Joint Detection and Multi-Object Tracking with Graph Neural Networks

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Abstract

Object detection and data association are critical components in multi-object tracking (MOT) systems. Despite the fact that these two components are highly dependent on each other, one popular trend in MOT is to perform detection and data association as separate modules, processed in a cascaded order. Due to this cascaded process, the resulting MOT system can only perform forward inference and cannot back-propagate error through the entire pipeline and correct them. This leads to sub-optimal performance over the total pipeline. To address this issue, recent work jointly optimizes detection and data association and forms an integrated MOT approach, which has been shown to improve performance in both detection and tracking. In this work, we propose a new approach for joint MOT based on Graph Neural Networks (GNNs). The key idea of our approach is that GNNs can explicitly model complex interactions between multiple objects in both the spatial and temporal domains, which is essential for learning discriminative features for detection and data association. We also leverage the fact that motion features are useful for MOT when used together with appearance features. So our proposed joint MOT approach also incorporates appearance and motion features within our graph-based feature learning framework, leading to better feature learning for MOT. Through extensive experiments on the MOT challenge dataset, we show that our proposed method achieves state-of-the-art performance on both object detection and MOT.

1 Introduction

Object detection [22, 25, 33, 37, 48, 49, 52, 64, 66, 76] and data association [8, 12, 29, 40, 51, 59, 65, 68, 69, 70, 71] are critical components in multi-object tracking (MOT), which is commonly used in modern perception systems such as autonomous driving [3, 39, 61, 67, 75], and assistive robots [41, 55]. Prior work [8, 65, 70] in MOT often performs detection and data association with separate systems in a cascaded order, referred to as the tracking-by-detection pipeline. In such a pipeline, an object detector is trained separately from data association. At inference time, the detector first outputs detections, and then the data association component associates the detections across all frames. As MOT is dissected into two individual components in this pipeline, prior work in MOT primarily focuses on the data association component with the use of an off-the-shelf detector developed by the object detection community. However, under this pipeline, the overall MOT system lacks the ability...
of back-propagating the error through the entire model. As a result, the combination of the two independently trained components in this cascaded pipeline can yield an undesired sub-optimal performance.

To improve MOT performance, we investigate 1) joint optimization between the detection and data association components, and 2) when jointly optimized, how we can learn the best shared features that are compatible with both components. To the best of our knowledge, there are already few works [1, 6, 18, 57, 63, 73] have attempted to address the joint MOT problem. [1, 6, 18] proposed to unify object detector with a model-free single-object tracker. The tracker first uses Convolutional Neural Networks (CNNs) to extract the appearance features from the detection in the previous frame and from the image in the current frame. Based on these appearance features, the tracker regresses the location of the detected object to the current frame. As each object is tracked independently, the data association problem is naturally resolved. [57, 63, 73] proposed to extend object detector by adding a re-identification (Re-ID) [13, 34, 79] branch, which employ CNNs to extract the embeddings for positive and negative samples learned with the triplet loss. At test time, the embeddings obtained from the Re-ID branch can serve as an similarity measurement used by the Hungarian algorithm [58] for data association.

Our observations from above existing joint MOT frameworks are two-fold: 1) the feature extracted by CNNs for each object at each frame is independent both from the same object in other frames (if exists) and from other objects in any frame. However, we argue that object-object interactions, both within a single frame (spatial) and across multiple frames (spatial-temporal), can be beneficial to object localization and association. For example, for object detection, if an object exists in the previous frame, it is likely that this object also appears in the current frame at a nearby location no matter it is occluded or not. For data association, if similarity of two objects increases, then the similarity between any of these two objects and other objects should decrease to avoid confusion in data association; 2) existing joint MOT works mostly leverage the appearance feature, either through the single-object tracker or through the Re-ID branch. We think that, in addition to the appearance feature, motion features have been proven to be also useful in the MOT community [28, 29, 77]. As a result, we think it is necessary to also incorporate the motion feature in the joint MOT approach in order to improve discriminative feature learning for data association.

