Trajectory Ensemble: Multiple Persons Consensus Tracking across Non-overlapping Multiple Cameras over Randomly Dropped Camera Networks

Yasutomo Kawanishi Daisuke Deguchi Ichiro Ide Hiroshi Murase
Nagoya University
Furo-cho, Chikusa-ku, Nagoya, Aichi, JAPAN
kawanishi@i.nagoya-u.ac.jp

Abstract

Multiple person tracking over a camera network is usually performed by matching person images between adjacent cameras. It easily fails by a temporal appearance change of the persons caused by environmental illumination and observation orientation of a camera. To solve this problem, matching person images across not only adjacent cameras but also cameras multiple hops away in the camera network is effective, but such relaxation of spatio-temporal cues also cause tracking failure due to the increase of matching candidates. To avoid the failure, we introduce "Random Camera Drop" to generate different camera networks which relax the spatio-temporal cues partially and randomly. We then, integrate tracking results over the networks to a consensus tracking result by a novel concept "Trajectory Ensemble", an extension of unsupervised ensemble learning for the multiple person tracking over a camera network problem. We evaluated the framework on several virtual datasets generated from a public dataset, "Shinpuhkan 2014 dataset" and confirmed that the proposed method achieves the highest tracking results among several comparative methods.

1. Introduction

Many surveillance cameras have been installed in our daily environment and utilized for observing activities of persons (Figure 1). The goal of our research is to obtain trajectories of persons by using multiple surveillance cameras whose views do not overlap. In this paper, the term "trajectory" stands for a sequence of camera views where a person visited. It has a lot of potential commercial applications and great importance for business growth. If we could obtain trajectories of multiple persons, we can utilize them for various purposes such as finding suspicious persons in a shopping mall, finding similar spots, or planning shop reallocation for sales growth. For obtaining trajectories of multiple persons, multiple person tracking across multiple cameras is a fundamental technique. For statistical analysis of trajectories, the tracjectories do not need to be obtained in real-time. Thus, we focus on off-line tracking.

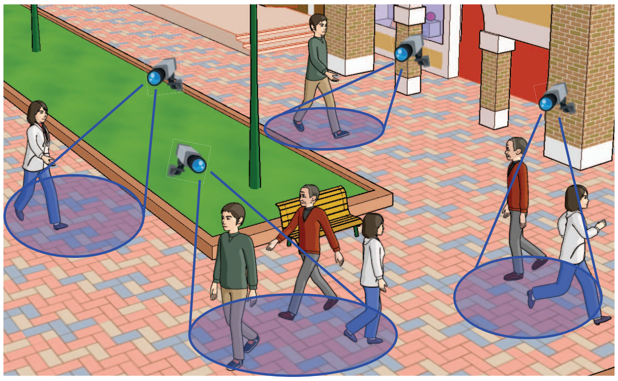
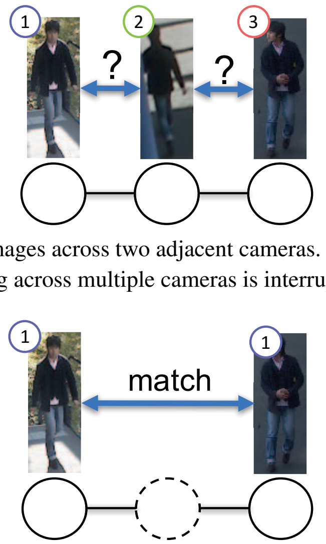


Figure 1. An environment observed by multiple cameras whose views do not overlap.

Most existing methods attempt to track persons across multiple camera views by utilizing appearance features and certain spatio-temporal cues to re-identify and associate persons across adjacent camera views [1, 2, 3, 4, 5]. Appearance features are usually based on color histograms and texture descriptors [6, 7, 8]. Recently, as same as other computer vision applications, Deep Learning based approaches are also applied to this field [9, 10, 11]. Spatio-temporal cues are commonly based on the adjacency of camera views and the distribution of travel time between adjacent camera views [12, 13, 14, 15, 16].

Appearance features are easily affected by illumination in a camera view and the positional relationship between a camera and a person. Illumination in a camera view and direction of the camera are different among cameras, while appearance features vary even for the same person. Therefore, in case of multiple person tracking across multiple cameras based on similarity comparison, temporal change

2160-7516/17 $31.00 © 2017 IEEE
DOI 10.1109/CVPRW.2017.190



(i) Matching images across two adjacent cameras. Matching fails and tracking across multiple cameras is interrupted twice.

