TrackNet: Simultaneous Object Detection and Tracking and Its Application in Traffic Video Analysis

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Abstract—Object detection and object tracking are usually treated as two separate processes. Significant progress has been made for object detection in 2D images using deep learning networks. The usual “tracking-by-detection” pipeline for object tracking requires that the object is successfully detected in the first frame and all subsequent frames, and tracking is done by “associating” detection results. Performing object detection and object tracking through a single network remains a challenging open question. We propose a novel network structure named TrackNet that can directly detect a 3D tube enclosing a moving object in a video segment by extending the faster R-CNN framework. A Tube Proposal Network (TPN) inside the trackNet is proposed to predict the objectness of each candidate tube and location parameters specifying the bounding tube. The proposed framework is applicable for detecting and tracking any object and in this paper, we focus on its application for traffic video analysis. The proposed model is trained and tested on UAVDETRAC, a large traffic video dataset available for multi-vehicle detection and tracking, and obtained very promising results.

Index Terms—object detection, multiple object tracking (MOT), surveillance, vehicle tracking.

I. INTRODUCTION

OBJECT detection and object tracking have been two longstanding challenges for the computer vision community, and much progress has been made on both fronts. For object detection, complex hand-crafted features plus shallow classifiers such as HOG+SVM [1] and multiple resolution image pyramids plus multiple filters such as DPM [2] were both popular detection pipelines. In recent years, Convolutional Neural Networks (CNN) have enjoyed great development and CNN based methods such as [3], [4], [5], [6], [7], [8] have been setting up new records in object detections in still images. Object tracking, especially Multi-Object Tracking (MOT), has many real-world applications including intelligent transportation [9], [10], virtual/augmented reality, robot navigation, etc. Most existing MOT systems can be classified into two groups [11]: Detection Based Tracking (DBT) and Detection Free Tracking (DFT). DBT requires object being detected for every frame followed by a tracker that links the detection regions based either on object features or probabilistic movement characteristics. The performance of DBT highly depends on the performance of the employed object detector. DFT on the other hand, requires manual initialization of objects in the initial frame and couldn’t handle uninitialized objects.

We argue that object detection and tracking should not be treated as two independent tasks, but rather, effective object detection in video should employ both spatial appearance and temporal motion features. In this work, we propose a unified network structure for simultaneous object detection and tracking. Our network treats a group of consecutive pictures (GoP) as a 3D volume, and detects moving objects in the GoP as tubes within it.

A. Motivations for Tube Proposals

Bounding box proposal generation is an essential step for most state-of-the-art object detection systems [3], [4], [5] (excluding proposal-free detectors [6], [8]). What’s more, [12] proposed to combine multiple object proposals from different proposal generation methods such as Selective Search [13], Edge Boxes [14], and RPN [5] to boost the recall performance. [15] proposed to recursively refine object proposals with multiple iterations. In this work, we propose to use tube proposals instead of box proposals. One obvious advantage of tube proposals over box proposals is the convenience of getting all objects’ spatial-temporal locations in one shot. A bounding tube is readily available after one forward pass instead of N times of forward passes plus post-processing association. Secondly, instead of extracting spatial contextual information using separate subnetworks [16], tube proposals on multiple consecutive frames naturally provides global and local context in the spatial-temporal domain. The other advantage of tube proposals is its role to provide a much stronger regularization during training. Suppose that there are B moving objects, which appeared in each of the N frames. If we first detect B box proposals in each frame, we would have to examine $B^N$ possible tubes, while there are only B tubes that are correct. Ground truth bounding tubes occur very rarely in this high-dimensional space, and each one of them carries highly structured information implicitly. This sparsity and implicit structure information will serve as very strong regularization:
only tubes with certain spatial and motion features over the entire GoP are good candidates. This motion pattern regularization is even more obvious when dealing with traffic videos, as shown in figure 1. Therefore, the step from proposing boxes to proposing tubes is a very natural extension.