Based on the above observations, we propose a new approach for joint MOT that can explicitly model the object-object interactions and leverage the motion feature in a single unified MOT framework. To exploit the spatial-temporal object-object interactions, we introduce Graph Neural Networks (GNNs) into the object detection and data association components in our joint MOT pipeline. As a result, the feature extracted for each object is not isolated and can be adapted with respect to features of other objects across spatial and temporal domains via feature interaction. Also, we employ a Recurrent Neural Networks to model temporal motion dynamics for each tracklet. The motion and appearance features are then concatenated together and fed into GNNs to model the interactions. We show in the experiments the importance of the motion feature learning and GNNs to MOT performance.

To summarize, our contributions are as follows:

1. A new object detector that leverages GNNs for interaction modeling;
2. A data association network with GNNs to improve discriminative feature learning;
3. A new joint MOT framework, encompassing both appearance and motion features in the unified framework.
4. State-of-the-art performance on MOT challenge dataset for both object detection and multi-object tracking tasks among published works.

2 Related Work

Object Detection. There have been tremendous advances in image-based object detection since large-scale datasets such as PASCAL VOC [17] and COCO [36] have been introduced. In terms of architecture design, anchor-based object detector [24, 38, 48, 49] has been the most popular one in the past few years. Recently, a new type of detector that models objects as points has been proposed [31, 80] and achieves impressive performance. However, image-based methods suffer from unstable detections across frames as they only use a static image as the input. To deal with the issue, video object detection [46, 72, 82] has been investigated which uses video as the input. Although producing more temporally-consistent detections than image-based methods, existing video-based methods did not explicitly model the object-object interaction. Our proposed GNN-based detector is related to video-based detection methods but significantly different in that we not only use information from adjacent frames but also explicitly model the spatial-temporal interactions between objects in the feature space using GNNs. We believe that our method with explicit interaction modeling can further improve the overall detection performance.

Multi-Object Tracking. Recent MOT work primarily focuses on the data association component in the tracking-by-detection pipeline, which can be split into online and batch methods. Online methods [4, 5, 53, 54, 77, 81] only require information up to the current frame in order to perform data association and can be useful to online applications. On the other hand, batch methods [2, 9, 14, 42, 45, 50] need to have access to global information (i.e., information up to the current frame and also information from future frames), which can theoretically achieve higher accuracy than online methods but not applicable to online scenarios. We restrict the scope of this paper to online methods. Different from prior online methods that use off-the-shelf detections and primarily focus on the data association component, our method jointly optimizes the detection and data association which improves performance in both tasks. Moreover, our method leverages GNNs to model complex hierarchical object-object interactions and encompasses both appearance and motion features in joint MOT.

Joint Detection and Multi-Object Tracking. To enable error back-propagation in the entire MOT pipeline and improve overall performance, there are already a few works [1, 6, 18, 57, 63, 73] attempted to jointly optimize the detection and data association for MOT. As introduced before, prior joint detection and MOT methods can be mostly split into two categories: 1) unify a single-object tracker with an object detector; 2) add a Re-ID branch to the object detection network. For example, [6] builds on top of the Faster-RCNN [49] and make its bounding box regression head multi-purpose, i.e., not only used to refine the detection boxes but also served as a single object tracker to regress the object location from the last frame to the current frame. Our method shares a similar spirit with these prior joint MOT works but goes beyond them by explicitly modeling the high-order interactions between objects and improving discriminative feature learning in detection and MOT using GNNs.

Graph Neural Networks. GNNs were first introduced by [23] to process data with a graph structure directly with neural networks. The key idea of GNNs is to define a computational graph with nodes and edges relating each other, and then update the node and edge features based on the node-node, node-edge, and edge-edge interactions, i.e., a process that is called feature aggregation. Each with a unique feature aggregation rule, different versions of GNNs
(e.g., GraphConv [44], GCN [30], GAT [56], etc) were proposed and have shown to be effective. Specifically, in computer vision, we have seen significant improvement using GNNs in many sub-fields such as point cloud classification [5], single object tracking [21], and semantic segmentation [10, 78]. Despite that advances have been achieved with GNNs in many fields, there is no published work leveraging GNNs to model object interactions in object detection and data association for MOT. To the best of our knowledge, our work is the first introducing GNNs to joint detection and MOT and has shown improved performance.