(ii) Matching images across two non-adjacent cameras. Matching is successfully performed.

Figure 2. Matching over a camera network. White circles connected by lines show adjacent camera views.

in the appearance of a person could easily cause an interruption in the tracking or switching to another person (Figure 2 (i)).

To avoid the interruption of tracking across multiple cameras, we considered that matching person images not only between two adjacent camera views but also between other camera views several hops away over a camera network could be a solution. However, it will also cause more failure in the matching due to the increase of candidates.

Skipping cameras in the network is likely to relax spatio-temporal cues partially (Figure 2 (ii)). Instead of skipping cameras, we consider to drop cameras from the network. We introduce “Random Camera Drop” to generate different camera networks which randomly relaxes the spatio-temporal cues. By tracking multiple persons over the generated networks, we can obtain multiple tracking results. By introducing a novel concept “Trajectory Ensemble”, which is an extension of unsupervised ensemble learning [17, 18] for the multiple person tracking over a camera network problem, the tracking results are integrated and the consensus tracking result is obtained.

The rest of the paper is organized as follows: First, we define the problem of multiple person tracking over a camera network and discuss the difficulty of a straightforward approach in Section 2. In Section 3, details of the proposed method “Trajectory Ensemble” are introduced. Experimental results are reported in Section 4. Finally, we conclude this paper in Section 5.

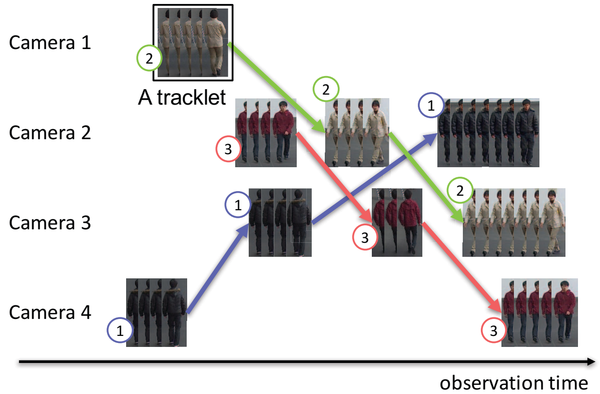


Figure 3. “Multiple Person Tracking across Multiple Cameras.” Each number enclosed with a circle is a label assigned for the corresponding tracklet. In this example, tracking is successfully performed and consistent labels are assigned to the persons.

2. Multiple person tracking over a camera network

2.1. Problem setting and basic approach

Let us consider the situation that multiple cameras whose views do not overlap are installed in an environment like a shopping mall, and multiple persons walk in the environment as shown in Figure 1. When a person enters a camera view, the person is detected and tracked until the person exits the camera view. Then an image sequence of the person (tracklet) $r_i = \{m_{ij}\}_{j=1}^{n_i}$ is obtained. Here, m_{ij} denotes an image of the cropped person and n_i denotes the number of frames the person was tracked in the camera view. Here, for simplicity, we do not consider false detections, namely, detection of non-persons and miss-detections. In this paper, “multiple person tracking across multiple cameras” is a problem that assigns consistent label of the same person to tracklets $\{r_1, r_2, \ldots\}$ obtained by multiple cameras $\{c_1, c_2, \ldots, c_N\} \in C$ (Figure 3).

Since it is difficult to decide if two tracklets are of the same person only by image features, spatio-temporal cues are introduced. Here, spatio-temporal cues consist of adjacency of cameras and traveling time between two camera pairs, which are described by a directed graph $G = \langle C, E \rangle$ where $C = \{c_1, c_2, \ldots, c_N\}$ and $E = \{(c_j, c_k) | c_j, c_k \in C\}$ denote a set of vertices and a set of edges, respectively. Each vertex corresponds to a camera view, and two cameras connected by an edge are adjacent. We define “adjacent cameras” as two cameras where persons can travel between them without crossing other camera views. Each edge is assigned parameters that represent the distribution of traveling time between the two cameras connected by the edge. In this problem setting, the distribution of traveling time is

