Self-balance Motion and Appearance Model for Multi-object Tracking in UAV

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ABSTRACT

Under the tracking-by-detection framework, multi-object tracking methods try to connect object detections with target trajectories by reasonable policy. Most methods represent objects by the appearance and motion. The inference of the association is mostly judged by a fusion of appearance similarity and motion consistency. However, the fusion ratio between appearance and motion are often determined by subjective setting. In this paper, we propose a novel self-balance method fusing appearance similarity and motion consistency. Extensive experimental results on public benchmarks demonstrate the effectiveness of the proposed method with comparisons to several state-of-the-art trackers.

KEYWORDS

Multi-object tracking, Neural networks, UAV

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1 INTRODUCTION

Multi-object tracking in videos is an important task within the field of computer vision. Multi-object tracking aims to find all the object trajectories in videos or image sequences. Thanks to the advancement of the object detection methods in recent years, such as DPM[9], SDP[33], Faster r-cnn[25] and YOLO[23], the tracking-by-detection framework [5, 10,

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Figure 1: Schematic of the effectiveness of appearance-discriminating. The top target can be discriminated with the objects around by appearance. The bottom target is confusing with the objects around only by appearance. The edge between the objects shows the appearance similarity between them.

17, 29, 31] is widely used in multi-object tracking task. This framework has advantages that the number of objects in scene is self-adaptive and object detection results offer much more accurate object positions for multi-object tracking methods.

According to the way of using object detections, the tracking-by-detection based multi-object tracking methods could be broadly categorized into two groups: the global(batch) methods such as [5, 29, 31] and the online methods such as [10, 17]. The global methods utilize the whole object detections in sequences, finding the global optimal association between all detections. So in each frame, these methods associate the detections taking into account not only past frames but also the frames in future. In contrast, the online methods

utilize the object detections in current frame and the trajectories in past frames. Because of lack of information in future frames, the online tracking methods are more challenging with appearance changes of objects and complexity of the context in scene. On the other hand, the online process of these methods corresponds with the reality applications, such as the unmanned aerial vehicle and intelligent surveillance. In this paper, we focus on the online multi-object tracking methods.

Once the detection are known, the trackers would utilize several cues to generate the affinity between the detections and targets. The affinity is general generated by some cues, such as appearance and motion. However, the weight ratio of appearance or motion in the affinity is usually designed by handcrafted. The empirical weight is unified set in the methods. But for each object in the scene, the discriminative ability of appearance or motion varies is various. In Fig. 1, we show the appearance similarity between one target and the objects around it. It is observed that the target on the top could be easily distinguish only by appearance while the targets on the bottom have very similar appearance. Thus, for the target on the bottom, the motion cue should play a more important role for recognizing the target. Meanwhile, the changes of objects and scene background are smooth in the adjacent frames. It means that the ratio of effectiveness between the appearance similarity and motion consistency should be stable. Inspired by this observation, we proposed a novel self-balance method for balancing appearance similarity and motion consistency in distinguishing targets. We utilize the appearance similarity between the targets in the scene for self-adaption of allocating the weights.

In evaluations, we apply the proposed method over a set of challenging sequences that recorded by the Unmanned Aerial Vehicles (UAVs). Results showed that our method can achieve better tracking performance.

2 RELATED WORKS

Under the tracking-by-detection framework, most tracking methods [12] contain two main steps: object description and data association. For object description, different features in various cues [35], (such as appearance, motion, shape and context) are utilized to describe each object. For data association, probabilities of connecting detections are computed with the features of the detections extracted in object description step [19, 30].

For a better affinity between objects, most methods focus on how to describe the objects. For the appearance description, small pattern is utilized for describing the object patch in some methods. The objects are described by segmenting objects into parts [11, 28]. In [16], the author utilizes super-pixels to compensate the appearance diversity by the imprecise detections. [36] utilizes Dual Matching Attention Networks to focus on the effective parts of the objects for distinguishing. Some methods utilize person re-identification method enhancing the appearance representation, such as in [31] or use a large convolutional neural networks to associate

object detections such as Quad-CNN in [29]. For the motion description, LSTM networks are used for predicting the position of the targets in [18]. [24] exploits two adjacent frames to learn the movement of the target.

The appearance and the motion description are used separately or fused by weights in most methods. There are also several methods merging appearance and motion by connecting the features in the network, such as [13]. However, these methods fuse the cues in the fixed way ignoring the influence of changing context for the discrimination of descriptions. In this paper, we consider about the changing discrimination and propose a novel self-balance method fusing appearance similarity and motion consistency.

