A LARGE SCALE URBAN SURVEILLANCE VIDEO DATASET FOR MULTIPLE-OBJECT TRACKING AND BEHAVIOR ANALYSIS

Guojun Yin, Bin Liu, Huihui Zhu, Tao Gong, Nenghai Yu

University of Science and Technology of China,
Key Laboratory of Electromagnetic Space Information, The Chinese Academy of Sciences,
{gjyin,zhuhui33,gt950513}@mail.ustc.edu.cn, {flowice,ynh}@ustc.edu.cn

ABSTRACT

Multiple-object tracking and behavior analysis have been the essential parts of surveillance video analysis for public security and urban management. With billions of surveillance video captured all over the world, multiple-object tracking and behavior analysis by manual labor are cumbersome and cost expensive. Due to the rapid development of deep learning algorithms in recent years, automatic object tracking and behavior analysis put forward an urgent demand on a large scale well-annotated surveillance video dataset that can reflect the diverse, congested, and complicated scenarios in real applications. This paper introduces an urban surveillance video dataset (USVD) which is by far the largest and most comprehensive. The dataset consists of 16 scenes captured in 7 typical outdoor scenarios: street, crossroads, hospital entrance, school gate, park, pedestrian mall, and public square. Over 200k video frames are annotated carefully, resulting in more than 3.7 million object bounding boxes and about 7.1 thousand trajectories. We further use this dataset to evaluate the performance of typical algorithms for multiple-object tracking and anomaly behavior analysis and explore the robustness of these methods in urban congested scenarios.

1. INTRODUCTION

With the rapid development of digital acquisition and storage technologies, video surveillance has become one of the most important safety monitoring methods widely used all around the world. As a very active research field in the computer vision area, the main goal of the research on the surveillance video is to effectively analyze and extract information from a large amount of unstructured video data acquired by the surveillance cameras, automatically detect, track and identify the targets, analyze various behaviors of the targets, understand various events occurring in the scene, and alarm suspicious events, to provide technical support for public security.

Among various research topics in surveillance video analysis and scene recognition, multiple-object tracking and behavior analysis is one of the major research fields. After the proposition of the concepts of intelligent transportation and smart city, more and more researchers have begun to focus on object tracking and behavior analysis in the surveillance videos [1][2]. However, the explosive growth of the number of vehicles and populations has resulted in more congested and complicated urban environments, which brings many new challenges to the research on the surveillance video.

As many object tracking and anomaly behavior analysis algorithms have been proposed to deal with the congested and complicated scenarios [3][4][5][6], the corresponding public challenging datasets are required to provide the fair comparison. However, there are only several real-world urban surveillance video datasets serving the purpose of evaluating the performance and robustness of object tracking and behavior algorithms. And most of the existing surveillance video datasets [16] used in the previous works are relatively small and simple, which makes them less qualified to assess the performance in real-world applications for more and more congested and complex scenarios.

In the current work, we propose a large scale urban surveillance video dataset (USVD) with congested and complex scenarios for multiple-object tracking and anomaly behavior analysis. To the best of our knowledge, it is to-date the largest and most realistic public dataset for real video surveillance. There are mainly four advantages in our dataset compared with the existing datasets.

Realistic. All the data are from the real public surveil-
Table 1. Comparison of existing datasets in urban environments (object tracking and detection).

| Dataset                              | #Clips | #Annotated frames | #Tracks | #Boxes | #Density | Camera | Task                        |
|--------------------------------------|--------|-------------------|---------|--------|----------|--------|-----------------------------|
| MIT Traffic[2]                       | 20     | 520               | -       | 2054   | 3.95     | static | Pedestrian detection       |
| Caltech Pedestrian[1]                | 11     | 250000           | -       | 350000 | 1.40     | dynamic | Pedestrian detection       |
| Daimler Pedestrian ** [7]            | 1      | 21790            | -       | 56492  | 2.50     | dynamic | Pedestrian detection       |
| KITTI Tracking ** [8]                | 21     | 7923             | 917     | 8896   | 1.12     | dynamic | Multiple object tracking   |
| MOT Challenge 2015 2D [9]            | 22     | 11286            | 1221    | 101345 | 8.98     | diverse | Multiple object tracking   |
| MOT Challenge 2016 [10]              | 14     | 11235            | 1342    | 292733 | 26.06    | diverse | Multiple object tracking   |
| MOT Challenge 2017 [10]***           | 14     | 11235            | 1331    | 300373 | 26.73    | diverse | Multiple object tracking   |
| Our dataset                          | 52     | 217706           | 7175    | 2758824 | 17.75 | static | Object detection and tracking |