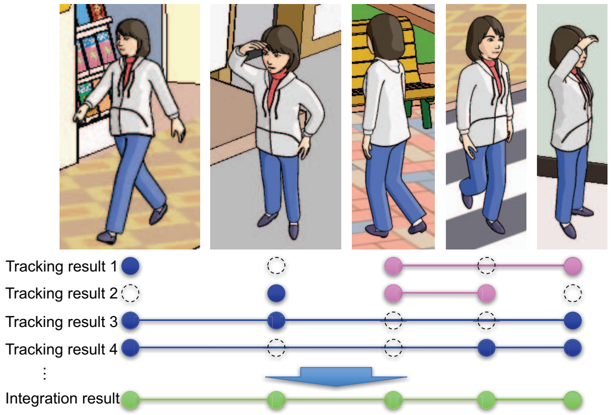
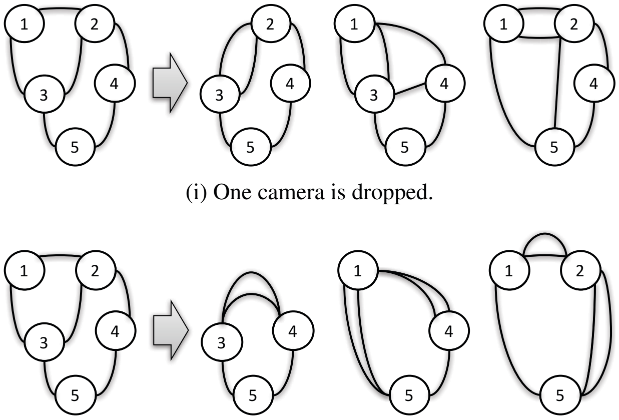


Figure 4. The concept of Trajectory Ensemble. These images are observed by different cameras. Dashed circles indicate that the tracklets are not used for "weak" tracking since the corresponding cameras are dropped in the sub-networks.



(i) One camera is dropped.

(ii) Two cameras are dropped.

Figure 5. Sub-networks generated by Random Camera Drop. Some camera pairs have multiple edges to keep the original routes.

given by a Gamma distribution whose parameters are proportional to the distance between the two cameras.

Given a camera network G, matching candidates with a tracklet r_i obtained by camera c are limited to tracklets obtained by the adjacent cameras of c. The candidates are also limited to temporally reachable ones. Among the candidates, the same person ID is assigned to the tracklets where the similarity is higher than a threshold. The similarity is measured with the similarity of appearance features and the likelihood of the observation time. We call this procedure which tracks multiple persons by using camera network information as "Multiple Person Tracking over a Camera Network".

In practice, greedy strategy which matches tracklets along their observation time is often used. Like intra-camera person tracking based on global data association [19], it can also be formulated as a label assignment problem. In this case, label assignments are optimized by Minimum Cost Flow Algorithm [20].

2.2. Difficulties in multiple person tracking over a camera network

In multiple person tracking over a camera network, when some tracklets obtained by cameras which are installed in different environments or orientations, appearances of the tracklets may seem different even though they are of the same person. As a result, since their similarity becomes low, they may not be matched or may be matched to different persons. In the former case, tracking of the person terminates and another label will be given to the remaining tracklets.

3. Trajectory Ensemble

3.1. Overview

Multiple persons tracking over a camera network can easily fail when the appearance of a person changes due to environmental illumination and observation settings.

We introduce "Random Camera Drop" to generate several different camera networks which relax spatio-temporal cues partially and randomly. Here, we call each randomly dropped camera network as a "sub-network". In different sub-networks, since the network topology is different, candidates for the tracklet matching are different. Therefore, we can obtain different tracking results from sub-networks. The proposed method integrates these tracking results by "Trajectory Ensemble" (Figure 4), which is an extended concept of Cluster Ensemble [17]. Note that it is a different approach to several existing methods based on combining multiple hypotheses [21, 22, 23].

Cluster Ensemble is an instance of Unsupervised Ensemble Learning. The main concept of Cluster Ensemble is the integration of data in terms of several "weak" clustering results clustered by changing the clustering criterion. We extend this concept to multiple person tracking over a camera network. The proposed method tracks persons over multiple sub-networks ("weak" tracking) and integrates the "weak" tracking results.

3.2. Sub-network generation by Random Camera Drop

From an initial camera network $G = \langle C, E\rangle$, each sub-network is generated by the following procedure.

1. A camera $c_j \in C$ is selected randomly.
2. Let $\mathcal{N}(c_j)$ be a set of adjacent cameras of camera c_j.

3. For all pairs of $c_k, c_l \in \mathcal{N}(c_j), k \neq l$, add an edge (c_k, c_l) to the network. Let the parameters of the edge (c_k, c_l) be the sum of the parameters of edges (c_k, c_j) and (c_j, c_l). If the edge (c_k, c_l) already exists, the network contains multiple edges (c_k, c_l) assigned with different parameters.