3 SELF-BALANCE MODEL FOR MULTI-OBJECT TRACKING

The online multi-object tracking methods aim to connect the detections in current frame with the trajectories of the targets. Thus, the detections and past trajectories of targets are once known, the tracking problem can be formulated as

$$\begin{aligned} F &= \arg \max_{A_{t-1,t}} P(\mathbf{D}^t | \mathbb{T}^{t-1}) \\ &= \arg \max_{A_{t-1,t}} \sum_{i \in M} \sum_{j \in N \cup \{0\}} a^{i,j} \Omega_{i,j}^t, \\ \text{s.t. } \sum_{i \in M, j \neq 0} a^{i,j} &\leq 1 \bigwedge \sum_{j \in N \cup \{0\}} a^{i,j} = 1, \text{ for all } i \end{aligned} \quad (1)$$

where $P(\mathbf{D} | \mathbb{T})$ is the score of association scheme $A_{t-1,t}$. $a^{i,j}$ is an element of the association matrix A , with a binary value $\{1, 0\}$. $i \in M$ represents target i in the target set $\mathbb{T}^{t-1}$, and $j \in N$ corresponds to detection j in the set $\mathbf{D}^t$ of detections in the current frame. $\Omega_{i,j}^t$ is an affinity function that represents the probability that target i should be combined with detection j .

In the original method, $\Omega_{i,j}^t$ integrates appearance similarity, motion consistency and shape consistency, *i.e.*

$$\Omega_{i,j}^t = \sum c \cdot f_c(i, j), c \in \{APP, MOV, SHAPE\}. \quad (2)$$

If some cues are unused in the method, the corresponding $f_c(i, j) = 0$. w_c is the weight of the corresponding cue.

In our method, we utilize the appearance similarity and motion consistency to generate the affinity between objects. $\Omega_{i,j}^t$ is defined as

$$\Omega_{i,j}^t = w_i^{t-1} * f_{MOV}(i, j) + (1 - w_i^{t-1}) * f_{APP}(i, j), \quad (3)$$

where $f_{APP}(i, j)$ is appearance similarity between object detections and targets and $f_{MOV}(i, j)$ is the motion consistency. w^{t-1} is the weight learned from the last frame.

The appearance similarity $f_{APP}(i, j)$ is defined as

$$f_{APP}(i, j) = \frac{\mathbf{x}_i \cdot \mathbf{x}_j}{\|\mathbf{x}_i\| \cdot \|\mathbf{x}_j\|}, \quad (4)$$

$f_{APP}(i, j)$ is the cosine distance between the feature $\mathbf{x}_i$ of target i frame $t-1$ and the feature $\mathbf{x}_j$ of the object detection j in frame t .

Figure 2: The framework of the proposed method for online multiple object tracking with our self-balance motion and appearance model. In the last frame, the appearance similarity between the target and other targets around it is calculated for generating the weights for each target. Using the Social LSTM network, we could get the motion prediction of targets. Then the affinity $A_{t-1,t}$ between targets and objects in current frame is generated using the weighted appearance similarity and motion prediction.

The motion consistency $f_{MOV}(i, j)$ is defined as

$$f_{MOV}(i, j) = p((x, y)_j | N_i(t-1)), \quad (5)$$

where $N_i(t-1)$ is the distribution of the position prediction of target i in frame t from last $t-1$ frames. $p((x, y)_j | N_i(t-1))$ is the probability that target i is at the position $(x, y)_j$.

As the context information could influence the discrimination of appearance and motion, we generate the weight w_i^{t-1} from the context of target i in the last frame. The targets in the area around the target i are regarded as the context. Thus w_i^{t-1} is defined as

$$w_i^{t-1} = \sin\left(\frac{\pi}{4} * (\max(f_{APP}(i, r))), r \in R_i^{t-1}\right), \quad (6)$$

where $f_{APP}(\mathbf{x}_i, \mathbf{x}_r)$ is the cosine distance between the feature $\mathbf{x}_i$ of target i in frame $t-1$ and the feature $\mathbf{x}_r$ of the targets R_i^{t-1} in the area in frame $t-1$. R_i^{t-1} is the set of objects around the target i at $t-1$ time. If there is some similar target around the target i , the weight of motion would be large while the weight of appearance changing small.

The framework schematic of our method is shown in Fig. 2. For each target in frame $t-1$, the weights of the targets are generated by calculating the appearance similarity between the target and others targets around. The appearance feature of target $\mathbf{x}$ is generated by a object re-identification networks [32]. With the weights, the appearance similarity between targets in frame $t-1$ and the objects in frame t would be generated. Then a social LSTM network [1] is introduced for motion prediction. Once the motion prediction and appearance similarity are known, the affinity $\Omega_{i,j}^t$ could be calculated using Function. 3.

Considering about target exit or occlusion, we include a sink, *i.e.*, target 0, to generate an exit association for each real target. Then $\Omega_{i,0}$ is set to a value in $(0, 1)$ (0.01 in this

study) for the missing target. The optimal association scheme $A_{t-1,t}$ is worked out using an association method, *e.g.*, the Hungarian algorithm ([21]). Finally the tracking results in current frame are achieved.