II. RELATED WORK

Object Detection in Images. Object detection in images has progressed rapidly in recent years [4], [5], [6], [7], [8]. Girshick et al. first introduced R-CNN [4] to identify and label objects in 2D images. From object region proposals that are generated by an independent algorithm (e.g., selective search [13], Edge Boxes [14]), R-CNN runs a forward pass once for each proposed region to determine whether this region contains an object. The same authors further improved R-CNN to fast R-CNN[17] by sharing convolution feature maps among all object region proposals, and hence only one forward pass for all region proposals is needed. Faster R-CNN [5] further improved upon fast R-CNN by introducing a region proposal network (RPN) that directly regresses fixed “anchors” to object region proposals from feature maps extracted using a 2D convolutional network.

Object Detection in Videos. Most systems proposed so far for identifying (and tracking) moving objects in videos rely on 2D object detection in each frame, which is computationally expensive and does not jointly consider object(s’) motion information. Some systems (e.g., [18], [19]) have used explicit motion information (e.g. optical flow) as a linking feature to associate detection regions or to smooth detection scores as a post-processing step. Those motion information is derived separately outside of the network and is not integrated organically with the network training. Inspired by the correlation and regression based trackers such as [20], [21], [22], [23], [24] proposed a D&T framework which relies on a resNet-101 as frame-level feature extractor and two parallel region proposal networks (RPN) to generate 2D box proposals. The detected boxes are associated using a proposed ROI tracking module by computing the correlation map between the feature maps. Another work in [25] first uses SSD[6] to detect objects and extracts corresponding spatial features through ROI pooling to create per-frame feature. Then an association LSTM is proposed to regress and associate object locations given the frame-level feature tensor for past \(\tau\) consecutive frames as input.

Tube Proposal Based Works. A more related branch of works with this paper is the tube proposal based methods such as [27], [28], [29], [30]. In all these works, the initial anchor tubes are generated from duplicating the same bounding box (anchor) across multiple frames. Such a tube describes a non-moving object and will be called “stationary tubes”. Spatial per-frame features are then pooled from the same box location across multiple frames. The 3D region proposals in [28] are two-frame micro-tubes, which are a pair of bounding boxes spanning 2 video frames separated by a predefined temporal interval \(\Delta\) (\(\Delta=1\) or 2), which are almost consecutive frames. During training, the intersection-over-union (IoU) and regression loss are computed between the ground truth pair and the proposal pair. Whereas in our implementation, GoP length \(T\) can be varying and much longer than 2 frames, e.g. 8 or 16. What’s more, our network uses a loss function that considers the difference between box positions and the ground truth locations in every intermediate frame. In terms of features, [28] uses spatial feature fusion from VGG feature maps only for the front and ending frames. [30] fuses spatial and motion information from two streams: a SSD[6] as the appearance detector and a motion detector taking the optical flow images as input.

The major limitations of the above prior work are two-fold. Firstly, stationary anchor tubes correspond to objects with no motion in \(N\) frames, which tend to have very low overlap with ground truth tubes covering moving objects. This has serious negative impact on the network training: Only those anchor tubes with sufficient overlap with ground truth tubes can be used for tuning the tube offset regression module, and using stationary anchors significantly reduces such positive anchor tubes. Second, models which pool only spatial features do not explicitly exploit motion information, which is an important cue for moving object detection and tracking. Our proposed network differs from these prior work in the following aspects: 1) Our model initializes anchor tubes based on the motion
vectors near the anchor location to allow non-stationary tubes as starters. 2) Our end-to-end network captures the spatial and temporal information simultaneously over all frames using both 2D and 3D convolutional neural networks for feature extraction, which does not require a separate input such as the flow images as in [30]. It is faster than fusing features from CNN and features from other techniques, and simpler than using LSTM to learn the feature associations/correlations. 3) In the tube refinement stage, 3D (as opposed to 2D) tube-ROI pooling enables features from different box locations to be pooled. 4) The loss function for the tube position regression considers the ground truth positions of the object in all frames, even when we parameterize the tube position using linear interpolation from two bounding boxes in the beginning and ending frames. Thus the detected final tube maximizes the overlap with the ground-truth object over all frames. This is particularly important when the underlying object does not follow a linear trajectory.