3 Approach

Our method aims at simultaneously achieving detection and data association in a unified MOT framework. As an online MOT method, we recursively build tracklets through the entire video by performing detection and association in every two adjacent frames. We refer to the previous frame as $F_{t-1}$ and the current frame as $F_t$ in every two frames. Then, the goal is to obtain detections $D_t = \{D^1_t, D^2_t, ..., D^K_t\}$ in the current frame $F_t$ where $K$ is the number of detections, and in the meantime associate $D_t$ in frame $F_t$ with tracklets $T_{t-1} = \{T^1_{t-1}, T^2_{t-1}, ..., T^N_{t-1}\}$ in the previous frame $F_{t-1}$ where $N$ is the number of tracklets.

In Figure 1, our method contains: (a) a feature extractor to extract appearance and motion features; (b) a graph neural network to update object node features through interaction which are further used by the detection and data association heads. For object detection, we employ the anchor-based method. Specifically, we define a set of anchors in frame $F_t$ as $A_t = \{A^1_t, A^2_t, ..., A^M_t\}$, where $M$ is the number of anchors and each anchor is parameterized by $A^m_t = \{x_c, y_c, w, h, i, c\}$ where $x_c, y_c, w, h$ are the center coordinates, width and height of the anchor, $i$ is the identity initialized as unknown, and $c$ is the class of the anchor either positive or negative. Also, we define ground truth (GT) objects in frame $F_t$ as $O_t = \{O^1_t, O^2_t, ..., O^B_t\}$ where $B$ is the number of GT objects in frame $F_t$, with each $O^b_t = \{x_c, y_c, w, h, c\}$. Then, the goal of the detection component is to obtain detections $D_t$ from the anchor set $A_t$ which matches with the GT object set $O_T$ in terms of the object location. In addition to the detection component, we also perform data association at the same time in order to obtain the identity $I$ for each detected object in $D_t$ in frame $F_t$. Specifically, given associated tracklets $T_{t-1}$ in frame $F_{t-1}$ where each tracklet is parameterized as $T^n_{t-1} = \{x_c, y_c, w, h, I\}$ and $I$ is ready known, the goal of the data association component is to match $A_t$ with $T_{t-1}$ so that we can pass the known identity to the anchors $A_t$ and ultimately detections $D_t$.

3.1 Appearance and Motion Feature Extractor

Appearance Feature Extraction. As shown in Figure 1, we employ an appearance feature extractor to extract features $f_a$ from the anchor set $A_t$ in frame $F_t$ and from tracklets $T_{t-1}$ in frame $F_{t-1}$. Specifically, we use DarkNet53 network with three spatial pyramids proposed in YOLOv3 [21] as our appearance feature extractor. To obtain appearance feature for $A_t$, we feed the entire image in frame $F_t$ to the appearance feature extractor. For tracklets $T_{t-1}$, we crop the image patch for all tracked objects in $F_{t-1}$, resize them to (32, 96) in width and height dimensions, and feed them to the same appearance feature extractor, i.e., DarkNet53.

Motion Feature Extraction. Motion information provides potential locations for objects in the next frame and thus can be beneficial to both detection and data association. To leverage the motion information, we incorporate a motion extractor in our method and obtain motion feature $f_m$ from anchors $A_t$ and tracklets $T_{t-1}$. Since we have access to the past trajectories of the tracklets $T_{t-1}$ up to the frame $F_{t-1}$, we employ a Long-Short Term Memory (LSTM) [44] network to model the location ($\{x_c, y_c, w, h\}$) dynamics of these tracklets in the past $P$
Figure 1: **Proposed Network.** (a) Appearance and motion feature extractor: we extract the motion feature $f_m$ using LSTM and MLP shown in red from tracklets $T_{t-1}$ and anchors $A_t$ respectively. A shared DarkNet53 shown in blue is used to extract the appearance feature $f_a$ from $T_{t-1}$ and $A_t$ as well. (b) Graph Neural Network: we design a GNN module shown in purple to model the object-object interactions through feature aggregation. The detection head uses the node feature from anchors to predict bounding boxes, while the data association head learns to regress the similarity matrix based on the edge features.

frames. Additionally, to obtain the motion feature for anchors $A_t$ which only have location information in the current frame $F_t$, we use a three-layer Multi-Layer Perceptron (MLP) to process the anchor location. Despite that the motion feature can be obtained in a straightforward way using LSTM and MLP in our method, we emphasize that prior joint detection and MOT works have not yet incorporated this important information into their systems while we unify both appearance and motion features in our joint MOT framework. After we obtain the motion feature $f_m$ and appearance feature $f_a$ for $A_t$ and $T_{t-1}$, we concatenate both features and feed into the GNNs as the initial object node features for interaction modeling.