4. Remove camera c_j and edges connected to c_j.

We show an example of an initial camera network and sub-networks generated by the procedure in Figure 5.

3.3. Multiple person tracking over each sub-network

Persons are tracked over each sub-network G_s ($s = 1, 2, \ldots, S$). For these "weak" tracking, tracklets observed by the dropped cameras are ignored and not used.

By the "weak" tracking over each sub-network G_s, labels L_s are assigned for all tracklets r_i ($i = 1, 2, \ldots, M$). The labels are identical to those of tracklets determined as the same person's. For the tracklets which are not used for the "weak" tracking, a missing value (NA) is assigned. This label assignment L_s can be considered as a "weak" tracking result.

3.4. Trajectory Ensemble

The final result is calculated by integrating the "weak" tracking results using the extended concept of Cluster Ensemble [17]. The original Cluster Ensemble clusters samples into the same cluster when the samples are clustered into the same cluster in most "weak" clustering results. By clustering vectors whose elements are labels of weak clustering results, the consensus clustering results are obtained.

A number of labels are assigned to a tracklet r_i by the "weak" tracking results L_s ($s = 1, 2, \ldots, S$). For each tracklet r_i, let $\boldsymbol{\ell}_i = (l_{i1}, l_{i2}, \ldots, l_{iS})$ be a vector consisting of labels assigned by the "weak" tracking results.

For a pair of tracklets r_{i_1} and r_{i_2}, the pair can be considered that they are of the same person when the same labels are assigned in most of the "weak" tracking results. Therefore, by clustering all tracklets in terms of the similarity of the vectors $\boldsymbol{\ell}_{i_1}$ and $\boldsymbol{\ell}_{i_2}$ corresponding to tracklets r_{i_1} and r_{i_2}, the consensus tracking results, namely, the final label assignment is obtained.

In this case, since elements of a vector $\boldsymbol{\ell}_i$ are labels, the difference between them are meaningless. Additionally, the vector contains the missing value NA. Therefore, we define a similarity function $\mathrm{sim}(\cdot, \cdot)$ of vectors $\boldsymbol{\ell}_{i_1}$ and $\boldsymbol{\ell}_{i_2}$ by modifying L_0-norm considering missing values as follows:

$$\mathrm{sim}(\boldsymbol{\ell}_{i_1}, \boldsymbol{\ell}_{i_2}) = \sum_{s=1}^{S} I(l_{i_1 s}, l_{i_2 s}) \quad (1)$$

$$I(a, b) = \begin{cases} 1 & \text{if } a \neq b,\ a \neq \mathrm{NA},\ b \neq \mathrm{NA} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

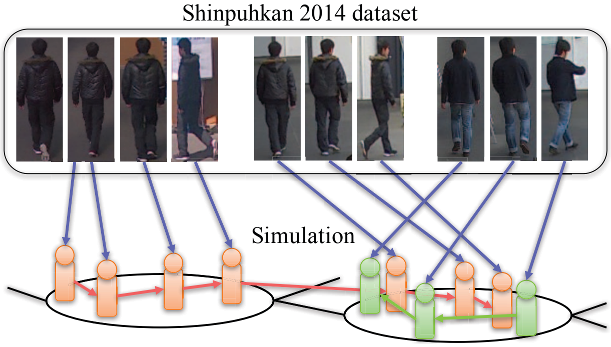


Figure 6. Virtual dataset generation. Once a simulated person is observed by a camera, an image corresponding to the person is sampled from the Shinpuhkan 2014 dataset.

By clustering based on this similarity function, the final label assignment for all tracklets are obtained. Here, we simply use agglomerative hierarchical clustering. We set the number of clusters for this as the average of the number of labels assigned for each "weak" tracking.

4. Evaluation

4.1. Dataset

Although there are some publicly available image datasets for multiple person tracking across multiple cameras [9, 24, 25, 26, 27, 28], each of them contains just one or few scenarios of person movements. To evaluate on many scenarios of person movements, we generated several virtual datasets from a publicly available dataset, "Shinpuhkan 2014 dataset" [28]. As similar to Kokura *et al.* [29], we randomly generated the structure of a camera network and simulated the movement of persons. In the simulation, first, cameras are randomly placed in a scene, neighboring cameras are connected by edges, and then some edges are randomly removed. For each pedestrian, the source and the destination cameras are randomly selected and a path between them is randomly selected. We assumed that when a person passes in a camera view, the person is detected by the camera virtually. At that time, an image of the corresponding person is selected from Shinpuhkan 2014 dataset as shown in Figure 6.