III. TrackNet Model Architecture

A. Two Stream Feature Extraction and Transformation

In order to utilize both spatial and temporal features, our network is based on VGG net trained from ImageNet and C3D trained from UCF101 for video classifications. Figure 2 provides an overview of the trackNet structure. We divide a video into group of pictures (GoP) of fixed length $T$ (8 frames in our implementation) and feed the raw video frames in each GoP into a two-stream backbone structure, where

- the first branch is a VGG16 subnetwork with convolutions and spatial max-poolings and the second branch is a C3D-like subnetwork with 3D convolutions and spatial-temporal max-poolings. These two kinds of features compliment each other in that one focuses more on appearance whereas the other focuses more on motions. The resulting 2D feature maps ($T \times h \times w \times 512$, reshape to $1 \times h \times w \times 512T$) and the spatial-temporal feature maps ($1 \times \frac{T}{8} \times h \times w \times 512$) then separately go through a “squashing” convolutional layer (bottleneck layer) with $1 \times 1$ kernel size, which reduces the number of feature maps to 128 for each stream. Squashed feature maps are concatenated afterwards.

Spatial Transformer.

When dealing with real-world videos, sometimes the network will observe objects’ frontal appearance, whereas at other times, the side appearances of objects will be observed. Inspired by [26], we utilized a learnable module, the spatial transformer, to map the concatenated features from different viewing angles into a “unified” manifold. We used affine transformation in our case, however, one can use more complicated transformations to suit their cases as indicated in [26]. Our transformer has a very simple structure with only one convolutional layer and one fully connected layer as shown in figure 2. Six affine transformation parameters $\theta$ will be output from the fully connected layer and then used to transform the original concatenated feature maps $U$. Instead of sampling from the original feature maps using a regular mesh grid $G$, the sampling grid will be transformed using $\theta$ to $T_{\theta}(G)$, which
order to have better initial tube candidates, we utilize motion
tracking. This way, we can predict the position and speed of objects accurately. Consider the typical scenes from
video surveillance, where objects may move in a semi-linear fashion. These linear trajectories
are easier to track than non-linear ones. However, when the objects are stationary or tilted,
we need a different approach. In such cases, we use stationary tubes.

The first step in the process is to construct an anchor tube. A naive way to construct an anchor tube is to have the same bounding box positions in all frames. This step is necessary to consider every possible tube. Consider a short video segment with $K$ frames ($K = 256$ features). Essentially, the objectness score for each anchor is determined from a $3 \times 3 \times K$ feature tensor. Anchor tubes with high 3D-IoU will be selected as positive proposals and assigned label $+1$, whereas anchor tubes with low 3D-IoU scores (partially overlapped) will be assigned label $-1$ and the remaining anchor tubes (including pure background) will be ignored. The classification module is trained with the cross-entropy classification loss $L_{clsTPN}$ with respect to their ground truth label. In figure 3, the tube classification module is shown. The heat map is the objectness score output, where bigger (warmer) values indicate higher probabilities of containing objects in that location. Here we only show one heat map corresponding to one set of anchor tubes.

Tube Offset Regression Module. Anchor tubes will be ranked based on their objectness scores. For tubes with higher scores, the offsets between the corner positions of the tubes and ground truth positions are computed as the regression targets. The regression module will be trained to generate these regression targets from the input $3 \times 3 \times K$ features. Given $M$ candidate anchor tubes at each feature map location, the offsets will be predicted as offsets to the ground truth positions of the tubes. Following R-CNN, we

use the center position and width and height to parameterize the position of a rectangular bounding box in each frame. The offsets of these parameters between the bounding boxes of all frames in an anchor tube (ST) and those in the ground truth tube (GT) are our 3D tube regression target for this anchor tube. We adopt the parameterization of the 4 coordinates in [4], but similar as [8], we normalize the spatial coordinate by the actual width and height of the video frame, so that the normalized coordinate and hence the 4 parameters are all in the range of [0,1], which helps the convergence speed. The 3D Tube regression targets for positive anchor tube $i$ at frame $t$ is defined as:

