Learning to associate detections for real-time multiple object tracking

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Abstract—With the recent advances in the object detection research field, tracking-by-detection has become the leading paradigm adopted by multi-object tracking algorithms. By extracting different features from detected objects, those algorithms can estimate the objects’ similarities and association patterns along successive frames. However, since similarity functions applied by tracking algorithms are handcrafted, it is difficult to employ them in new contexts. In this study, it is investigated the use of artificial neural networks to learning a similarity function that can be used among detections. During training, the networks were introduced to correct and incorrect association patterns, sampled from a pedestrian tracking data set. For such, different motion and appearance features combinations have been explored. Finally, a trained network has been inserted into a multiple-object tracking framework, which has been assessed on the MOT Challenge benchmark. Throughout the experiments, the proposed tracker matched the results obtained by state-of-the-art methods, it has run 58% faster than a recent and similar method, used as baseline.

Keywords—MOT, Multiple-object online tracking, Monocular camera, Computer vision, Machine learning

I. INTRODUCTION

Multiple object tracking (MOT) is a popular topic in Computer Vision due to its wide range of applications (e.g., robotics, autonomous driving vehicles, video surveillance). MOT works by managing the creation and death of new targets, while keeping their identities over a video sequence [9]. To identify targets with high accuracy, a tracker must solve problems related to illumination changes, camera motion and target occlusions, to name a few [15]. Given the high accuracy presented by latest object detectors [22, 27], most of state-of-the-art multiple-object trackers consider the tracking-by-detection paradigm [31, 14, 11].

Tracking-by-detection models multiple-object tracking as an association problem between detections extracted from a $N$ length video sequence (Figure 1). Formally, an object detector is applied to the $F_t$ frame obtained at the current $t$ time-step. Next, the tracker uses the bounding box of each detection to identify and describe the state of its targets. At the next $t + 1$ time-step, the same detector is applied to the $F_{t+1}$ frame. The tracker considers the new detections, alongside previously estimated states, to update its set of targets. The procedure is repeated until the detector is applied to all $N$ frames.

One of the main challenges in object tracking is the association problem [23]. Online tracking-by-detection algorithms usually employ graph-optimization techniques to solve this problem. For such, each set of disjoint $S_t$ vertices represents the detections extracted from the $F_t$ frame, while each edge contains the association cost between a pair of detections from distinctive sets. The set of pairs that minimizes the total association cost can be determined through graph optimization methods, such as network flow [13] and linear programming [8] algorithms.

To estimate the association cost between detections, tracking-by-detection algorithms model their targets according to different features, such as appearance and motion. Classical appearance models include the use of pixel templates [20] and color histograms [19, 26]. However, models based on convolutional neural networks have shown promising discriminant results, due to their ability to extract deep visual features from detections [12]. Other popular motion models include particle filters [17] and Kalman filter [35]. Additionally, trackers can combine appearance and motion models [11].

Although recent trackers employ several descriptive models to associate detections, their final similarity functions are based on heuristics [31, 29, 4]. As a consequence, they present the following drawback: designed functions might be context-domain dependent. Thus, their adaptation to new scenarios is
not simple. Besides, being heuristic-based, they are not scalable to handle new descriptor features, which could improve tracking quality.

By looking for patterns in a dataset, Machine Learning (ML) algorithms can discover a similarity function between detections in the context of multiple-object tracking-by-detection [7]. Recent works explore ML ability to associate detections; deep learning models have been specifically assessed on this task [25][23][1]. Although they are capable of modeling targets according to several features and estimate their similarity, because of their complex architectures (i.e., CNN and LSTM networks), they are not suitable for online real-time applications.

This work investigates a tracking method that uses a simpler, yet feature-scalable and context-adaptable, ML model to estimate the association cost between detections in the tracking-by-detection context (Figure 2). The model receives as input high-level motion and appearance features from the detections. By using ML to learn and adapt the predictive model, although any regression algorithm could induce this model, the use of MLP neural networks was defined because of their compact architecture, which is suitable for real-time applications. As discussed later in this paper, the model induced by those networks accomplished low error rates as a regressor, despite of their simplicity. The main benefits of the proposed approach are:

1) High adaptability to various scenarios, since a different association cost can be learned for different datasets;
2) Simple machine learning architecture restricted to calculation of association cost, which is used for online real-time tracking.

