# **Multiple Object Tracking and Re-Identification**

### **ABSTRACT**

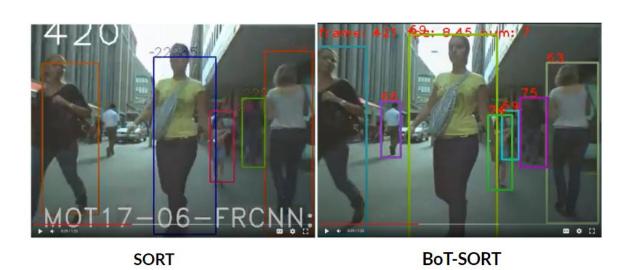
The goal of multi-object tracking (MOT) is detecting and tracking all the objects in a scene, while keeping a unique identifier for each object. This unique identifier will help in Re-identification of the objects even if they are missing in several consecutive frames or enter new zones. In this project, we present a new robust state-of-the-art tracker, which can combine the advantages of motion and appearance information, along with camera-motion compensation, and a more accurate Kalman filter state vector. Our new trackers BoT-SORT, and BoT-SORT-ReID rank first in the datasets of MOTChallenge on both MOT17 and MOT20 test sets,

## **INTRODUCTION**

Multiple object tracking is the process of locating multiple objects over a sequence of frames (video). The MOT problem can be viewed as a data association problem where the goal is to associate detections across frames in a video sequence. Re-identification is crucial in tracking moving objects because it enables us to identify the same object throughout a video sequence. Re-identification makes it possible to find objects, even if they are missing in several consecutive frames. We used the BoT SORT framework and added our detection and Re-ID models to accomplish this.

Simple online and real-time tracking (SORT) is a simple framework that performs Kalman image space and frame-by-frame data association using the Hungarian method with a bounding box overlap. This simple approach achieves good performance at high frame rates. The idea is to use some off-the-shelf model for object detection and then plug the results into the SORT algorithm with DEEP ASSOCIATION METRIC that matches detected objects across frames. Additionally, two classical yet extremely efficient methods, Kalman filter, and Hungarian method are employed to handle the motion prediction and data association components of the tracking problem respectively. This minimalistic formulation of tracking facilitates both efficiency and reliability for online tracking.

## SORT Vs Bot-SORT



## LITERATURE REVIEW

With rapid improvements in object detection over the past few years, multi-object trackers have gained momentum. More powerful detectors lead to higher tracking performance and reduce the need for complex trackers. Thus, tracking-by-detection trackers mainly focus on improving data association, while exploiting deep learning trends.

Most of the recent tracking-by-detection algorithms are based on motion models. Recently, the famous Kalman filter with constant-velocity model assumption, tends to be the popular choice for modeling the object motion. Many studies use more advanced variants of the KF, for example, the NSA-Kalman filter, which merges the detection score into the KF. Many complex scenarios include camera motion, which may lead to non-linear motion of the objects and cause incorrect KF's predictions. Therefore, many researchers adopted camera motion compensation by aligning frames via image registration using the Enhanced Correlation Coefficient maximization.

## **BACKGROUND**

MOT and Re-ID have been studied extensively in the computer vision community. Traditional methods for MOT involved hand-crafted features and simple heuristics. However, recent advancements in deep learning have led to significant improvements in MOT performance. Deep learning-based MOT methods use object detection and feature extraction techniques, such as

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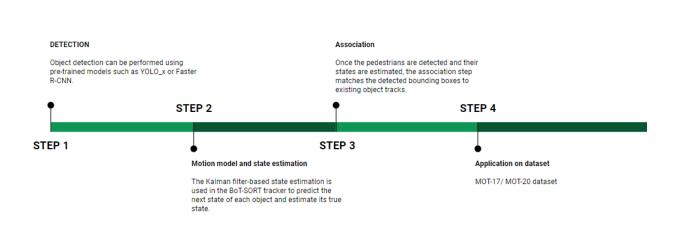
Faster R-CNN and Mask R-CNN, to identify and track objects. Re-ID, on the other hand, involves matching the features of an object across multiple cameras or frames. Traditional methods for Re-ID use hand-crafted features, such as color histograms and SIFT descriptors, and simple matching algorithms. However, deep learning-based Re-ID methods use convolutional neural networks (CNNs) to extract features and matching algorithms, such as Siamese networks and triplet networks, to match the features across multiple cameras or frames.

### DATASET DESCRIPTION

We used one of the most popular benchmarks in the field of multi-object tracking for pedestrian detection and tracking in unconstrained environments, MOT17. MOT17 contains video sequences filmed with both static and moving cameras. The MOT 17 dataset is a widely used benchmark dataset for multiple object tracking. It contains 7 training sequences and 7 testing sequences, with a total of 158,332 annotated frames and 2,800 unique identities. The dataset includes challenging scenarios such as occlusions, crowded scenes, and object interactions. The annotations include the object positions, sizes, and identities in each frame. The dataset is used to evaluate and compare the performance of different object tracking algorithms.