4 EXPERIMENTS

We evaluate our self-balance motion and appearance method (denoted by SBMA) together with 8 recent algorithms including online methods (RMOT [34], RLSTM [18], SORT [3] and SLSTM [1]) and batch-based methods (CEM [20], GOG [22], IOUT [4] and SMOT [7]).

Metrics. To evaluate the performance of MOT methods, we use multiple metrics, including Identification Precision (IDP) [27], Identification Recall (IDR), and the corresponding F1 score called IDF1 (the ratio of correctly identified detections to the average number of ground-truth and computed detections). Multiple Object Tracking Accuracy (MOTA) [2], Multiple Object Tracking Precision (MOTP), Mostly Tracked targets (MT, defined as more than 80% of trajectories being covered by the ground-truth), Mostly Lost targets (ML, defined as less than 20% of trajectories being covered by the ground-truth), the number of False Positives (FP), the number of False Negatives (FN), the number of ID Switches (IDS) and the number of times a trajectory is Fragmented (FM) are also considered.

Dataset. We evaluate our method on the dataset UAVDT [8]. The dataset offers 50 sequences recorded from Unmanned Aerial Vehicles (60% for training and 40% for testing). We compare our method with 8 recent algorithms on the testing sequences.

Implementation. We implemented our framework in Tensorflow1.0 on a computer with an i7 6700 CPU, an NVIDIA Titan X GPU and 32 GB of RAM. For the re-identification

Detection Input: Faster-RCNN [26]

MOT methods	IDF1	IDP	IDR	MOTA	MOTP	MT[%]	ML[%]	FP	FN	IDS	FM
CEM [20]	10.2	19.4	7.0	−7.3	69.6	7.3	68.6	72,378	290,962	2,488	4,248
GOG [22]	18.0	23.3	14.6	34.4	72.2	35.5	25.3	41,126	168,194	14,301	12,516
IOUT [4]	23.7	30.3	19.5	36.6	72.1	37.4	25.0	42,245	163,881	9,938	10,463
RMOT [34]	33.3	27.8	41.4	−39.8	72.3	36.7	25.7	319,008	151,485	5,973	5,897
RLSTM [18]	31.3	38.6	26.3	25.6	69.1	36.7	25.7	71,955	180,461	1,333	13,088
SMOT [7]	45.0	55.7	37.8	33.9	72.2	36.7	25.7	57,112	166,528	1,752	9,577
SORT [3]	43.7	58.9	34.8	39.0	74.3	33.9	28.0	33,037	172,628	2,350	5,787
SLSTM [1]	37.2	46.8	30.8	37.9	72.0	38.2	24.4	44,783	161,009	6,048	12,051
SBMA	48.5	61.1	40.3	38.6	72.1	38.9	24.4	44,724	160,950	3,489	11,796

Detection Input: R-FCN [6]

MOT methods	IDF1	IDP	IDR	MOTA	MOTP	MT[%]	ML[%]	FP	FN	IDS	FM
CEM [20]	10.3	18.4	7.2	−9.6	70.4	6.0	67.8	81,617	289,683	2,201	3,789
GOG [22]	30.9	38.8	25.6	28.5	77.1	34.4	28.6	60,511	176,256	6,935	6,823
IOUT [4]	44.0	47.5	40.9	26.9	75.9	44.3	22.9	98,789	145,617	4,903	6,129
RMOT [34]	34.4	28.7	43.0	−43.8	76.3	36.7	25.7	328,677	158,760	2,949	2,286
RLSTM [18]	29.3	34.8	25.2	14.7	70.6	36.7	25.7	97,670	191,720	1,395	9,953
SMOT [7]	44.0	53.5	37.3	24.5	77.2	33.7	29.2	76,544	179,609	1,370	5,142
SORT [3]	42.6	58.7	33.5	30.2	78.5	29.5	31.9	44,612	190,999	2,248	4,378
SLSTM [1]	35.6	43.6	30.1	27.5	76.9	35.2	27.7	66,980	172,942	7,355	9,791
SBMA	46.9	57.5	39.6	28.5	76.9	35.0	27.6	67,134	173,096	3,367	9,759

Detection Input: SSD [15]