The remaining of this paper is organized as follows: Section II describes the main aspects of the proposed method; Section III details its evaluation in a tracking scenario; results are presented in Section IV and discussed in Section V. Finally, Section VI presents the main conclusions.

II. PROPOSED METHOD FOR TRACKING-BY-DETECTION

The proposed method, named SmartSORT after the work of [29], adopts an online tracking-by-detection paradigm with frame-by-frame data association, which is described by Algorithm 1. Its main aspects are presented next.

A. Track modeling and handling

In this study, it was taken into consideration a single-hypothesis tracking scenario where the state of each z\(\_i\) target with id \(i\) at \(t\) time is modeled as:

\[
s^t_i = [u, v, h, r, a]^T
\]

(1)

where \(u\) and \(v\) represent, respectively, the horizontal and vertical pixel positions of the center of the target, \(h\) stands for the height, \(r\) stands for the aspect ratio of its bounding box and finally \(a\) denotes its appearance descriptor. The \(s^t_i\) target state is updated every time there is an association with a \(d_j\) detection (Algorithm 1 of Algorithm 1). In this case, the target incorporates the detected bounding box, as well as its appearance descriptor (Figure 3). The former is the output of a CNN framework [29], which computes the deep appearance descriptor.
features of \(d_j\) (algorithm 1 of algorithm 1). If no association occurs, \(z_i\) retains its state.

Our tracker considers the framework proposed by \cite{3} for track handling: each \(z_i\) target has a \(L_i\) loss counter, which is incremented when no associations between a \(d_j\) detection and \(z_i\) occur during a tracking iteration, and set to 0 otherwise. If the value of \(L_i\) exceeds a given \(L_{\text{max}}\) threshold, the tracker deletes the \(z_i\) target, since it assumes that \(z_i\) has permanently left the scene (algorithm 1 of algorithm 1). The tracker creates new targets for each detection that cannot be associated (algorithm 1 of algorithm 1). During their first three frames, these new targets are considered to be tentative. The tracker discards every tentative whose loss counter is incremented (algorithm 1 of algorithm 1).

B. Data association

The SmartSORT tracker models the frame-by-frame association between new detections and existing targets as an assignment problem. To compute the association cost between targets and detections, it evaluates motion and appearance information (i.e., their bounding boxes and appearance descriptors). However, unlike related algorithms \cite{32,29}, SmartSORT computes this cost using a regression model induced by a machine learning algorithm (Figure 2). In this work, we considered MLP neural networks trained with the Backpropagation algorithm \cite{5}. Thus, given the \(f(d_j, z_i)\) feature vector, related to the \(j\)-th \(d_j\) detection and \(i\)-th \(z_i\) target, the regression model calculates their \(c_{j,i} \in [-1, 1]\) association cost. The model calculates this cost for every possible combination of detection-track pair. Subsection II-C details the structure of this model.

Once the regression model has computed every association cost, it optimally solves the assignment problem via the Hungarian method \cite{10} (algorithm 1 of algorithm 1). Additionally, it discards associations whose cost is higher than a \(C_{\text{max}}\) threshold value, as the tracker admits that they are unfeasible. Since the output space of the regression model is symmetrical, \(C_{\text{max}}\) has been considered as being 0, so the margin that separates feasible and unfeasible associations can be maximized. It is important to notice that \(C_{\text{max}}\) is the only hyper-parameter related to the data association step of SmartSORT.

C. Cost estimation regression model

The main contributions of SmartSORT rely on its cost estimation regression model, which was designed to compute a similarity score between a \(z_i\) target and a \(d_j\) detection based on their motion and appearance information (algorithm 1 of algorithm 1). Considering that Equation 1 expresses the state of \(z_i\), the regression model was initially projected to receive as input the \(f\) feature vector, defined as:

\[
f_{d_j, z_i} = [u, v, h, \Delta u, \Delta v, \Delta h, \Delta r, \Delta a, \Delta t]
\] (2)

In Equation 2, \(u, v, h\) and \(r\) refer to the bounding box dimensions of \(z_i\) target; while \(\Delta u, \Delta v, \Delta h\) and \(\Delta r\) represent the normalized differences between the bounding box dimensions of \(d_j\) detection and \(z_i\); \(\Delta a\) is the cosine distance between the \(d_j\) and \(z_i\) appearance descriptors; and \(\Delta t\) measures the number of tracking iterations the \(z_i\) target has not been associated with any detection (i.e. the value of its \(L_i\) loss counter).