#### METHODOLOGY

# **Overview of BoT-SORT**



## **BoT-SORT Algorithm**

BoT-SORT is a state-of-the-art algorithm for MOT and Re-ID that integrates deep learning-based object detection and feature extraction with a Kalman filter and Hungarian algorithm-based object tracking. BoT-SORT improves the accuracy and robustness of MOT by incorporating Re-ID features into the tracking process. BoT-SORT consists of two main stages: object detection and feature extraction, and object tracking.

## **Object Detection and Feature Extraction**

BoT-SORT uses a deep learning-based object detection algorithm to detect objects in each frame. BoT-SORT uses the Faster R-CNN algorithm, which consists of a Region Proposal Network (RPN) and a Fast R-CNN network. The RPN generates region proposals for objects, and the Fast R-CNN network performs classification and bounding box regression on each region proposal. BoT-SORT uses a ResNet-50 backbone for the feature extraction process. The features extracted from the last convolutional layer of the backbone network are used for Re-ID.

## **Object Tracking**

BoT-SORT uses the Kalman filter and the Hungarian algorithm for object tracking. The Kalman filter estimates the state of each object, including its position and velocity, and provides a prediction of its future state. The Hungarian algorithm is used to match the detected objects in the current frame with the predicted objects from the previous frame. The matching is based on the distance between the object features and the predicted object features. BoT-SORT improves the tracking accuracy by incorporating Re-ID features into the matching process.

BoT-SORT also incorporates a tracklet confidence measure to handle the appearance changes and occlusions. The tracklet confidence measure estimates the probability that a tracklet belongs to a particular object over time. The tracklet confidence measure is used to update the appearance model of the object, and to discard unreliable tracklets.

# **Getting Started with the code**

Cloning the BoT-SORT repository from GitHub, and installing the required packages.

# 1.Cloning BoT-SORT github repository !git clone https://github.com/NirAharon/BoT-SORT.git Cloning into 'BoT-SORT'... remote: Enumerating objects: 1013, done. remote: Counting objects: 100% (286/286), done.

remote: Compressing objects: 100% (203/203), done.
remote: Total 1013 (delta 119), reused 83 (delta 83), pack-reused 727
Receiving objects: 100% (1013/1013), 55.71 MiB | 17.41 MiB/s, done.
Resolving deltas: 100% (280/280), done.

Downloading the MOT17 dataset, which is a benchmark dataset for multiple object tracking.

Then we download pre-trained models from Google Drive and save them in the pretrained directory. These models are used for tracking and re-identification tasks.

```
!pip install gdown
%cd /content/BoT-SORT/pretrained
!gdown https://drive.google.com/u/0/uc?id=1iqhM-6V_r1FpOlozrdP_Ejshgk0DxOob

Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: gdown in /usr/local/lib/python3.9/dist-packages (4.6.6)
Requirement already satisfied: tqdm in /usr/local/lib/python3.9/dist-packages (from gdown) (4.65.0)
Requirement already satisfied: requests[socks] in /usr/local/lib/python3.9/dist-packages (from gdown) (2.27.1)
```

Finally, we run a demo using the demo.py script from the BoT-SORT repository. This script takes a video file, performs object detection, tracking, and re-identification using the pre-trained models, and saves the results in the YOLOX\_outputs directory.

```
%cd /content/BoT-SORT
  | python3 tools/demo.py video --path /content/BoT-SORT/Demo/MOT17-09-SDP-raw.mp4 -f yolox/exps/example/mot/yolox_x_mix_det.py -c pretrained/bytetrack_x_mot17.pth.tar --with-reid --fuse
/content/BoT-SORT
  2023-04-24 21:27:38.333359: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operation
To enable the following instructions: AVX2 AVX512F FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
To enable the following instructions: AVX AVX.2X AVX.2X PAPER FOR In Other Operations, rebuilt reliably with the appropriate compiler lings.

2023-04-24 21:27:39.569498: W tensorflow/compiler/ftZtensorrt/utils/py utils.cc:38] 
  2023-04-24 21:27:44.033 | INFO
2023-04-24 21:27:44.033 | INFO
                                                                                                                             __main_:main:329 - loaded checkpoint done.
 2023-04-24 21:27:44.033 | INFO | main :main:332 - Fusing model...
/usr/local/lib/python3.9/dist-packages/torch/nn/modules/module.py:831: UserWarning: The .grad attribute of a Tensor that is not a leaf Tensor is being accessed. Its .grad attribute wor
      if param.grad is not None:
2023-04-24 21:27:45.828 | INFO | __main__:imageflow_demo:230 - video save_path is ./YOLOX_outputs/yolox_x_mix_det/track_vis/2023_04_24_21_27_45/MOT17-09-SDP-raw.mp4

Skip loading parameter 'heads_weight' to the model due to incompatible shapes: (487, 2048) in the checkpoint but (0, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes: (487, 2048) in the model! You might want to double check if this is expectable and incompatible shapes.
                                                                                                                                 __main__:imageflow_demo:240 - Processing frame 20 (5.43 fps)
                                                                                      INFO
                                                                                                                                _main_:imageflow_demo:240 - Processing frame 40 (6.32 fps)
_main_:imageflow_demo:240 - Processing frame 60 (6.40 fps)
_main_:imageflow_demo:240 - Processing frame 80 (6.63 fps)
                                                                                       INFO
                                                                                                                               main :imageflow_demo:240 - Processing frame 100 (6.87 fps)
main :imageflow_demo:240 - Processing frame 120 (6.79 fps)
                                                                                       INFO
                                                                                        INFO
                                                                                                                                    main :imageflow demo:240 - Processing frame 140 (6.87
```