$$
\begin{bmatrix}
\Delta X^i_t \\
\Delta Y^i_t \\
\Delta W^i_t \\
\Delta H^i_t
\end{bmatrix} = \begin{bmatrix}
\frac{(GT_{center}.x) - (ST_{center}.x)}{W_{gt}^i} \\
\frac{(GT_{center}.y) - (ST_{center}.y)}{H_{gt}^i} \\
\log\frac{(GT_w)}{(ST_w)} \\
\log\frac{(GT_h)}{(ST_h)}
\end{bmatrix} - \begin{bmatrix}
\frac{(ST_{center}.x)}{W_{gt}^i} \\
\frac{(ST_{center}.y)}{H_{gt}^i} \\
\log\frac{(ST_w)}{(ST_w)} \\
\log\frac{(ST_h)}{(ST_h)}
\end{bmatrix}
$$

By learning to regress to these targets, the system can derive the refined locations for all anchor tubes that have high overlap with ground truth bounding tubes. We have explored two ways to wire the tube offset regression module: (1) directly predicting offsets of all frames and (2) utilizing linear interpolation.

**Option 1: Directly predict tube parameters.** In this structure, we directly estimate the offsets of every frame. Given a video GoP of length $T$, the regression network directly predicts $4 \times T$ parameters for every tube. As our straight tube candidates are spreading over all pixel locations, the regression network is implemented using a convolution layer with $4 \times T \times M$ output maps.

**Option 2: Linear interpolation of bounding box offsets from offsets at two frames.** Despite the fact that an object inside a video can have arbitrarily complex motions, most objects’ motions are very smooth in real-world videos. Given a short enough time period, we can approximate the trajectory of each corner of the bounding tube with a straight line. This is particularly true for traffic videos containing moving vehicles. Motivated by this observation, instead of determining the offsets of the corner positions in all frames, the regression network only estimates the offsets in the beginning and ending frames, and linearly interpolate the offsets in other frames. During training, the regression loss considers the difference between the true offsets (targets) and the estimated offsets for all frames, which are interpolated from the offsets in the beginning and ending frames. The advantage of this approach is that only 8 parameters are estimated for a given tube, as opposed to $4 \times T$ parameters. Compared to directly estimating the offset at every frame, this approach also implicitly applies a smoothness constraint along the corner trajectories and prevents the network to generate erratic trajectories.

We implement the interpolation using a convolution layer with spatial $1 \times 1$ kernel. For example, if we have a video segment with length $T = 8$ frames, $\Delta X_1, \Delta Y_1, \Delta W_1, \Delta H_1, \Delta X_T, \Delta Y_T, \Delta W_T, \Delta H_T$ are the predicted center offsets and width and height offsets at the first frame ($t = 1$) and the last frame ($t = 8$). The offset at time frame $t$ can be easily implemented using a convolutional layer with $1 \times 1 \times 2 \times 8$ kernel matrix:

$$K = \begin{bmatrix}
1, 6/7, 5/7, 4/7, 3/7, 2/7, 1/7, 0 \\
0, 1/7, 2/7, 3/7, 4/7, 5/7, 6/7, 1
\end{bmatrix}
$$

If we view the first frame prediction result (with 4 channels for 4 parameters) and the last frame prediction result as 2 separate input feature maps, then these 2 feature maps convolving with this $1 \times 1 \times 2 \times 8$ kernel will produce 8 feature maps, corresponding to predicted offsets for all 8 frames. Note that we could implement higher order interpolation by using more than 2 input feature maps and setting the kernel matrix accordingly. We could also train the kernel matrix as part of the regression network to learn the appropriate interpolation kernel.

We adopted option 2 (linear interpolation) for tube proposals during TPN stage to save parameters and constrain smooth motions, and relaxed to option 1 (predict all) in the post-TPN stage to further refine locations.

**C. post-TPN: Classification and Refinement**

As shown in Figure 2, the tube proposal network generates many tube proposals, whose positions are determined by the original candidate tubes and the predicted offsets. Proposal tubes with high objectness scores will go through a second stage of classification and regression. In this stage, tube proposals will be further classified into different classes (such as car, bus, van etc. for UA-DETRAC dataset). The position offsets for the tube will also be refined. Instead of using the features pooled from the $3 \times 3$ neighborhood on the feature map as in TPN, features specific for the proposal tube regions are pooled using the tube pooling.