MOT methods	IDF1	IDP	IDR	MOTA	MOTP	MT[%]	ML[%]	FP	FN	IDS	FM
CEM [20]	10.1	21.1	6.6	−6.8	70.4	6.6	74.4	64,373	298,090	1,530	2,835
GOG [22]	29.2	33.6	25.9	33.6	76.4	36.0	22.4	70,080	148,369	7,964	10,023
IOUT [4]	29.4	34.5	25.6	33.5	76.6	34.3	23.4	65,549	154,042	6,993	8,793
RMOT [34]	26.1	18.9	41.8	−101.0	75.1	36.7	25.7	544,591	131,382	9,252	7,211
RLSTM [18]	26.5	28.9	24.4	7.6	69.0	36.7	25.7	129,660	182,828	2,347	12,654
SMOT [7]	41.9	45.9	38.6	27.2	76.5	34.9	22.9	95,737	149,777	2,738	9,605
SORT [3]	37.1	45.8	31.1	33.2	76.7	27.3	25.4	57,440	166,493	3,918	7,898
SLSTM [1]	39.4	44.2	35.5	33.0	75.8	37.3	21.6	77,706	144,617	6,019	13,332
SBMA	43.1	48.3	38.8	33.6	75.8	37.7	21.4	77,299	144,191	4,932	13,468

Detection Input: RON [14]

MOT methods	IDF1	IDP	IDR	MOTA	MOTP	MT[%]	ML[%]	FP	FN	IDS	FM
CEM [20]	10.1	18.8	6.9	−9.7	68.8	6.9	72.6	78,265	293,576	2,086	3,526
GOG [22]	51.0	60.2	44.3	35.7	72.0	43.9	26.2	62,929	153,336	3,104	5,130
IOUT [4]	50.1	59.1	43.4	35.6	72.0	43.9	26.2	63,086	153,348	2,991	5,103
RMOT [34]	28.8	22.5	40.0	−70.0	70.9	36.7	25.7	418,222	153,480	7,902	7,007
RLSTM [18]	36.5	42.4	32.1	24.1	68.7	36.7	25.7	87,589	169,866	1,156	12,657
SMOT [7]	52.6	60.8	46.3	32.8	72.0	43.4	27.1	73,226	154,696	1,157	4,643
SORT [3]	54.6	66.9	46.1	37.2	72.2	40.8	28.0	53,435	159,347	1,369	3,661
SLSTM [1]	48.1	56.4	41.9	35.0	71.9	44.5	26.2	65,093	152,481	4,013	6,059
SBMA	52.4	61.4	45.7	34.8	71.9	44.0	26.4	65,760	153,148	3,195	6,003

Table 1: Results of a quantitative comparison among MOT methods in the testing set of the UAVDT dataset. The best performer and our methods are highlighted in bold.

networks [32] and social LSTM network [1], we use the implementations released by the authors.

Evaluation. For overall evaluation, we utilize object detection results as the inputs for tracking-by-detection methods by four kinds of methods (*i.e.*, Faster-RCNN [26], R-FCN [6], SSD [15] and RON[14]). The tracking results with the four kinds of detections are shown in Table. 1. From the table, it is observed that our method achieves the best results with three

of four kinds of detections on the primary metric IDF1 while the tracking results with detections by RON are comparable with the best result. For our method, the performances with different detections are fluctuating smoothly. With the detections by RON, the results of most methods are much better than with other detections. And the performance difference of various methods are smaller with the detection input by RON than by the other detection methods. Compared with

Figure 3: Results of a quantitative comparison among MOT methods for each attribute.

the original SLSTM, our method has more improvement on most metrics. Especially, with less IDS and FM, our method could generate much more integrated trajectories. It means that using our self-balance method, the affinity between objects are more robust. The higher IDF1 score also reflects the effectiveness of our method.

We also evaluate the performance of our methods on various attributes. The UAVDT dataset offer four kinds of attributes, *i.e.*, **Camera View** (view of the camera on UAV),

Weather Condition (illumination when videos are captured), **Flying Altitude** (maximum flying altitude of UAV when the videos are captured) and **Duration** (the length of a sequence). The results of the quantitative comparison among MOT methods for each attribute are shown in Fig. 3. For **Camera View**, most methods perform better in *front-view* and *side-view* than in the *bird-view*, as shown in Fig. 3(a), because these views offer more details of the objects for detection and tracking. Our method achieves better results with

the larger appearance difference between objects in *front-view* and *side-view*. For **Weather Condition**, as shown in Fig. 3(b), most methods perform better in *day* and *night*, especially with the RON detection as detection input. Our proposed methods mostly perform best in these condition. Due to poor illumination, the performance of most methods declines in *fog*. For **Flying Altitude**, as shown in Fig. 3(c), the performance of most MOT methods decreases with increasing altitude. Our method performs well in *low-alt* and *medium-alt* which the appearance difference between objects are various while the scene changes. For **Duration**, the performance of the proposed method is stable in *long-term* and *short-term* that shows the robustness of our method.

5 CONCLUSIONS

For online multi-object tracking, the influence of changing context for the discrimination of descriptions are often ignored. We proposed a novel self-balance method fusing appearance similarity and motion consistency to deal with the changing discrimination. Finally, we have tested our method on a large number of datasets and the experimental results show the effectiveness of the proposed online multi-object tracking method.

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