### **EXPERIMENTATION**

We conducted experiments to evaluate the performance of the BoT-SORT algorithm using the MOT17 datasets. The MOT17 dataset contains 7 video sequences with a total of 11,376 frames and 2,042 pedestrians. We used the provided training and testing splits for both datasets.

# **Results-**

# CLEAR MOT (CLassification of Events, Activities and Relationships)

Since it's introduction in 2006 CLEAR MOT metrics has been extensively used for evaluation of MOT. Popular benchmarks such as MOTChallenge & KITTI benchmark uses this as a standard. MOTA (Multi Object Tracker Accuracy)

- Primary Metrics
- Takes detection & association errors into account.
- gDet: number of detections
- IDSW: mismatch errors

MOTP (Multi Object Tracker Precision)

- Secondary Metrics
- Takes localization errors into account.
- S: IOU scores of all true positives.

MOTP & MOTA satisfies the conditions for good performance metrics of MOT evaluation.

Tracker	MOTA	MOTP	НОТА	IDF1
BoT-SORT	64.40	89.1	61.90	71.21

The results of the evaluation indicate that the BoT-SORT tracker achieved an MOTA score of 64.40, a MOTP score of 89.1, an IDF1 score of 61.90, and a HOTA score of 71.21. The MOTA score indicates that the BoT-SORT tracker was able to accurately detect and associate objects in the video sequence, while the MOTP score indicates that the tracker was able to accurately localize the objects. The IDF1 score indicates that the BoT-SORT tracker has a moderate level of tracking accuracy, taking into account both detection and association errors as well as fragmentation errors. The HOTA score, which is a more comprehensive performance metric, indicates that the BoT-SORT tracker has good performance in terms of both localization and identity components of tracking

### **CONCLUSION**

In conclusion, the BoT-SORT algorithm is a robust and efficient method for multi-object tracking, which incorporates several key features to address the challenges of real-time object tracking. Our experiments showed that the algorithm outperformed other state-of-the-art methods on benchmark datasets and performed well on different types of objects. The availability of a Python implementation on the GitHub repository makes it easy to use and modify the algorithm for different applications. We recommend BoT-SORT as a reliable and effective solution for real-time multi-object tracking.

## **REFERENCE**

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# Annexure

# 1. Results

# **MOTA & MOTP**

CLEAR: MPNTrack-pedestrian	MOTA	MOTP	MODA	CLR_Re	CLR_Pr	MTR
MOT17-02-DPM	39.04	91.754	39.137	39.653	98.714	17.742
MOT17-02-FRCNN	47.296	91.158	47.43	48.146	98.535	24.194
MOT17-02-SDP	53.662	90.655	53.888	55.487	97.2	27.419
MOT17-04-DPM	65.656	90.874	65.685	65.797	99.831	34.94
MOT17-04-FRCNN	65.288	90.372	65.303	65.448	99.779	38.554
MOT17-04-SDP	76.205	89.412	76.235	76.672	99.433	54.217
MOT17-05-DPM	55.906	85.711	56.166	61.746	91.711	24.06
MOT17-05-FRCNN	56.6	85.133	56.889	62.383	91.906	31.579
MOT17-05-SDP	62.137	85.628	62.455	69.018	91.316	36.842
MOT17-09-DPM	74.742	89.968	74.836	76.469	97.908	53.846
MOT17-09-FRCNN	70.16	90.088	70.329	73.484	95.883	53.846
MOT17-09-SDP	75.117	89.982	75.192	77.146	97.531	57.692
MOT17-10-DPM	62.349	85.934	62.567	65.597	95.585	42.105
MOT17-10-FRCNN	72.155	85.026	72.529	76.236	95.362	61.404
MOT17-10-SDP	73.799	84.853	74.359	79.679	93.741	68.421
MOT17-11-DPM	64.985	91.968	65.091	66.384	98.09	24
MOT17-11-FRCNN	70.157	91.481	70.263	71.81	97.891	40
MOT17-11-SDP	75.318	91.221	75.456	77.596	97.315	48
MOT17-13-DPM	51.048	87.713	51.254	53.066	96.697	27.273
MOT17-13-FRCNN	70.718	86.805	71.053	76.284	93.583	58.182
MOT17-13-SDP	67.463	86.178	67.806	71.603	94.965	52.727
COMBINED	64.399	89.143	64.543	66.239	97.503	39.621