* The statistics of Daimler Pedestrian detection dataset only includes test split.
** The statistics of KITTI Tracking dataset only includes training split and boxes include the bounding boxes of DontCare labels.
*** The sequences in MOT17 Challenge are the same as MOT16 sequences with a new, more accurate ground truth.

...real-world.

Complex. The dataset is comprised of 7 typical scenarios with 16 different congested scenes. There are frequent occlusion, deformation, various viewpoints and diverse targets in these congested scenes.

Large Scale. The dataset consists of over 200k annotated frames and more than 3.7 million bounding boxes of about 7.1 thousand unique trajectories.

Well-Annotated. All the bounding boxes are manually annotated and checked. The annotation includes location, size, object category, occlusion, and trajectory identity.

We also use the proposed dataset to evaluate the performance of typical algorithms for multiple-object tracking and anomaly detection and explore the robustness of these methods in urban congested conditions.

2. RELATED WORKS

In the recent years, the computer vision community has created benchmarks for video related tasks such as scene recognition, pedestrian & object detection, object tracking, action recognition, anomaly behavior detection and etc. Despite the potential pitfalls of such datasets, they have proved to be extremely helpful to advance the state-of-the-arts in the corresponding areas [11, 9, 12, 13]. An overview of examples of the existing datasets in urban environments for object detection and tracking is shown in Tab. 1.

Real Urban Video Datasets. The MIT Traffic dataset [2] is an example of the recent efforts to build more realistic urban traffic surveillance video datasets for research on pedestrian detection and activity analysis. It includes a traffic video sequence of 90 minutes long, recorded by a stationary camera and the whole sequence is divided into 20 clips. The size of the scene is 720 by 480. In order to evaluate the performance of human detection on this dataset, the ground truth of the pedestrians of some sampled frames are manually labeled. There are in total 520 annotated frames and 2054 bounding boxes in the dataset.

The Caltech Pedestrian dataset [14] consists of approximately 10 hours of 640 × 480 30Hz video taken from a vehicle driving through the regular traffic in an urban environment. All the data is roughly divided in half, setting aside 6 sessions for training and 5 for testing. About 250000 frames with a total of 350000 bounding boxes and 2300 unique pedestrians are annotated.

The Daimler Monocular Pedestrian Detection dataset [7] is another dataset for pedestrian detection in urban environments. The training set contains 15560 pedestrian samples (image cut-outs at 48 × 96 resolution) and 6744 additional full images without pedestrians for extracting negative samples. The test set contains an independent sequence with more than 21790 images and 56492 pedestrian labels (fully visible or partially occluded), captured from a vehicle during a 27 min driving through the urban traffic.

Although they are helpful to evaluate the performance of pedestrian detection algorithms in real surveillance video to some extent, the three datasets mentioned above only include some uncrowded urban scenes and a few annotated bounding boxes, which is relatively simple compared to the complex and congested traffic conditions nowadays.

MOT Datasets. Recently, the KITTI benchmark [8] is introduced for challenges in autonomous driving, which includes stereo flow, odometry, road and lane estimation, object detection as well as tracking. Some of the sequences include crowded pedestrian crossings, making the dataset quite challenging, but the camera is moving, while the conventional traffic surveillance video varies greatly.

MOT challenge 2015 [9], challenge 2016 [10] and challenge 2017 [10] are the recent challenging benchmarks for multiple object tracking. The videos in the benchmarks are diverse, and some of which are selected from the existing datasets, e.g. KITTI Tracking dataset. However, the dataset consists of various video types including surveillance videos and moving-camera videos. Therefore, it motivates us to establish a public challenging urban surveillance video dataset which is more realistic to evaluate the performance of various algorithms for object tracking and behavior analysis.