### 3.2 Graph Neural Network

**Graph Construction.** To model the object-object interactions between $A_t$ and $T_{t-1}$ with GNNs, we need to first construct a graph. Specifically, we formulate each anchor in $A_t$ and each tracklet in $T_{t-1}$ as a node in the graph, denoted as $h_i$ and $h_j$ respectively. For edge construction, we leverage prior knowledge about the MOT. As we know that anchors $A_t$ can only match to tracklets $T_{t-1}$ and vice versa, we construct edges only between $A_t$ and $T_{t-1}$ across two frames, i.e., edge does not exist within $A_t$ or $T_{t-1}$. Also, we use features of $A_t$ and $T_{t-1}$ obtained from the feature extractor as the initial node feature in our graph.

**Graph Feature Aggregation.** After constructing the nodes and edges, we define the feature aggregation rule in each layer of the GNNs for node and edge feature update. Specifically, we employ the aggregation rule proposed in GraphConv [44], described as below:

$$h'_i = \text{ReLU}(\Theta_1 h_i + \sum_{j \in \mathcal{N}(i)} \Theta_2 h_j),$$  

(1)

where $h_i$ denotes an anchor node feature, and $\mathcal{N}(i)$ is the neighborhood of $h_i$, i.e., a set of tracklet nodes. $\Theta_1$ and $\Theta_2$ are two different linear layers, which allow the graph to choose how much to update the node feature from its neighbors’ features (e.g., update solely from its neighbors or nothing from them) in each layer. Symmetrically, we also update the node feature of $h_j$ for tracklets based on its neighborhood nodes of the anchors. As shown in
Figure 1 where we have multiple graph layers, we apply this same graph feature aggregation rule for every node in each layer of the graph, with each layer having different weights.

**Object Detection Head.** Once we have updated object node features through several GNN layers, we use the node features from the final GNN layer for object detection. As we only perform detection in frame $F_t$ for anchors $A_t$, we use the node feature $h_t$ for bounding box classification and regression. The detection head is several convolutional layers that reduce high-dimensional node features to the same dimension as the detection targets (i.e., $O_t$).

**Data Association Head.** In addition to object detection, we also perform data association for MOT. Specifically, the data association head uses an edge regression module to compute a similarity matrix $S_{M \times N}$ that describes the pairwise similarity between each anchor in $A_t$ and each tracklet in $T_{t-1}$. The edge regression between two nodes is described as below:

$$S_{ij} = \sigma(h_i - h_j),$$  \hspace{1cm} (2)

where $\sigma$ is a three-layer MLP with ReLU activation between layers and $S_{ij}$ is the similarity measurement between anchor node $h_i$ and tracklet node $h_j$. We use the subtraction operation between two node features to obtain the edge feature. At test time, we feed the obtained similarity matrix $S$ to the Hungarian algorithm [58] to solve data association.

### 3.3 Training and Losses

The training objective of our proposed method is composed of two parts: 1) object detection loss $L_{\text{detection}}$; 2) data association loss $L_{\text{association}}$, which can be summarized as follows:

$$L_{\text{total}} = \sum_{l=1}^{L} (L_{\text{detection}}^l + \lambda_d L_{\text{association}}^l),$$  \hspace{1cm} (3)

where $L$ refers to the number of GNN layers. At each training iteration, we sample two random adjacent frames and compute the above loss to train our network. We set $\lambda_d = 1$.

**Detection Loss.** The goal of the detection head is to classify anchors as positive or negative and regress the positive anchors to the correct location. To compute the loss, we need to first compute the GT class for each anchor (i.e., positive or negative) for classification and assign a GT target for each anchor for regression. We define an anchor to be positive if it has an Intersection Over Union (IoU) larger than 0.5 with any GT object. An anchor is defined to be negative if it has IoU less than 0.4 with all GT objects. Anchors are ignored if they do not meet the above criteria, i.e., has IoU with at least one GT object larger than 0.4 and has IoU with all GT objects less than 0.5. If there are more than one GT targets that have IoU larger than 0.5 with an anchor, we assign the GT target with the highest IoU to that anchor.