**Tube Pooling.** ROI pooling was introduced in [32], which enables different proposal regions to be described by the same dimensional feature vectors. In our case, a proposal tube consists of bounding boxes in different frames that are different in sizes and locations. Pooling based on one particular bounding box inside the tube would be deficient. Instead of pooling from the same ROI location multiple times as in [27], the union of all bounding boxes in a proposal tube is found and features covering the union region are extracted from the transformed feature maps $V$. After the tube pooling, this feature vector is then fed into a post-TPN subnetwork, which further assesses its class and refines the tube position information.

There are two fully connected (fc) layers and another two fc layers for predicting classification scores and offsets separately. In our implementation, 256 proposal tubes (half positive, half negative) are considered and $7 \times 7 \times 256$ features are pooled from feature map $V$ using the tube union ROI, leading to a total of $256 \times 7 \times 7 \times 256$ features. For the offset regression, similar to the TPN regression module, either linear interpolation or directly predicting offsets at all frames can be chosen.

**D. Multi-task Loss to Train the TrackNet**

Both classification loss and regression loss are used to penalize the proposed tubes. For the TPN, the predicted
objectness score for each anchor tube will have the cross-entropy classification loss \( L_{\text{cls}_{\text{TPN}}} \) with respect to their ground truth label. Positive anchor tubes will have the regression loss \( L_{\text{reg}_{\text{TPN}}} \) with respect to the offset targets. During the post-TPN stage, true class labels (e.g. background, car, bus, van) are used for the cross-entropy loss \( L_{\text{cls}} \). Both regression losses \( L_{\text{reg}_{\text{TPN}}} \) and \( L_{\text{reg}} \) use the smooth \( l_1 \) loss defined in \([17]\).

The above losses are combined to form the total loss for a proposal tube: 

\[
L(s_i, p_i) = 
\begin{align*}
&\lambda_1 \times L_{\text{cls}}(l_i, s_i) + \lambda_2 \times \sum_{t=1}^{T} L_{\text{reg}}(\text{tar}_{i,t}, p_{i,t}) \\
&+ \lambda_3 \times L_{\text{cls}_{\text{TPN}}}(l_i, s_i) + \lambda_4 \times \sum_{t=1}^{T} L_{\text{reg}_{\text{TPN}}}(\text{tar}_{i,t}, p_{i,t}) \\
&+ \lambda_5 \times L_{\text{smooth}}
\end{align*}
\]

where \( l_i \) is the ground truth label for anchor tube \( i \), \( s_i \) is the predicted objectness score or the specific class score for anchor tube \( i \), \( \text{tar}_{i,t} \) is the ground truth target, a four-parameter vector representing the offsets between the ground truth location and the location of positive anchor tube \( i \) at time \( t \), i.e. \( \text{tar}_{i,t} = [\Delta X^g_t, \Delta Y^g_t, \Delta W^g_t, \Delta H^g_t] \). And \( p_{i,t} \) is the predicted offset vector, i.e. \( p_{i,t} = [\Delta X_t, \Delta Y_t, \Delta W_t, \Delta H_t] \).

When we use the option of directly regressing box locations in each frame, we add a smoothness loss term \( L_{\text{smooth}} \) to further enhance the smoothness (quasi-linearity) of the tube, which can be derived from the total variation of the tube positions or the average position change between two frames. The \( \lambda \)s control the weights for different losses. From experiments, we found these hyper parameters are not very sensitive. We set \( \lambda_{1,2,3,4} = 1 \) and \( \lambda_5 = 0.001 \) in all of the following experiments. The multi-task loss for training is defined as:

\[
L_{\text{multi-task}} = \sum_{i=1}^{N_{\text{tubes}}} L(s_i, p_i)
\]