3. LARGE SCALE URBAN SURVEILLANCE VIDEO DATASET

An example sequence in our proposed dataset is shown in Fig. 2 in which the trajectory distribution only includes the trajectory location in the adjacent 100 frames (4 seconds) and the bounding boxes of dotted line mean the completely-occluded target. The targets we are interested in urban environments are movable individuals or units, e.g., pedestrian,
car or van, rather than the stationary objects, e.g., trees, pillars or traffic lights. In this section, we introduce our large scale urban surveillance video dataset (USVD) in details.

3.1. Data Collection
The videos in the dataset are captured from 54 surveillance cameras distributed in public places. We collect 3888 hours of video (over 5 TeraBytes of data in total and 72 hours of video for each camera captured from 7:00 to 19:00 for 6 days) and select 16 representative challenging scenes based on the factors, e.g., density, diversity, occlusion, deformation, viewpoint, motion and etc. The scenes we selected are shown in Fig. 1 and the ID numbers in the corners represent the scenarios in turn: street, crossroads, hospital entrance, school gate, park, pedestrian mall and public square.

3.2. Annotation
In order to evaluate the performance of the object tracking and behavior analysis algorithms, we proposed a clear protocol that was obeyed throughout the annotation of the entire dataset to guarantee the consistency. The annotation rule includes the following aspects:

Class. We annotated 7 classes of targets in urban scenarios, including pedestrian, riding, car, van, bus, tricycle, and truck. The queries used for each of the classes are listed as follows: 1) pedestrian: single pedestrian, including the walking person, skating person and sitting person, but not including the person on the vehicle, e.g., bicycle, motorcycle, scooter. Note that the pictures on the advertising boards were regarded as the background. 2) riding: two-wheel vehicle with people on it, e.g., bicycle, motorcycle and scooter. The annotated bounding box surrounds the extent of both the vehicle and the person. The person-riding is considered as one moving individual rather than divided into vehicle and person. Although it looks almost the same as a pedestrian from the waist up, the person on a vehicle will be considered as a part of the vehicle and will not be annotated as pedestrian which is different from the annotation in [9] [10]. The parked cycles without people will be ignored and regarded as background. 3) car: four-wheel vehicle for the purpose of several-person transport, such as hatchback, sedan, SUV, MPV, taxi, jeep, convertible, etc. 4) van: four-wheel medium-size passenger-car or van for the purpose of transport of a small number of cargo or used for engineering operations, such as ambulance, van, etc. 5) bus: four-wheel vehicle for the purpose of taking a large number of persons, and bigger than a van, such as bus, mini-bus, coach, etc. 6) tricycle: three-wheel vehicle for cargo or passenger transport, and the bounding box surrounding the extent of both vehicle and person or cargo. 7) truck: four-wheel vehicle for cargo transport, such as pickup, garbage truck, lorry, fire engine, trailer, etc.

Minimal size. For the case of the target size, too small targets will be ignored to make sure that the annotation accuracy is not forfeited in congested and complex scenes. The size threshold is defined as 60 in pixels for the bounding box’s longest side. If the bounding box’s longest side of a target is less than 60 pixels in the whole trajectory, the target will be ignored. However, for the targets whose bounding box’s longest side is less than 60 pixels only at part of the trajectory, we still annotate these too-small targets in order to remain the complete trajectory. All too-small boxes in a trajectory will ignored when evaluating the performance of the multiple-object tracking methods.

3.3. Data Statistics
Ultimately, we have annotated 32 sequences in total. The total number of annotated frames is over 200k, resulting in 4.3 million bounding boxes and about 7.1k unique trajectories, much more than the annotation in MOT challenge 2017 (30.6k bounding boxes of 1.3k trajectories in 11.2k frames). The average density of the sequence, which means the average number of the annotated targets per frame, is almost 20. Therefore, the scenes in our dataset are extremely congested and challenging. The sequences are divided into two subsets, i.e. training split and test split and the statistics of the annotated sequences are listed in Tab. 2.