The values \(u, v, h\) and \(r\) provide to the model information about the absolute position and dimensions of the \(z_i\) target, which allows SmartSORT to understand the relation between the motion of \(z_i\) and the angle of the camera. On the other hand, \(\Delta u\) and \(\Delta v\) distances are especially useful for discriminating unfeasible associations between targets, while \(\Delta h\) and \(\Delta r\) enable SmartSORT to understand their geometry. At the same time, \(\Delta a\) distance allows the model to distinguish targets based on their visual cues (i.e. their deep appearance features extracted by a CNN framework). Finally, SmartSORT can use \(\Delta t\) to understand the temporal dependence of the motion and appearance features of a target, which is particularly useful for occlusion handling.

To increase its capability of motion understanding, it has been decided to expand the input \(f\) feature vector to include past positional information. Hence, instead of only considering the distances between positional and visual features of targets and detections at the current time-step, a sliding window strategy has been adopted, where the final \(g\) feature vector has the form:

\[
g_{d_j, z_i} = [f_{d_j, z_i}, f_{s_i}^{N-1}, \ldots, f_{s_i}^{N-N}]
\] (3)

In Equation 3, \(f\) corresponds to the feature vector defined by Equation 2, \(d_j\) is the \(j\)-th detection extracted at \(t+1\) time; \(s_i^t\) represents the state of \(z_i\) target at \(t\) time; and \(N\) is the length of the temporal sliding window. This strategy enables the tracker to understand not only the motion behavior of a target but also its temporal appearance variance. Figure 4 illustrates our sliding window strategy.

As mentioned before, SmartSORT has been designed to use a model that outputs a \(c_{j,i} \in [-1, 1]\) similarity score, which represents the association cost between a \(d_j\) detection and a
A SmartSORT evaluation has three steps: 1) to build an association dataset, 2) to train a MLP neural network and validate its regression model, and 3) to incorporate the model in the method and assess SmartSORT on a tracking benchmark. The following sections describe each of these steps.

A. Association dataset

A dataset with associations between targets was built by initially sampling positive and negative examples from the seven training sequences in the MOT Challenge Benchmark 2016 [13]. These sequences have annotations indicating the bounding box and the identity of 517 targets along 5516 frames. For a temporal window of size two, each example has the form:

\[(s^f_i, s^{f+n}_j, Y)\] (4)

In Equation 4 \(s^f_i\) is the state of \(i\) id \(z_i\) target at \(f\) index frame; \(n \in \{0, N - f\}\) is a random temporal displacement, which is inferior to the difference between the total \(N\) frames number, where \(z_i\) target is present, and the \(f\) index; and \(Y\) is the label of the example. Thus, for positive examples, \(i = j\) and \(Y = -1\), while \(i \neq j\) and \(Y = 1\) for negative examples.

Because this benchmark does not provide detections labeled by their id target, a sampling strategy that considered target-to-target instead of detection-to-target associations was used. After collecting the initial examples, their features have been extracted according to Equations 2 and 3. Hence, each final example has the form:

\[(g(z_i, z_j), Y)\] (5)

In Equation 5 \(z_i\) and \(z_j\) correspond to targets of \(s^f_i\) and \(s^{f+n}_j\) states, respectively. Overall, the final dataset has 129,959 examples of correct and incorrect associations between targets.

B. Model training

As part of the experiments with MLP trained by Backpropagation, the hyper-parameters has been tuned using grid-search, including the temporal sliding window length of the input feature vector. The association dataset has been divided into disjoint train and validation partitions. On the former, the sliding window length has been fixed and grid-searches with 3-fold cross-validation have been performed, tuning the number of hidden layers and neurons of the network. After finding the best hyper-parameter values for that specific sliding window length, the MLP network has been trained on the whole training partition and its prediction performance on the validation set has been evaluated.

Concluded these experiments for different lengths of sliding windows, the best model according to its MSE error on the validation set has been selected. The best model had a 8.29e-2 error. It was an MLP network receiving 49 attribute values, from a sliding window of size 5, and only one 7 neurons hidden layer. To keep the network efficiently trainable [2] and map its output to \([-1, 1]\), the activation functions used in its hidden and

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**Algorithm 2:** Association cost estimation.