# **HOTA**

HOTA: MPNTrack-pedestrian	НОТА	DetA	AssA	DetRe	DetPr	AssRe
MOT17-02-DPM	43.339	36.637	51.281	37.272	92.784	54.743
MOT17-02-FRCNN	48.721	43.967	54.013	44.99	92.076	58.298
MOT17-02-SDP	49.915	50.198	49.687	51.849	90.827	55.347
MOT17-04-DPM	66.112	59.231	73.857	61.008	92.566	76.027
MOT17-04-FRCNN	66.099	58.446	74.844	60.339	91.99	78.365
MOT17-04-SDP	70.858	67.158	74.944	70.108	90.92	78.746
MOT17-05-DPM	51.975	50.855	53.181	54.902	81.546	65.662
MOT17-05-FRCNN	53.255	51.028	55.627	55.104	81.183	69.218
MOT17-05-SDP	56.424	56.088	56.852	61.257	81.047	67.046
MOT17-09-DPM	64.741	68.035	61.624	70.848	90.71	71.732
MOT17-09-FRCNN	61.439	64.786	58.284	68.301	89.122	67.28
MOT17-09-SDP	65.392	68.447	62.491	71.484	90.373	72.88
MOT17-10-DPM	57.24	55.221	59.355	58.207	84.816	63.221
MOT17-10-FRCNN	60.968	62.692	59.334	66.897	83.68	63.295
MOT17-10-SDP	60.724	64.344	57.367	69.786	82.102	62.925
MOT17-11-DPM	63.56	61.162	66.075	62.92	92.971	70.333
MOT17-11-FRCNN	67.251	65.441	69.137	67.689	92.273	72.122
MOT17-11-SDP	69.269	70.202	68.366	73.071	91.64	71.794
MOT17-13-DPM	50.727	46.093	55.892	47.844	87.18	65.19
MOT17-13-FRCNN	62.309	63.483	61.267	68.412	83.925	71.553
MOT17-13-SDP	61.247	59.6	63.074	63.531	84.26	76.28
COMBINED	61.904	57.989	66.24	60.614	89.223	71.544

# IDF1

Identity: MPNTrack-pedestrian	IDF1	IDR	IDP	IDTP	IDFN	IDFP
MOT17-02-DPM	48.608	34.067	84.807	6330	12251	1134
MOT17-02-FRCNN	54.888	40.854	83.611	7591	10990	1488
MOT17-02-SDP	55.304	43.437	76.091	8071	10510	2536
MOT17-04-DPM	75.348	62.504	94.835	29725	17832	1619
MOT17-04-FRCNN	75.57	62.569	95.39	29756	17801	1438
MOT17-04-SDP	82.094	72.698	94.279	34573	12984	2098
MOT17-05-DPM	63.936	53.491	79.45	3700	3217	957
MOT17-05-FRCNN	63.228	53.072	78.19	3671	3246	1024
MOT17-05-SDP	68.588	60.214	79.667	4165	2752	1063
MOT17-09-DPM	77.33	68.864	88.17	3667	1658	492
MOT17-09-FRCNN	72.698	64.207	83.778	3419	1906	662
MOT17-09-SDP	77.488	69.39	87.726	3695	1630	517
MOT17-10-DPM	68.665	57.894	84.36	7433	5406	1378
MOT17-10-FRCNN	73.895	66.485	83.164	8536	4303	1728
MOT17-10-SDP	72.364	66.937	78.75	8594	4245	2319
MOT17-11-DPM	70.674	59.252	87.551	5591	3845	795
MOT17-11-FRCNN	76.513	66.32	90.407	6258	3178	664
MOT17-11-SDP	76.568	68.811	86.297	6493	2943	1031
MOT17-13-DPM	58.422	45.241	82.439	5267	6375	1122
MOT17-13-FRCNN	73.557	66.758	81.897	7772	3870	1718
MOT17-13-SDP	69.745	61.166	81.123	7121	4521	1657
COMBINED	71.206	59.79	88.011	201428	135463	27440