All the targets are grouped into 7 classes defined in Sec. 3.2 with an unique class ID for each one. The class
Table 2. Statistics of sequences included in the proposed dataset.

| Train sequences | Test sequences |
|-----------------|----------------|
| Seq | Resolution | Length | Tracks | Boxes | Density | Seq | Resolution | Length | Tracks | Boxes | Density |
| 01 | 1280 x 1080 | 10601 | 340 | 91055 | 11.389 | 02 | 1280 x 720 | 10989 | 219 | 70982 | 10.7766 |
| 03 | 1920 x 1080 | 11000 | 389 | 234806 | 21.3460 | 04 | 1920 x 1080 | 11101 | 460 | 241924 | 21.7930 |
| 05 | 1920 x 1080 | 4500 | 500 | 246923 | 54.8718 | 06 | 1920 x 1080 | 3500 | 407 | 209580 | 59.8629 |
| 07 | 1280 x 720 | 6001 | 178 | 67160 | 11.1915 | 08 | 1280 x 720 | 6001 | 174 | 71361 | 11.8915 |
| 09 | 1280 x 720 | 6000 | 250 | 80973 | 13.4955 | 10 | 1280 x 720 | 7501 | 253 | 100381 | 13.3823 |
| 11 | 1280 x 720 | 7500 | 363 | 80416 | 10.7221 | 12 | 1280 x 720 | 7501 | 465 | 92760 | 12.3664 |
| 13 | 1920 x 1080 | 2700 | 94 | 27964 | 10.3570 | 14 | 1920 x 1080 | 2801 | 141 | 42252 | 15.0846 |
| 15 | 1280 x 720 | 5000 | 166 | 74398 | 14.8796 | 16 | 1280 x 720 | 5001 | 164 | 73601 | 14.7173 |
| 17 | 1280 x 720 | 7000 | 193 | 101165 | 14.4521 | 18 | 1280 x 720 | 7001 | 212 | 103357 | 14.7632 |
| 19 | 1280 x 720 | 7501 | 99 | 48517 | 6.4681 | 20 | 1280 x 720 | 7501 | 86 | 50832 | 6.7767 |
| 21 | 1280 x 750 | 111 | 161220 | 21.4960 | 24 | 1280 x 720 | 7501 | 101 | 150504 | 20.0645 |
| 23 | 1280 x 720 | 5000 | 177 | 93921 | 18.7842 | 26 | 1280 x 720 | 5001 | 173 | 92729 | 18.5421 |
| 27 | 1280 x 720 | 7500 | 177 | 117658 | 15.6877 | 28 | 1280 x 720 | 7501 | 207 | 140885 | 18.6755 |
| 29 | 1280 x 720 | 5000 | 168 | 103983 | 20.7924 | 30 | 1280 x 720 | 5000 | 230 | 119420 | 23.8840 |
| 31 | 1280 x 720 | 4001 | 239 | 201006 | 50.2389 | 32 | 1280 x 720 | 6000 | 333 | 306315 | 51.0525 |
| Total | | 104305 | 3429 | 1779866 | 17.0636 | Total | | 107401 | 3744 | 1978955 | 18.4258 |

Table 3. Target number of each class in sample sequences. The number in brackets is percentage of each class in one sequence.

| Seq | Pedestrian | Riding | Car | Van | Bus | Tricycle | Truck |
|-----|------------|--------|-----|-----|-----|----------|-------|
| 02  | 2.7k (2.56%) | 4.0k (3.51%) | 100.9k (88.16%) | 4.4k (3.93%) | 1.9k (1.50%) | 0.0k (0.02%) | 0.5k (0.50%) |
| 09  | 5.5k (6.79%) | 11.6k (14.28%) | 52.1k (64.16%) | 1.9k (2.35%) | 8.6k (10.65%) | 11.0k (1.36%) | 0.3k (0.42%) |
| 11  | 7.1k (8.49%) | 34.8k (41.31%) | 29.6k (35.18%) | 0.0k (0.00%) | 6.0k (7.17%) | 2.2k (2.66%) | 4.3k (5.20%) |
| 18  | 59.7k (57.47%) | 9.7k (9.35%) | 24.8k (23.51%) | 0.0k (0.07%) | 0.7k (0.69%) | 8.6k (8.32%) | 0.5k (0.58%) |
| 24  | 140.6k (93.43%) | 9.8k (6.57%) | 0.0k (0.00%) | 0.0k (0.00%) | 0.0k (0.00%) | 0.0k (0.00%) | 0.0k (0.00%) |
| 32  | 251.1k (81.98%) | 1.2k (0.39%) | 54k (17.63%) | 0.0k (0.00%) | 0.0k (0.00%) | 0.0k (0.00%) | 0.0k (0.00%) |
| Overall | 1665.1k (44.30%) | 405.0k (10.78%) | 1496.3k (39.81%) | 51.1k (1.36%) | 81.8k (2.18%) | 38.0k (1.01%) | 21.2k (0.57%) |