IV. EXPERIMENTS

Dataset. Most of the object detection dataset are 2D images, such as ImageNet \([33]\), PASCAL VOC \([34]\), Microsoft COCO \([35]\), etc. In the ILSVRC2015 challenge, ImageNet \([33]\) introduced the VID task with 30 categories to attract attention in the object detection in videos. However, most of the videos contain very few dominant objects, whereas in real world, multiple object detection (MOD) and multiple object tracking (MOT) need to be addressed simultaneously. For example, in traffic analysis and autonomous driving, accurate vehicle detection and tracking, especially in the busy urban area, remains a big challenge. Existing works on vehicle tracking in urban areas such as \([36, 37]\) utilized traditional methods such as background modeling or feature points tracklet clustering, have limited performances. To evaluate our model regarding both MOD and MOT, we use the UA-DETRAC\([31]\) dataset, which consists of challenging video sequences captured from real-world traffic scenes with different viewing angles.

We split the dataset into 45 training and 15 testing videos and made sure that both training and testing covers all different camera views. The video lengths range from around 700 frames to around 2500 frames. This dataset spans a variety of different weather such as sunny, cloudy, rainy and night. We did not split the dataset to ensure that the training and testing set each includes samples taken under different weather conditions. However, the trained model turns out to be pretty robust to different weather conditions, see figure 6.

A. Training

During training, 8 sequential video frames are randomly selected from the training set (we will talk about the “skip frame” training trick in section IV-A1). We first fine-tune the VGG branch alone under the framework of faster R-CNN \([5]\) using the whole training set as a warmup. The proposed TrackNet is then trained with the VGG branch frozen. We also fine-tune the last convolution layer (conv5a, conv5b) in the C3D backbone. The initial learning rate was 0.001 and was reduced by 10 times after 10K iterations. We used Adam optimizer and trained the model for total 50K iterations. We evaluate the trackNet using the standard COCO API \([35]\). Some visual detection and tracking results are in Figure 6.

1) Training with “Skip frames” In the current implementation, during training, 8 consecutive video frames are randomly selected from the training set. However, due to the fact that different vehicles possess different speeds in different views (e.g. larger motion when vehicles are nearer the camera, smaller motion in the back; larger motion in
Table I: Detection results of different variants of trackNet on UA-DetRac dataset (evaluated using COCO API). The average precision (AP)(%) rates are reported under different settings (i.e. IoU thresholds; bounding box area). All trackNet variants reported here used 300 top proposals during the test except the one indicated with 2000 proposals.

| Variant | Tθ(G) | VGG | C3D | LP | AP@IoU: 0.10:1.0 | 0.10 | 0.50 | small | AP area: medium | large |
|---------|------|-----|-----|----|-----------------|-----|------|------|----------------|-------|
| C3D head only (no VGG, no transformer, predict all) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| C3D head only w/ LP (no VGG, no transformer, interpolate) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| TrackNet (no transformer) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| TrackNet* Left view only | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| TrackNet* Right view only | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| TrackNet* Frontal view only | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| TrackNet (2000 ROI during test) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| TrackNet* (train w/ flipped) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| TrackNet* (train w/ skip) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Below: Increase squash dimension from 128 to 512:

| Variant | Tθ(G) | VGG | C3D | LP | AR@IoU: 0.1 | 0.3 | 0.5 | AR num maxDets: 1 | 10 | 100 |
|---------|------|-----|-----|----|-------|-----|-----|-----------------|----|-----|
| squashVGG512noC3D | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| squashVGG512noC3D (train w/ skip) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| squashVGG512 C3D512 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| squashVGG512 C3D512 (train w/ skip) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Table II: The average recall (AR)(%) rates are reported under different settings (i.e. IoU thresholds; thresholds on max detections per image).

| Variant | Tθ(G) | VGG | C3D | LP | AR@IoU: 0.1 | 0.3 | 0.5 | AR num maxDets: 1 | 10 | 100 |
|---------|------|-----|-----|----|-------|-----|-----|-----------------|----|-----|
| squashVGG512noC3D | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| squashVGG512noC3D (train w/ skip) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| squashVGG512 C3D512 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| squashVGG512 C3D512 (train w/ skip) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Object Detection Performance and Ablation Analysis.

We consider all bounding tubes generated by trackNet and evaluate all bounding boxes in each frame. Table I and II show the average precision (AP) and average recall (AR) rates for different evaluation conditions. The criteria for labeling a detection as a true match is stricter when one increases the IoU threshold.