As same as Shinpuhkan 2014 dataset, the number of persons in the simulation was 24 and the number of cameras was 16. An example of a generated camera network is shown in Figure 7. Parameters representing the traveling time distribution between each adjacent camera pair were determined based on the distance between them. The minimum traveling time of each adjacent camera pair varied depending on the distance between the cameras. The maximum of the minimum traveling time was about 5 minutes.

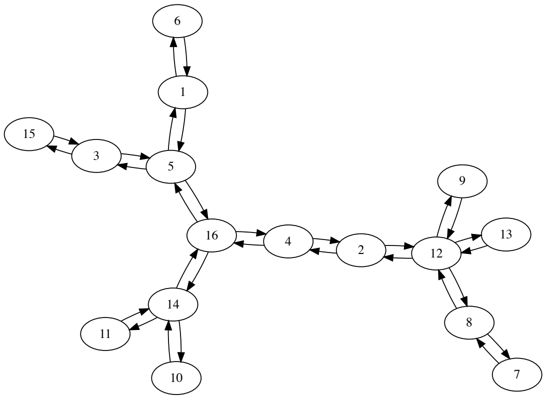


Figure 7. Example of a generated camera network.

The intervals of new person arrival in the observation area were set between 20 seconds and 5 minutes. Once a person entered an observation area, the person traveled between more than 7 camera views. For each person, the traveling time between a camera pair is randomly selected according to the traveling time distribution of the camera pair. Under this setting, the average traveling time of a person over the camera network was about 15 minutes.

4.2. Features and comparison methods for the evaluation

Since developing a new image feature is out of the scope of this paper, we simply used an HSV color histogram for the image feature. To suppress affection of the background, we cropped the center half regions (half in both height and width) of input images before the feature extraction. To make it robust to illumination change, Adaptive Histogram Equalization [30] was applied to the input images before conversion to HSV color space.

The similarity of two tracklets $f(r_{i_1}, r_{i_2})$ was calculated by multiplying the appearance similarity and the likelihood of the temporal relationship as follows:

$$f(r_{i_1}, r_{i_2}) = f_{\text{app}}(r_{i_1}, r_{i_2}) f_{\text{temp}}(r_{i_1}, r_{i_2}|\mathbf{e}), \qquad (3)$$

where $\mathbf{e}$ denotes the edges between two cameras where the tracklets r_{i_1} and r_{i_2} were observed, respectively. The appearance similarity of two tracklets was determined by selecting the maximum appearance similarity between images of the two tracklets as follows:

$$f_{\text{app}}(r_{i_1}, r_{i_2}) = \max_{m_1 \in r_{i_1}, m_2 \in r_{i_2}} f_{\text{app}}(m_1, m_2). \qquad (4)$$

The appearance similarity of two images was calculated by histogram intersection of HSV color histograms. The likelihood of the temporal relationship was calculated by the probability density function of the Gamma distributions whose parameters were assigned to the edge $e \in \mathbf{e}$ as follows:

$$f_{\text{temp}}(r_{i_1}, r_{i_2}|\mathbf{e}) = \max_{e \in \mathbf{e}} f_{\text{pdf}}(r_{i_1}, r_{i_2}|e). \qquad (5)$$

Table 1. Averaged ARI over five datasets.

Methods	Averaged ARI
Greedy	0.169
MinCostFlow	0.472
Trajectory Ensemble	**0.581**

4.3. Evaluation criterion

We generated five virtual datasets and evaluated on the averages of the five tracking results.

As the evaluation criterion, we used Adjusted Rand Index (ARI) [31, 32]. ARI measures the similarity between two label assignments. The value becomes 1 when all the label assignments are the same and it can be less than 0 when the assignments are worse than chance rate.