**Data:** \(Z\) set of targets, \(D\) set of detections, \(C_{\text{max}}\) cost threshold

**Result:** \(C\) set of association costs between targets and detections

\[
B \leftarrow 0; \\
\text{foreach } z \in Z \text{ do} \\
\quad \text{foreach } d \in D \text{ do} \\
\quad \quad B \leftarrow B + g(d, z); \\
\quad \text{end} \\
\text{end} \\
C \leftarrow \text{regressionModel}(B); \\
\text{foreach } c \in C \text{ do} \\
\quad \text{if } c > C_{\text{max}} \text{ then} \\
\quad \quad C \leftarrow C - c; \\
\quad \text{end} \\
\text{end}
\]
output layers were, respectively, ReLU and hyperbolic tangent. To induce the final model with Backpropagation Smooth L1 has been employed as loss function, SGD with momentum as the optimizer and a fixed learning rate of $2e^{-3}$. Those parameters were empirically chosen.

C. Tracking evaluation

The proposed tracker has been evaluated on the testing sequences of the MOT Challenge Benchmark 2016 [18]. This benchmark assesses the performance of multiple pedestrians trackers on seven different challenging video sequences, each of them presenting various camera setups and lighting conditions. Similarly to [29], our tracker considered as input detections generated by a Faster R-CNN framework [32]. Moreover, similarly to that work, our evaluation test was conducted with $L_{max} \approx 3$ and the detections used as threshold a 0.3 confidence score. The same CNN framework proposed by [29] has also been employed as appearance descriptor for targets and detections.

The benchmark adopts the following metrics to assess the performance of trackers:

- Multi-object tracking accuracy (MOTA): the overall accuracy of the tracker in terms of identity switches, false positives and false negatives;
- Multi-object tracking precision (MOTP): the precision of the bounding box positions predicted by the tracker;
- Mostly tracked (MT): the ratio of ground-truth trajectories that are covered by a track hypothesis for at least 80% of their respective life span;
- Mostly lost (ML): the ratio of ground-truth trajectories that are covered by a track hypothesis for at most 20% of their respective life span;
- Identity switch (ID): the total number of times a ground-truth trajectory was assigned to a different id;
- Fragmentation (FM): the total number of times a trajectory was interrupted during tracking.
- Runtime: the tracking speed measured in Hz, without considering the detection step.

Our evaluation test was conducted on an Intel i3-7020U CPU with 4GB of RAM. The appearance features used by SmartSORT were extracted through an Nvidia GeForce GTX 1050 mobile GPU. Since SmartSORT was designed as an improvement of DeepSORT and both methods virtually share the same appearance feature extraction routine, SmartSORT’s speed was initially measured without considering the time it takes to extract visual features. To compute its overall runtime speed, we combined its already measured tracking speed with the total time DeepSORT takes to extract appearance features through an Nvidia GeForce GTX 1050 mobile, which is 147s, as reported by its authors. [29].

IV. EXPERIMENTAL RESULTS

Figure 5 illustrates a comparison between results obtained by SmartSORT on the MOT Challenge 2016 Benchmark against the performance of its baseline in terms of tracking accuracy and runtime frequency. Since both trackers share the same detection feature extraction routine, their reported speed does not consider the time taken to perform that task.

Table I presents the overall results obtained by SmartSORT on that benchmark, as well as the performance of its primary baseline and other online trackers submitted to the same challenge. Among these trackers, there are methods based on motion modeling by Kalman and particle filtering (SORT and EA-PHD-PF) and appearance modeling by deep neural networks (POI, CNNMT and RAN).

Finally, Figure 6 illustrates some of the results obtained by SmartSORT when applied to the benchmark.

V. DISCUSSION

According to Figure 5, SmartSORT, the proposed method, was able to perform its tracking routine at a frequency of 90 FPS against 40 FPS performed by its baseline [29], a 125% processing speed gain at a 1 percent tracking accuracy cost. This result can be explained by the efficient computation batch performed by its regression model, which calculates the pair-wise association cost between all the currently observed detections and all tracks in a single matrix operation. At the same time, SmartSORT does not perform any filtering computation, as opposed to its baseline. Hence, its tracking management routine has a lower computational cost.