In order to understand the roles the major design components are playing, different variants of trackNet are trained and tested. In Table I and II, we show the comparisons between trackNet without transformer, trackNet without VGG feature concatenation, trackNet without transformer or VGG in either “predicting all” mode or “linear interpolation (LP)” mode during TPN and the full-version trackNet*. We further split the training and testing dataset based on the viewing angles into left view, right view and frontal view, and show the performances when training and testing only on the sub-datasets separately. From the table it is clear that the performances got boosted after VGG concatenation and inserting spatial transformer. The linear interpolation (LP) has conveniently served as an implicit smoothness regularization during TPN stage and improved the performance with even fewer parameters. Regarding dataset, the levels of difficulty are different...
Fig. 6. Examples of the predicted bounding tubes. We draw the bounding tube for the entire 8-frame long GoP on the middle frame with the bounding boxes for current frame highlighted in yellow. The centroids of tubes are connected as the tracklets. TrackNet is robust to different lighting conditions and able to cover both small and large vehicle sizes with different aspect ratios. It also generates more “sparse” bounding tubes for fast-moving vehicles and “denser” bounding tubes for slower vehicles or vehicles that are further away.

for different viewing angles, for example, frontal view sub-dataset is the easiest. The proposed model is improved after we augmented the training data by horizontally flipping. We expect the proposed model will perform even better given more training data and/or using other data augmentation tricks. Training with “skip frames” also helps to boost the performance.

Based on the observations we can see that the proposed model has a higher precision rate (less false positives) thanks to the joint appearance and motion information. A candidate tube is considered to be an object only if both spatial and motion features are strong. However, the proposed model has limited power in terms of precise localization. Some “not-so-tight” boxes can be spotted in the result visualization, figure 6, which is expected given the features are from a GoP level, compared with frame level features with higher temporal resolutions.

For a video segment of $T$ frames long, the feature dimension is $512 \times T$ from the VGG branch, and 512 from the C3D branch. By squashing the feature dimension from both branches into 128, the computation is significantly reduced, making the proposed model more efficient. On the other hand, this huge dimension reduction may have lost some feature details, making the model less accurate in locating objects precisely. Indeed, the performance gets higher if using larger feature dimensions, see the second part “increase squash dimension from 128 to 512” in both I and II. For example, the model named “squashVGG512 C3D512” has squashed feature dimensions of both feature streams into 512, which is a direct comparison with the trackNet∗ where both feature streams are squashed into 128. The mAP gets improved from 37.47% to 40.45% after increasing the squashing dimension from 128 to 512.

V. CONCLUSIONS

We present the trackNet, which can detect and track multiple objects in videos jointly by generating bounding tubes. Utilizing the spatial-temporal features extracted by a 3D convolutional neural network in addition to the spatial features from the VGG network, the trackNet generates tube proposals and further classifies them and refines their locations. TrackNet consists of three stages: (1) feature extraction and spatial transformation, (2) Tube proposal network(TPN), and (3) post-TPN classification and refinement. We explored several ways to perform tube proposal and offset regression. TrackNet was trained and tested on the challenging traffic video dataset UA-DETRAC and achieved very promising results. In future work, we would like to improve trackNet in terms of more precise localization. Pooling features from multiple scales in spatial and temporal domain will be tested and linear interpolation structure will be relaxed to allow more complex motion...
Fig. 7. More examples of the predicted bounding tubes. The 1st and the 3rd row show the middle bounding boxes on the middle frame, while the 2nd and the 4th row show the bounding tubes with the centroid tracklets.

patterns.  

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We provide two videos https://drive.google.com/drive/folders/1mpbfOq1ESJ4oXSlolbGhpxPR6CuOy?usp=sharing: 1. Detected bounding tubes and tracklets are shown in the video trackNet Tube.avi. Different test videos with different viewing angles, weather conditions, lighting conditions are shown. 2. We also show the per-frame bounding boxes in the video trackNet Box.avi as illustrated in figure IV. TrackNet*, trackNet without VGG or transformer are compared to show the improvement.
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