Multiple Object Tracking in Recent Times: A Literature Review

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Abstract—Multiple object tracking gained a lot of interest from researchers in recent years, and it has become one of the trending problems in computer vision, especially with the recent advancement of autonomous driving. MOT is one of the critical vision tasks for different issues like occlusion in crowded scenes, similar appearance, small object detection difficulty, ID switching, etc. To tackle these challenges, as researchers tried to utilize the attention mechanism of transformer, interrelation of tracklets with graph convolutional neural network, appearance similarity of objects in different frames with the siamese network, they also tried simple IOU matching based CNN network, motion prediction with LSTM. To take these scattered techniques under an umbrella, we have studied more than a hundred papers published over the last three years and have tried to extract the techniques that are more focused on by researchers in recent times to solve the problems of MOT. We have enlisted numerous applications, possibilities, and how MOT can be related to real life. Our review has tried to show the different perspectives of techniques that researchers used overtimes and give some future direction for the potential researchers. Moreover, we have included popular benchmark datasets and metrics in this review.

Index Terms—MOT, Multiple Object Tracking, Object Tracking, Occlusion, Computer Vision

I. INTRODUCTION

Throughout the last decade, real-life problems have been solved by deep learning-based algorithms. We have seen in recent years that deep learning has been extensively used in computer vision. Object Tracking is one of the very important tasks in computer vision. It comes just right after object detection. To accomplish the task of object tracking, firstly object needs to be localized in a frame. Then each object is assigned an individual unique id. Then each same object of consecutive frames will make trajectories. Here, an object can be anything like pedestrians, vehicles, a player in a sport, birds in the sky etc. If we want to track more than one object in a frame, then it is called Multiple Object Tracking or MOT. In MOT, we can track all objects of a single class or all objects of said classes. If we only track a single object, it is called Single Object Tracking or SOT. MOT is more challenging than SOT. Thus researchers proposed numerous deep learning-based architectures for solving MOT-related problems.

To make the last three years of research organized, we would like to do a literature review on MOT. This work includes these papers. There are also some review papers on MOT in previous years [1], [2], [3], [4]. But all of them have limitations. Some of them only include deep learning-based approaches, only focus on data association, only analyze the problem statement, do not categorize the paper well, and applications in real life are also missing.

We have tried to overcome all of these issues in this work. We have tried to go through almost every paper from 2020 to 2022 on MOT. After filtering out them, we have reviewed more than a hundred papers in this work. While going through the papers, the first thing that caught our attention is that there are many challenges in MOT. Then we made an attempt to find out different approaches to face those challenges. To establish the approaches, the papers have used various MOT datasets, and to evaluate their work, they have taken help from various MOT metrics. So we have included a quick review of the datasets. Additionally, we have included a summary of new metrics along with previously existing ones. We have also tried to list down some of the MOT applications among the vast use cases of Multiple Object Tracking. Going through these papers, some scope of work has drawn our attention, which was mentioned later on.

Therefore, to sum up, we have organized our work in the following manner:

1) Figuring out MOT’s main challenges
2) Listing frequently used various MOT approaches
3) Writing a summary of the MOT benchmark datasets
4) Writing a summary of MOT metrics
5) Exploring various applications

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II. MOT Main Challenges

Multiple Object Tracking has some challenges to tackle. Although occlusion is the main challenge in MOT, there are several other challenges that a tracker has to deal with in terms of an MOT problem.

A. Occlusion

Occlusion occurs when something we want to see is entirely or partially hidden or occluded by another object in the same frame. Most MOT approaches are implemented based only on cameras without sensor data. That’s why it is a bit challenging for a tracker to track the location of an object when they obscure each other. Furthermore, occlusion becomes more severe in a crowded scene to model the interaction between people [5]. Over time the use of bounding boxes to locate an object is very popular in the MOT community. But in crowded scenes, occlusions are very difficult to handle since ground-truth bounding boxes often overlap each other. This problem can be solved partially by jointly addressing the object tracking and segmentation tasks [7]. In literature, we can see appearance information and graph information are used to find global attributes to solve the occlusion [8], [9], [10], [11]. However, frequent occlusion has a significant impact on lower accuracy in MOT problems. Thus researchers try to attack this problem without bells and whistles. In Figure 1a, occlusion is illustrated. In Figure 1b, the red-dressed woman is almost covered by the lamp post. This is an example of occlusion.