We now define the detection loss. We use the smooth L1 loss for bounding box regression and the cross-entropy loss for classification. As we evaluate on MOT challenges with only pedestrians, the cross-entropy loss is reduced to a binary cross-entropy loss. The classification and regression losses at layer $l$ of GNNs are then defined as follows:

$$L_{\text{regression}}^l = \sum_{m,b \in \text{Pos}} \sum_{i \in \{x_c,y_c,w,h\}} \text{smooth}_L(\hat{A}^m_t[i] - O^b_t[i]),$$  \hspace{1cm} (4)

$$L_{\text{classification}}^l = -\sum_{m=1}^{M} \sum_{c} \log(\hat{A}^m_t[c]) + (1 - \hat{A}^m_t[c]) \log(1 - \hat{A}^m_t[c]),$$  \hspace{1cm} (5)

where $\text{Pos}$ denotes the set of positive anchors and their corresponding GT, $\hat{A}^m_t[\cdot]$ is the prediction of an anchor including predicted location and class label, and $A^m_t[c]$ denotes the GT class label of the anchor $A^m_t$. The detection loss at layer $l$ is then summarized as below:

$$L_{\text{detection}}^l = L_{\text{regression}}^l + L_{\text{classification}}^l.$$  \hspace{1cm} (6)

**Data Association Loss.** As we aim at achieving data association in parallel to object detection, we use features of anchors $A_t$ instead of output detections $D_t$ when associating with
the tracklets. To compute the loss, we first need to obtain the GT similarity matrix \( S_{GT}^{m,n} \) between anchors and tracklets. During training, we use GT objects \( O_{t-1} \) in the previous frame \( F_{t-1} \) as the tracklets. As there is no direct match between \( A_t \) and \( O_{t-1} \), we first match \( A_t \) with \( O_{t} \) using the same IoU criteria as in computing detection loss. Then, for each \( O^b_t \), we can look up for the corresponding \( O^b_{t-1} \) with the same identity \( I \) in the previous frame. If there exist a tracklet \( O^b_{t-1} \) with the same identity, we assign that identity to the anchor in \( A_t \) matched with \( O^b_t \). Anchors that are not matched with any tracklet in \( O_{t-1} \) are assigned an identity of unknown. Then, we can compute each entry in the GT similarity matrix \( S_{GT} \) as:

\[
S_{GT}^{m,n} = \begin{cases} 
1, & \text{if } A^m_t \text{ and } O^n_{t-1} \text{ have the same identity}, \\
0, & \text{otherwise}.
\end{cases}
\] (7)

We now discuss our association loss, which has three parts. With each entry in \( S_{GT} \) being 1 or 0, we first apply a binary cross-entropy loss independently on each entry of the matrix:

\[
L^l_{bce} = -\frac{1}{MN} \sum_i^n \sum_j^N S_{GT}^{ij} \log(\hat{S}_{ij}) + (1 - S_{GT}^{ij}) \log(1 - \hat{S}_{ij}).
\] (8)

Also, as one anchor can only be matched to at most one tracklet in \( O_{t-1} \), each row of \( S_{GT} \) is either a one-hot vector or an all-zero vector (i.e., no matched tracklet). For row \( i \) in \( S_{GT} \) with a one-hot vector, we employ a cross-entropy loss on that row:

\[
L^l_{ce} = -\frac{1}{N} \sum_j^N S_{GT}^{ij} \log(\frac{e^{S_{ij}}}{\sum_j^N e^{S_{ij}}}).
\] (9)

For rows in the GT matrix \( S_{GT} \) with all-zero vector, the objective is to suppress the values in the corresponding rows of the estimated matrix \( \hat{S}_{ij} \) to be as small as possible. For row \( i \) with all-zero vector, we employ a mean squared error loss with a Sigmoid function:

\[
L^l_{mse} = \frac{1}{N} \sum_j^N ||\text{sigmoid}(\hat{S}_{ij})||^2
\] (10)