Similar results are obtained when comparing SmartSORT to the other trackers in Table I. Even considering the time SmartSORT takes to extract visual features from detections, it runs significantly faster than most of the considered trackers. The only exceptions are IOU and SORT trackers, whose identity switches rates are, at least, 25% higher than those presented by SmartSORT. On the other hand, SmartSORT runs

![Figure 5: Comparison between SmartSORT and its baseline performances on the MOT Challenge 2016, assessing tracking accuracy versus runtime frequency. The presented frequencies do not consider the visual feature extraction step performed by both methods.](image-url)
Table I: Online tracking performances on the MOT Challenge 2016. All methods considered private detectors. Also, the presented runtime frequencies do consider the visual feature extraction step performed by those methods.

| Method         | MOTA | MOTP | MT  | ML  | ID  | FM  | Runtime |
|----------------|------|------|-----|-----|-----|-----|---------|
| RAN [6]        | 63.0 | 78.8 | 33.9%| 22.1%| 482 | 1251| 1.6 Hz  |
| CNNMT [16]    | 65.2 | 78.4 | 32.4%| 21.3%| 946 | 2283| 11 Hz   |
| EA-PHD-PF [24]| 52.5 | 78.8 | 19.0%| 34.9%| 910 | 1321| 12 Hz   |
| POI [32]       | 66.1 | 79.5 | 24.0%| 34.0%| 805 | 3093| 10 Hz   |
| IOU [4]        | 57.1 | 77.1 | 23.6%| 32.9%| 2167| 3028| 1 Hz    |
| SORF [3]       | 59.8 | 79.6 | 25.4%| 22.7%| 1423| 1835| 60 Hz   |
| DeepSORT [29]  | 61.4 | 79.1 | 32.8%| 18.2%| 781 | 2008| 17 Hz   |
| SmartSORT (this paper) | 60.4 | 78.9 | 21.9%| 16.1%| 1135| 2230| 27 Hz   |

at least 59% faster than all the other trackers in Table I, which use deep visual features to discriminate detections.

The speed gain of SmartSORT is even higher when compared with the LSTM-based tracker RAN, which extracts features from detections and compute their similarity through a single deep learning framework. This result demonstrates that even though SmartSORT considers a much simpler regression neural network, by presenting high-level deep appearance features and handcrafted motion features as input, it can model a similarity function whose processing time is considerably lower than a more complex network. At the same time, its tracking accuracy was less than 3% lower than the score obtained by the LSTM-based tracker.

Despite SmartSORT competitive speed and accuracy, its identity switches (ID) and fragmentation scores (FM) were, respectively, 45% and 11% higher than those presented by its baseline. Considering that both methods employ the same appearance feature extractor and the former applies the Kalman filter to encode motion information, this result suggests that the weakest point of SmartSORT is related to its sliding window strategy to predict the trajectory of a target based on its past positions. Thus, that approach may be vulnerable to wrong associations: once SmartSORT switches ids, it contaminates temporal windows with appearance and motion features of distinct targets. This noise may bring instability to its cost estimation, lasting until there is a streak of correct associations. Alternatives to solve this problem include replacing its MLP-based regression model by a time-series specific (e.g. vanilla recurrent neural network), while applying compression techniques, such as those based on singular value decomposition (SVD) and adaptive drop weight (ADW) [21, 30], so its runtime is not impaired.

Nonetheless, by assessing SmartSORT performance on the MOT Challenge 2016 benchmark, it was noticed that it presents high tracking accuracy, at the same time that it runs faster than the other trackers considered in this work. As a result, its overall cost-effectiveness is highly competitive, especially when considering its use in online tracking applications based on embedded systems.

VI. Conclusions

In this paper, we propose SmartSORT, a new online tracking-by-detection algorithm that uses a regression model to predict the association cost between detections based on high-level appearance and motion features. Since SmartSORT encodes these features through a temporal sliding window, it can run without need of a filtering algorithm. Results obtained from experimental evaluations of SmartSORT on the MOT Challenge benchmark have shown that its tracking accuracy is competitive with state-of-the-art online trackers, but at a lower computational cost. Therefore, SmartSORT presents highly competitive cost-effectiveness for online real-time tracking applications.
As future research, we intend to experiment the use of shallow machine learning architectures specifically designed to modeling sequential data (e.g. vanilla recurrent neural networks) instead of an MLP combined with sliding window. Moreover, in order to keep it suitable for online real-time tracking, we intend to investigate the use of compression techniques while still presenting high-level input features to the model. We also intend to experiment with the use of different training algorithms besides Backpropagation. We believe that those changes will boost the efficiency of training and improve the robustness of SmartSORT to wrong associations, which will increase its overall tracking accuracy.