Let us assume label sets $X = \{X_1, X_2, \ldots, X_A\}$ and $Y = \{Y_1, Y_2, \ldots, Y_B\}$ are assigned to n elements, n_{ij} be the number of elements where both X_i and Y_j are assigned. Let $n_{i.}$ and $n_{.j}$ be the number of elements where labels X_i and Y_j are assigned respectively. Then, ARI of label assignments X and Y is defined as follows:

$$\mathrm{ARI}(X,Y) = \frac{\sum_i \sum_j \binom{n_{ij}}{2} - \left[\sum_i \binom{n_{i.}}{2} \sum_j \binom{n_{.j}}{2}\right] \Big/ \binom{n}{2}}{\frac{1}{2}\left[\sum_i \binom{n_{i.}}{2} + \sum_j \binom{n_{.j}}{2}\right] - \left[\sum_i \binom{n_{i.}}{2} \sum_j \binom{n_{.j}}{2}\right] \Big/ \binom{n}{2}}. \qquad (6)$$

We used this criterion to measure similarities between tracking results (assigned labels) and the ground-truth (true person IDs).

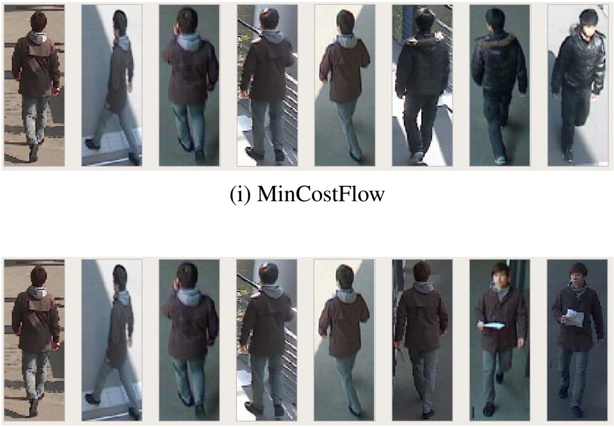
In the evaluation, since the proposed method randomly drops cameras, the result changes among trials of Random Camera Drop. Therefore, we performed the tracking evaluation ten times and averaged ARIs over their results.

4.4. Comparative methods

For the "weak" tracking of the proposed method, we used a Minimum Cost Flow based method. As comparative methods, we selected a greedy method (Greedy) and a Minimum Cost Flow based method without Trajectory Ensemble (MinCostFlow). All of them used the same features and similarity comparison method for tracklets.

4.5. Result and discussion

The results are shown in Table 1. As shown here, we confirmed that the proposed method achieved the highest



(i) MinCostFlow

(ii) Trajectory Ensemble

Figure 8. Examples of tracking results.

Table 2. Averaged ARIs in different parameters.

		Number of sub-networks S		
		50	100	150
Number of dropped cameras C_d	5/16	0.548	0.556	0.556
	7/16	0.573	0.572	0.576
	9/16	0.575	**0.581**	0.576
	11/16	0.457	0.526	0.578
	13/16	0.314	0.455	0.495

ARI. Comparing with the MinCostFlow, we confirmed the effectiveness of employing Trajectory Ensemble.

The tracking results by the MinCostFlow, which is a comparative method, and Trajectory Ensemble, which is the proposed method, are shown in Figure 8 (i) and (ii), respectively. The tracking target switched to another person in the comparative method, while the proposed method could keep tracking the same person.

To evaluate the effectiveness of Trajectory Ensemble, we further evaluated the tracking results while changing parameters of the number of sub-networks and the number of dropped cameras. As shown in Table 2, parameters $C_d = 9$, $S = 100$ achieved the highest ARI.

The higher C_d is, the more tracklets are not used for tracking. The more such tracklets are, the more missing values exist in vector $\boldsymbol{\ell}_i$ which consists of labels assigned by weak tracking results. Since it is hard to compare two vectors which contain many missing values, the tracking accuracy degrades.

If we set a higher value to the number of sub-networks S, various sub-networks are generated. Therefore we consider that Trajectory Ensemble works more effectively. In the evaluation, setting $S = 100$ achieved the highest accuracy. However, since the number of combinations of dropped cameras is ${}_{16}\mathrm{C}_9 = 11,440$ when the total number of cameras is 16, we need further evaluation by tuning S to higher values. On the other hand, when we set a higher value to S, since we need to process many sub-networks, it linearly increases the computation cost according to S. Therefore, we need to consider the trade-off between accuracy and computation cost.