pedestrian and car are the most frequent in our dataset, with 3148.0k bounding boxes of car and pedestrian versus 586.5k boxes for other classes in total. Furthermore, the diversity among different scenarios is relatively large. For example, the general roads include mostly cars (e.g., 83.3k bounding boxes versus 7.8k for others in total in Seq.01) while there are nearly only pedestrians in the square (e.g., 91.4k bounding boxes versus 2.4k for others in total in Seq.25). Tab. 3 lists the class statistics of some sample sequences owing to the limited space of paper.

Most of targets in the scenes are relatively small for the reason that the surveillance cameras are a bit far from the targets for wide visual field. The small targets, i.e., the longest size length of the bounding box 100 pixels, occupies 55.29% of all targets regardless of too small targets. After ignoring the too small targets, histograms of the pedestrian height and the car width are shown in Fig. 4.

Scale variation is one of major deformations of targets in the surveillance videos. The measure of the scale change is defined as $C = \sqrt{(H_{max} \times W_{max})/(H_{min} \times W_{min})}$, where $H$ and $W$ represent the height and width of bounding box, respectively. The maximum and minimum size of the target is calculated based on the entire trajectory. Scale change occurs frequently in our dataset. For example, the size of the bounding box will change greatly when the target is approaching the camera from a distance. The distribution of scale change (in pixels defined above) can be grouped into three intervals by the values: small: $1 \leq C < 1.5$, large: $1.5 \leq C < 2.5$, and huge: $C \geq 2.5$. Each of three intervals occupies separately 31.78%, 35.41% and 32.80% of all the targets. Most of the targets (trajectories) in our dataset encounter at least large scale change which makes our dataset very challenging.

Occlusion is also very frequent in the scenes which makes the object tracking very difficult. Nearly all the trajectories have been part-occluded and some of which are completely-occluded in our dataset. There are in total 596 trajectories in which at least 38k bounding boxes occluded completely.

The trajectory length is the time period from the appearance to disappearance of the target and depends on the speed and route of the target. The average trajectory length in our dataset is as long as 523.49 (20.94 seconds). Generally, the trajectory length of the fast target, e.g., car, is shorter than the slower one, e.g., pedestrian. Fig. 4 shows the histograms of trajectory length of pedestrians and cars.
4. APPLICATIONS AND EVALUATIONS

4.1. Detection

For each of seven classes defined in Sec. 3.2, the goal of the object detection is to predict the bounding boxes of each target of that class in a test image (if any), with associated real-valued confidence.

All images for object detection in our dataset are sampled from the sequences by one frame per second. There are in total 8485 annotated images and almost 160k bounding boxes for object detection, regardless of the too small and the completely-occluded targets. All images are divided into train split and test split following Tab. 2. Therefore, there are 4172 annotated images for training and 4296 images for test. The completely-occluded boxes will be ignored in both training and testing of detection methods. Faster RCNN [6] and Single Shot MultiBox Detector (SSD) [5] are the most typical algorithms for object detection and achieve very good performances for object detection in PASCAL VOC [13], COCO [12], and ILSVRC [15] datasets. In our experiments, Faster RCNN and SSD will be evaluated on the performance for object detection in urban congested environments.

The evaluation of the detectors in our experiments is the same as PASCAL VOC 2007 [13] and the performances are listed in Tab. 4. Among all the classes of targets, we select pedestrian and car for analysis of the Precision/Recall curve as shown in Fig. 5.