Then, we summarize the data association loss at layer \( l \) of the GNNs as follows:

\[
L^l_{association} = L^l_{bce} + L^l_{ce} + L^l_{mse}
\] (11)

### 3.4 Inference

**Post-Processing.** At inference time, in every two adjacent frames, our method outputs predicted anchor classes and locations and also the estimated similarity matrix \( \hat{S} \). To obtain the final detections \( D_t \), we run non-maximal Suppression (NMS) with an IoU threshold \( \tau_{nms} \) and confidence threshold \( \tau_{conf} \) on predicted anchors to reduce redundant anchors. To pass identities from tracklets \( T_{t-1} \) to anchors \( A_t \), we feed the estimated similarity matrix \( \hat{S} \) to the Hungarian algorithm. Given the matches from the Hungarian algorithm, we further reject a portion of the matches if the corresponding anchor \( A^m_t \) and tracklet \( T^n_{t-1} \) has a similarity score \( \hat{S}_{m,n} \) below the similarity threshold \( \tau_{sim} \) or their IoU is below an IoU threshold \( \tau_{iou} \). For tracklets and anchors that do not have corresponding matches, they will be handled by the tracking management to delete disappeared tracklets and initialize new tracklets. Note that, at the first frame of a video, we do not have any existing tracklets \( T_{t-1} \) in the previous frame. Therefore, we use the public detections provided by the dataset as initialization.

**Tracking Management.** To deal with disappeared tracklets and initialize new tracklets, we use tracking management during inference. Specifically, we define a birth threshold \( \tau_{birth} \) and a death threshold \( \tau_{death} \). If a detection in \( F_t \) does not have a matched tracklet in \( F_{t-1} \), we consider this detection as a potential birth object, which might be a new object entering the image or a false positive. Then, in the following \( \tau_{birth} \) frames, if this birth object continues...
Table 1: Quantitative evaluation of multi-object tracking on the MOT17 test set.

| Method        | MOTA(%)↑ | IDF1(%)↑ | MT(%)↑ | ML(%)↓ | FP↓   | FN↓   | IDS↓ |
|---------------|----------|----------|--------|--------|-------|-------|------|
| eTC17 [60]    | 51.9     | 58.1     | 23.1   | 35.5   | 36,164| 232,783| 2,288|
| FAMNet [11]   | 52.0     | 48.7     | 19.1   | 33.4   | 14,138| 253,616| 3,072|
| JBNOT [26]    | 52.6     | 50.8     | 19.7   | 35.8   | 31,572| 232,659| 3,050|
| Tracktor++    | 53.5     | 52.3     | 19.5   | 36.6   | 12,201| 248,047| 2,072|
| LSST17 [20]   | 55.7     | 62.3     | 20.4   | 40.1   | 26,091| 228,434| 1,243|
| Tracktor++v2  | 56.3     | 55.1     | 21.1   | 35.3   | 8,866 | 235,449| 1,987|
| **Ours**      | **56.4** | **42.0** | **16.7**| **40.8**| 17,421| 223,974| 4,572|

Figure 2: Qualitative evaluation of tracking performance on the MOT17 test set.

to appear and keep matched with the same identity, we initialize a new tracklet for this new object. In this way, we avoid initializing false positives as new tracklets to a large extent.

Meanwhile, when a tracklet in $F_{t-1}$ is not matched to any detection in $F_t$, we consider this tracklet as a potential death object, which might be either leaving the image or miss detected in frame $F_t$ due to occlusion. Instead of deleting this tracklet immediately, we keep it alive for $\tau_{\text{death}}$ frames. Only if this tracklet keeps non-matched for more than $\tau_{\text{death}}$ frames, we delete the tracklet. In this way, we can significantly reduce the number of false negatives and avoid the case deleting true positive tracklet. In brief, our tracking management initializes new tracklets if the new detections consistently appear in the image, and delete tracklets if these tracklets are consistently missing.

4 Experiments

Datasets. We evaluate on the MOT challenges [15, 16, 32, 43]. We use MOT17 for MOT evaluation, and use MOT17Det for detection evaluation. For tracking, MOT Challenges have two separate tracks in the leaderboard: public and private. Methods in the public track use public detections provided by the challenges while methods in the private track can use their own detections. As our method performs joint detection and data association, we compare against state-of-the-art published methods from both public and private tracks.