5. Conclusion

Multiple person tracking over a camera network can fail by a temporal appearance change of the persons caused by environmental illumination and observation orientation. To solve this problem, comparing person images across not only adjacent cameras but also cameras multiple hops away is effective. However, such relaxation of spatio-temporal cues will also cause tracking failure. We introduced "Random Camera Drop" to generate different camera networks which relax the spatio-temporal cues partially and randomly. We also introduced a novel concept "Trajectory Ensemble", an extension of unsupervised ensemble learning for multiple person tracking over a camera network problem. Using this concept, we integrated multiple "weak" tracking results over randomly dropped camera networks. We achieved the best performance among comparative methods on some virtually generated datasets.

Further analysis on the relationship between the ratio of dropping cameras and the number of randomly dropped camera networks is our future work.

Acknowledgement

Parts of this research were supported by MEXT, Grant-in-Aid for Scientific Research.

References

[1] D. Makris, T. Ellis, and J. Black. Bridging the Gaps between Cameras. In *Proc. 2004 IEEE Computer Society Conf. Comput. Vision and Patt. Recog.*, pages 205–210, 2004.

[2] B. Song and A. K. Roy-Chowdhury. Robust Tracking in a Camera Network: A Multi-Objective Optimization Framework. *J. Sel. Topics Signal Process.*, 2(4):582–596, 2008.

[3] A. Alahi, P. Vandergheynst, M. Bierlaire, and M. Kunt. Cascade of Descriptors to Detect and Track Objects across Any Network of Cameras. *J. Comput. Vision and Image Understanding*, 114(6):624–640, 2010.

[4] K. Chen, C. Huang, S. Hsu, and I. Chang. Multiple Objects Tracking across Multiple Non-overlapped Views. In *Proc. 2011 Pacific-Rim Symp. Image and Video Tech.*, pages 128–140, 2011.

[5] G. Lian, J. Lai, and W.-S. Zheng. Spatial-Temporal Consistent Labeling of Tracked Pedestrians across Non-overlapping Camera Views. *Pattern Recognition*, 44(5):1121–1136, 2011.

[6] D. Gray, S. Brennan, and H. Tao. Evaluating Appearance Models for Recognition, Reacquisition, and Tracking. In *Proc. 2007 Intl. Workshop on Performance Evaluation for Tracking and Surveillance*, volume 3, pages 41–47, 2007.

[7] M. Farenzena, L. Bazzani, A. Perina, V. Murino, and M. Cristani. Person Re-identification by Symmetry-Driven Accumulation of Local Features. In *Proc. 2010 IEEE Computer Society Conf. Comput. Vision and Patt. Recog.*, pages 2360–2367, 2010.

[8] S. Bak, E. Corvee, F. Bremond, and M. Thonnat. Boosted Human Re-identification using Riemannian Manifolds. *Image and Vision Computing*, 30(6–7):443–452, 2012.

[9] W. Li, R. Zhao, T. Xiao, and X. Wang. DeepReID : Deep Filter Pairing Neural Network for Person Re-Identification. In *Proc. 2014 IEEE Conf. Comput. Vision and Patt. Recog.*, pages 152–159, 2014.

[10] R. Zhao, W. Ouyang, and X. Wang. Learning Mid-level Filters for Person Re-identification. In *Proc. 2014 IEEE Conf. Comput. Vision and Patt. Recog.*, pages 144–151, 2014.

[11] E. Ahmed, M. Jones, and T. K. Marks. An Improved Deep Learning Architecture for Person Re-Identification. In *Proc. 2015 IEEE Conf. Comput. Vision and Patt. Recog.*, pages 3908–3916, 2015.

[12] V. Kettnaker and R. Zabih. Bayesian Multi-camera Surveillance. In *Proc. 1999 IEEE Computer Society Conf. Comput. Vision and Patt. Recog.*, pages 253–259, 1999.

[13] F. Porikli and A. Divakaran. Multi-camera Calibration, Object Tracking and Query Generation. In *Proc. 2003 IEEE Intl. Conf. Multimedia and Expo.*, volume 1, pages 653–656, 2003.

[14] O. Javed, K. Shafique, and M. Shah. Appearance Modeling for Tracking in Multiple Non-overlapping Cameras. In *Proc. 2005 IEEE Computer Society Conf. Comput. Vision and Patt. Recog.*, pages 26–33. Ieee, 2005.

[15] K. Tieu, G. Dalley, and W. L. Grimson. Inference of Non-Overlapping Camera Network Topology by Measuring Statistical Dependence. In *Proc. 2005 IEEE Intl. Conf. Comput. Vision*, pages 1842–1849, 2005.