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REFERENCES

[1] Alexandre Alahi, Kratarth Goel, Vignesh Ramanathan, Alexandre Robicquet, Li Fei-Fei, and Silvio Savarese. Social LSTM: Human Trajectory Prediction in Crowded Spaces. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 961–971. IEEE, jun 2016.
[2] R. Arora, A. Basu, P. Mianjy, and A. Mukherjee. Understanding deep neural networks with rectified linear units. ArXiv, abs/1611.01491, 2017.
[3] A. Bewley, Z. Ge, L. Ott, F. Ramos, and B. Upcroft. Simple online and realtime tracking. In 2016 IEEE International Conference on Image Processing (ICIP), pages 3464–3468, Sep. 2016.
[4] Erik Bochinski, Volker Eiselein, and Thomas Sikora. High-Speed tracking-by-detection without using image information. In 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), pages 1–6. IEEE, aug 2017.
[5] Y. L. Cun. A theoretical framework for back-propagation. In D. Touretzky, G. Hinton, and T. Sejnowski, editors, Proceedings of the 1988 Connectionist Models Summer School, CMU, Pittsburgh, PA, pages 21–28. Morgan Kaufmann, 1988.
[6] K. Fang, Y. Xiang, X. Li, and S. Savarese. Recurrent autoregressive networks for online multi-object tracking. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), pages 466–475, March 2018.
[7] Peter Flach. Machine Learning: The Art and Science of Algorithms That Make Sense of Data. Cambridge University Press, New York, NY, USA, 2012.
[8] Andreas Geiger, Martin Lauer, Christian Wojek, Christoph Stiller, and Raquel Urtasun. 3D Traffic Scene Understanding From Movable Platforms. IEEE Transactions on Pattern Analysis and Machine Intelligence, 36(5):1012–1025, may 2014.
[9] Xuan Gong and Zichun Le. A multiple object tracking approach that combines colour and depth information using a confidence measure. Pattern Recognition, 29(10):1504 – 1514, 2008.
[10] Shaul Oron, Aharon Bar-Hillel, and Shai Avidan. Real-time tracking-with-detection for coping with viewpoint change. Machine Vision and Applications, 26(4):507–518, may 2015.
[11] Li Zhang, Yuan Li, and Ramakant Nevatia. Global data association for multi-object tracking using network flows. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 1392–1400. IEEE, jun 2016.
[12] Nan Wang, Qi Zou, Quinlin Ma, Yaping Huang, and Di Luan. A light tracker for online multiple pedestrian tracking. Journal of Real-Time Image Processing, April 2020.
[13] N. Wijek, A. Bewley, and D. Paulus. Simple online and realtime tracking with a deep association metric. In 2017 IEEE International Conference on Image Processing (ICIP), pages 3645–3649, Sep. 2017.
[14] Y. Yang, K. Liang, X. Xiao, Z. Xie, L. Jin, J. Sun, and W. Zhou. Accelerating and compressing lstm based model for online handwritten chinese character recognition. In 2018 16th International Conference on Frontiers in Handwriting Recognition (ICFHR), pages 110–115, Aug 2018.
[15] Jun Huo Yoon, Chang-Ryool Lee, Ming-Hsuan Yang, and Kuk-Jin Yoon. Online Multi-object Tracking via Structural Constraint Event Aggregation. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 1392–1400. IEEE, jun 2016.
[16] F. Yu, W. Li, Q. Li, Y. Liu, X. Shi, and J. Yan. Poi: Multiple...
object tracking with high performance detection and appearance feature. *ECCV 2016 Workshops*, 9914, 2016.

[33] Hongkai Yu, Haozhou Yu, Hao Guo, Jeff Simmons, Qin Zou, Wei Feng, and Song Wang. Multiple human tracking in wearable camera videos with informationless intervals. *Pattern Recognition Letters*, 112:104 – 110, 2018.