Evaluation Metrics. We use the CLEAR MOT metrics [7] for MOT evaluation. For object detection, we report the Average Precision using the official MOT17Det evaluation protocol. To compare with state-of-the-art methods, we evaluate on the test set by submitting our results to the official MOT test server. Also, we divide the provided train set into two subsets: one for training and one for validation, and use the validation set for ablation study.

Implementation Details. We first pre-train the detection module on a pedestrian detection dataset with a learning rate starting at $10^{-5}$. Then, the entire network is trained on the target MOT dataset with a learning rate starting at $10^{-3}$. The learning rate decays by a factor of 0.1 every 10 epochs and we train the entire network for 60 epochs. We use the number of GNN layers $L = 1$ in our network for now and will explore how deeper GNN affects performance in the short future. At inference time, we find following hyper-parameters give the best performance $\tau_{\text{nms}} = 0.3$, $\tau_{\text{conf}} = 0.3$, $\tau_{\text{sim}} = 0.0001$, $\tau_{\text{iou}} = 0.1$, $\tau_{\text{birth}} = 5$, and $\tau_{\text{death}} = 7$.  

| Method    | AP↑ | MODA(%)↑ | TP↑ | FP↓ | FN↓ | Recall↑ | Precision↑ |
|-----------|-----|----------|-----|-----|-----|---------|-------------|
| DPM [19]  | 0.61| 31.2     | 78,007 | 42,308 | 36,557 | 68.1     | 64.8        |
| FRCNN [49]| 0.72| 68.5     | 88,601 | 10,081 | 25,963 | 77.3     | 89.8        |
| ZIZOM [35]| 0.81| 72.0     | 95,414 | 12,990 | 19,139 | 83.3     | 88.0        |
| SDP [74]  | 0.81| 76.9     | 95,699 | 7,599  | 18,865 | 83.5     | 92.6        |
| Ours      | 0.81| 79.3     | 98,830 | 8,007  | 15,734 | 86.3     | 92.5        |

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| Ours      | 0.81| 79.3     | 98,830 | 8,007  | 15,734 | 86.3     | 92.5        |

**Table 3:** Ablation study of multi-object tracking on the MOT17 validation set. We demonstrate the effectiveness of using GNNs and the motion feature for our joint MOT method.

| Motion | GNN | MOTA(%)↑ | IDF1(%)↑ | MT(%)↑ | ML(%)↓ | FP↓ | FN↓ | IDS↓ |
|--------|-----|----------|----------|--------|--------|-----|-----|------|
| ✗      | ✓   | 31.5     | 26.0     | 6.2    | 46.9   | 656 | 16,710 | 710  |
| ✓      | ✗   | 61.1     | 49.6     | 34.1   | 18.0   | 733 | 9,087 | 439  |
| ✓      | ✓   | 61.6     | 49.7     | 30.8   | 18.4   | 737 | 8,951 | 441  |

Evaluating Multi-Object Tracking. We show MOT performance of our proposed method in MOT17 test set and compare with published state-of-the-art methods in Table 1. We also show qualitative visualization of our tracker’s performance on MOT17 test set in Figure 2.

Evaluating Object Detection. We show our detection performance in MOT17Det dataset and compare with published state-of-the-art methods in Table 2. The results demonstrate that the performance of our detection is on par with state-of-the-art performance.

Ablation Study. We conduct ablation studies on the MOT17 validation set and show results for joint MOT in Table 3. We first run our full model with both GNN and motion feature on the validation set and give the highest results in the last row. Then, we deactivate GNNs and the motion feature one at a time for ablation experiments: (1) in the first row of the Table 3, we can see that the performance decreases significantly on MOTA when we do not use the motion feature, showing that combining the motion feature in our framework is important; (2) in the second row of the Table 3, we again see a drop in MOTA performance when the GNN is deactivated, demonstrating that the usefulness of the GNN feature learning.

5 Conclusion

In this work, we investigate one step further on how to jointly optimize object detection and data association. We introduced Graph Neural Networks into object detection and data association and proposed a novel approach for joint MOT. Through extensive experiments on MOT challenges, we achieved state-of-the-art performance and demonstrated the effectiveness of each component of our proposed method.

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