length, f_{base} and f are estimates computed by the baseline([11]) and our method, respectively, and e_{base} and e are relative errors w.r.t. the groundtruth. Our method outperforms the baseline in most cases (shown in bold).

Figure 6. Example of calibration results for: (a) indoor 4-people sequence; (b) outdoor campus sequence; (c) PETS09 sparse; (d) PETS09 dense. For each sequence: Top: original frame overlayed with calibration results. Middle: noisy foreground masks overlayed with major axes of inlier blobs. Bottom: registered top-down view of inlier blobs.

Figure 7. Re-projection evaluation. Manually labeled corresponding pedestrians in different views are plotted in straight-lines with the same color. The cross-view re-projections based on calibration are plotted in dashed lines.

5. Summary

We propose a novel framework for unsupervised surveillance camera network calibration. We take noisy foreground (pedestrian) blobs captured directly by the cameras without any cross-time or cross-view correspondence information. We first apply robust self-calibration to calibrate each camera w.r.t. the IWCS to reduce the DoF of the projective transformation to be estimated later, meanwhile pruning a large proportion of outlier blob observations. We then sequentially align all the IWCSs to a shared gWCS, during which we introduce truncated least-squares as a robust error metric to iteratively determine inlier correspondences, while applying a series of partial DLTs to solve for a projective transformation. We demonstrate the robustness of our algorithm against different camera settings, foreground qualities, outlier ratios and crowd densities via extensive experiments on synthesized image sequences as well as on publicly available real datasets.

Appendix: Groundplane Registration using Partial DLT

Given fixed ground-plane rotation α and local calibration matrix P_L , we linearize the equation sets by introducing variable z to resolve the ambiguity:

$$\begin{bmatrix} x \cdot z \\ y \cdot z \\ z \end{bmatrix} = P_L \cdot P_G \cdot \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}, \quad (18)$$

with

$$P_L = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} \quad (19)$$

$$P_G = \begin{bmatrix} \cos \alpha \cdot s, & -\sin \alpha \cdot s, & t_x \\ \sin \alpha \cdot s, & \cos \alpha \cdot s, & t_y \\ & & s \\ & & & 1 \end{bmatrix} \quad (20)$$

Via Gaussian elimination on the auxiliary variable z , we can reorganize Eqn. 18 to obtain 2 sets of constraints for each $2D - 3D$ point pair correspondence, so that the calibration parameters $[s, t_x, t_y]$ can be linearly solved:

$$\begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \end{bmatrix} \cdot \begin{bmatrix} s \\ t_x \\ t_y \end{bmatrix} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \quad (21)$$

where

$$\begin{aligned} m_{11} &= (p_{11}X + p_{12}Y - p_{31}X - p_{32}Y) \cos \alpha + (p_{12}X \\ &\quad - p_{11}Y - p_{32}X + p_{31}Y) \sin \alpha + (p_{13} - p_{33})Z \\ m_{21} &= (p_{21}X + p_{22}Y - p_{31}Y - p_{32}Y) \cos \alpha + (p_{22}X \\ &\quad - p_{21}Y - p_{32}Y + p_{31}Y) \sin \alpha + (p_{23} - p_{33})Z, \end{aligned}$$

and

$$\begin{aligned} m_{12} &= p_{11} - p_{31}x, & m_{22} &= p_{21} - p_{31}y, \\ m_{13} &= p_{12} - p_{32}x, & m_{23} &= p_{22} - p_{32}y, \\ u_1 &= -p_{14} + p_{34}x, & u_2 &= -p_{24} + p_{34}y, \end{aligned} \quad (22)$$

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