[16] O. Javed, K. Shafique, Z. Rasheed, and M. Shah. Modeling Inter-Camera Space-Time and Appearance Relationships for Tracking across Non-overlapping Views. *J. Comput. Vision and Image Uunderstanding*, 109(2):146–162, 2008.

[17] A. Strehl and J. Ghosh. Cluster Ensembles—A Knowledge Reuse Framework for Combining Multiple Partitions. *J. Machine Learning Research*, 3(35):583–617, 2003.

[18] A. Topchy, A. K. Jain, and W. Punch. A Mixture Model for Clustering Ensembles. In *Proc. 2004 IEEE Intl. Conf. Data Mining*, pages 379–390, 2004.

[19] L. Zhang, Y. Li, and R. Nevatia. Global Data Association for Multi-object Tracking using Network Flows. In *Proc. 2008 IEEE Computer Society Conf. Comput. Vision and Patt. Recog.*, pages 1–8, 2008.

[20] M. Klein. A Primal Method for Minimal Cost Flows with Applications to the Assignment and Transportation Problems. *Management Science*, 14(3):205–220, 1967.

[21] R. Tokola, W. Choi, and S. Savarese. Breaking the Chain: Liberation from the Temporal Markov Assumption for Tracking Human Poses. In *Proc. 2013 IEEE Intl. Conf. Comput. Vision*, pages 2424–2431, December 2013.

[22] Y. Xu, L. Qin, and Q. Huang. Coupling Multiple Alignments and Re-ranking for Low-Latency Online Multi-target Tracking. In *Computer Vision – ACCV 2014: 12th Asian Conf. Comput. Vision, Revised Selected Papers, part V*, pages 534–549, 2015.

[23] R. Kumar and D. Batra. Pose Tracking by Efficiently Exploiting Global Features. In *Proc. 2016 IEEE Winter Conf. on Applicat. of Comput. Vision*, pages 1–9, 2016.

[24] D. Baltieri, R. Vezzani, and R. Cucchiara. 3DPes: 3D People Dataset for Surveillance and Forensics. In *Proc. 2011 Intl. ACM Workshop on Multimedia Access to 3D Human Objects*, pages 59–64, 2011.

[25] A. Bialkowski, S. Denman, S. Sridharan, C. Fookes, and P. Lucey. A Database for Person Re-identification in Multi-Camera Surveillance Networks. In *Proc. 2012 Intl. Conf. Digital Image Computing: Techniques and Applications*, pages 1–8, 2012.

[26] J. Per, V. S. Kenk, R. Mandeljc, M. Kristan, and S. Kovacic. Dana36: A Multi-camera Image Dataset for Object Identification in Surveillance Scenarios. *Proc. 2012 IEEE Intl. Conf. Adv. Video and Signal-Based Surveillance*, pages 64–69, 2012.

[27] W. Li and X. Wang. Locally Aligned Feature Transforms across Views. In *Proc. 2013 IEEE Conf. Comput. Vision and Patt. Recog.*, pages 3594–3601, 2013.

[28] Y. Kawanishi, Y. Wu, M. Mukunoki, and M. Minoh. Shinpuhkan2014: A Multi-Camera Pedestrian Dataset for Tracking People across Multiple Cameras. In *Proc. 2014 Korea-Japan Joint Workshop on Frontiers of Comput. Vision*, 2014.

[29] T. Kokura, Y. Kawanishi, M. Mukunoki, and M. Minoh. Tracking Pedestrians Across Multiple Cameras via Partial Relaxation of Spatio-Temporal Constraint and Utilization of Route Cue. In *Proc. 2014 Asian Conf. Comput. Vision Workshops*, pages 587–601, 2014.

[30] S. M. Pizer, E. P. Amburn, J. D. Austin, R. Cromartie, A. Geselowitz, T. Greer, B. T. H. Romeny, and J. B. Zimmerman. Adaptive Histogram Equalization and Its Variations. *Comput. Vision Graph. Image Process.*, 39(3):355–368, 1987.

[31] L. Hubert and P. Arabie. Comparing Partitions. *J. Classification*, 2(1):193–218, 1985.

[32] J. M. Santos and M. Embrechts. On the Use of the Adjusted Rand Index as a Metric for Evaluating Supervised Classification. In *Proc. 2009 Intl. Conf. Artificial Neural Netw.*, pages 175–184, 2009.