4.2. Multiple Object Tracking

For multiple-object tracking, all the sequences are divided into training split and test split as shown in Tab. 2. The train sequence and the test sequence in the same row are both captured from the same scene. We take experiments on multiple-object tracking by using the detection results of SSD for its good performance on accuracy and speed. Evaluation metrics for multiple object tracking not only are desirable to summarize the performance into one single number to enable a direct comparison but also provide several performance estimates including information about the individual errors made by algorithms. Following a recent trend [9] [10], we employ two sets of measures as the evaluation metrics for multiple-object tracking: CLEAR metrics [16] and a set of track quality measures [17], e.g., MOTA and MOTP.

In our experiments, we use several multiple-object tracking algorithms (preferring real-time methods) as baseline methods: 1) TC_ODAL [3] proposed the tracklet confidence using the detectability and continuity of a tracklet, and formulated a multi-object tracking problem based on the tracklet confidence. 2) DP_NMS [20] introduced a greedy algorithm that sequentially instantiates tracks using shortest path computations and allows one to embed pre-processing steps, such as non-max suppression, within the tracking algorithm. 3) SORT [18] was introduced as a pragmatic approach to multiple object tracking where the main focus is to associate objects efficiently for online applications. 4) IOU [19] posed a shift that enables the deployment of much simpler tracking algorithms which can compete with more sophisticated approaches at a fraction of the computational cost. We take the default parameters as suggested by the authors and the quality measures of these baseline methods are listed in Tab. 5. The provided numbers may not represent the best possible performance for each method.

4.3. Anomaly Detection

Due to the urgent requirement of city security, anomaly detection and location is a vital task of video surveillance. Usually, the behaviors those rarely appeared in the videos are defined as anomaly behaviors [22]. It is common practice to detect anomaly behaviors when evaluation through modeling the normal videos in the training split (zero-shot learning). In the daily life, anomaly behaviors suffer vague definitions due to diverse scenes and relationships among objects. It is challenging to measure the diverse anomaly behaviors using the consistent standard.

Furthermore, we select parts of the annotated videos in our dataset for anomaly behavior detection. There are in total
45 sequence videos and 200 frames per sequence for training while 10 sequences for test. The anomaly behaviors in the test split include running, jumping, bicycling, motoring and etc. As for the evaluation metrics, following [22, 23, 21], we use AUC (area under curve) and EER (equal error rate) to measure the ROC curves.

In our experiments, we use several anomaly detection methods as the baselines as following: 1) Zhu et al. [21] used the HMOF features to distinguish anomaly behaviors in the videos through Gaussian Mixture Model and the visual tracking is adopted for the better detection. 2) The PT-HOF [24] were utilized to capture the fine-grained information and the consistency motion object (CMO) clusters similar point trajectories in a local region, for better anomaly localization. 3) Chen et al. [23] introduced a novel foreground object localization method and presented SL-MHOF, an effective descriptor modeling the local motion pattern while for appearance features, a CNN-based model is adopted. We take the default parameters as suggested by the authors and the ROC curves of these baseline methods are shown in Fig. [7]. The videos in our dataset are captured from the real surveillance of the congested crowds, much more complicated and challenging than other anomaly detection datasets. Therefore, there are a long distance of the methods for real practice although they achieve excellent performances in the other datasets.

5. CONCLUSION

In this work, we have proposed a challenging large scale urban surveillance video dataset, one of the largest and most realistic datasets, for object tracking and behavior analysis. The dataset consists of 16 scenes captured in 7 typical urban outdoor scenarios: street, crossroads, hospital entrance, school gate, park, pedestrian mall, and public square. We annotated over 200k video frames carefully, resulting in more than 3.7 million object bounding boxes and about 7.1k trajectories. The proposed dataset is pretty challenging and very suitable for evaluation on object tracking and anomaly detection in urban environments.

In the annotation procedure, we annotated a novel target class, group defined as one unit including at least two pedestrians walking together (close location with similar velocity and direction). In the future, the dataset will be extended for crowd analysis with the annotated information. On the other hand, there will be a big data expansion of the dataset owing to the annotated data occupies a small part of collected data by far.

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