B. Challenges for Lightweight Architecture

Though recent solution for most of the problems depends on heavy-weight architectures, they are very resource hungry. Thus in MOT, heavy-weight architecture is very counterintuitive to achieving real-time tracking. Therefore researchers always cherish lightweight architecture. For lightweight architecture in MOT, there are some additional challenges to consider [12]. Bin et al. mentioned three challenges for lightweight architecture such as,

- Object tracking architecture requires both pre-trained weights for good initialization and fine-tuned tracking data. Because NAS algorithms need direction from the target task and, at the same time, solid initialization.
- NAS algorithms need to focus on both backbone network and feature extraction, so that the final architecture can suit perfectly for the target tracking task.
- Final architecture needs to compile compact and low-latency building blocks.

C. Some Common Challenges

MOT architecture often suffers from inaccurate object detection. If objects are not detected correctly, then the whole effort of tracking an object will go in vain. Sometimes the speed of object detection becomes one major factor for MOT architectures. For background distortion, object detection sometimes becomes quite difficult. Lighting also plays a vital role in object detection and recognition. Thus all of these factors become more important in object tracking. Due to the motion of the camera or object, motion blurring makes MOT more challenging. Many times MOT architecture finds it hard to decide an object as true incomer or not. One of the challenges is the proper association between the detection and tracklet. Incorrect and imprecise object detection is also a consequence of low accuracy in many cases. There are also some challenges, such as similar appearance confuses models frequently, initialization and termination of tracks is a bit crucial task in MOT, interaction among multiple objects, ID Switching (same object identified as different in consecutive frames through the object did not go out of frame). Due to non-rigid deformations and inter-class similarity in shape and other appearance properties, people and vehicles create some additional challenges in many cases [13]. For example, vehicles have different shapes and colors than people’s clothes. Last but not least, smaller-sized objects make a variety of visual elements in scale. Liting et al. try to solve the problem with higher resolution images with higher computational complexity. They also used hierarchical feature map with traditional multiscale prediction techniques [14].

III. MOT Approaches

The task of multiple object tracking is done normally in two steps: object detection and target association. Some focus on object detection; some focus on data association. There is a diversity of approaches for these two steps. The approaches can not be differentiable whether it is a detection phase or an association phase. Sometimes we can see the overlapping of
the approaches. Most of the papers use various combinations of MOT components. So we can not say that the approaches are independent of each other. Yet we have tried to figure out the frequently used approaches so that they can help in making decisions of which one to follow.

A. Transformer

Recently there have been many works regarding Computer Vision [15] implemented by transformer, so as in MOT. It is a deep learning model which has two parts like the other models: Encoder and Decoder [16]. The encoder captures self-attention, whereas the decoder captures cross-attention. This attention mechanism helps to memorize context for long term. Based on query key fashion, transformer is used to predict the output. Though it has been used solely as a language model in the past, in recent years, vision researchers have focused on it to take advantage of contextual memoization. In most cases, in MOT researchers try to predict the location of the next frame of an object based on previous information, where we think transformer is the best player to handle. As transformer is specialized to handle sequential information, frame by frame processing can be done perfectly by transformer. A whole summary of transformer based approach in MOT is presented in Table I.

Peize et al. have built TransTrack [17], using the transformer architecture where they produce two sets of bounding boxes from two types of queries, i.e., object query and track query, and by simple IoU matching, they decide the final set of the boxes, which is the tracking box for every object. It is totally as same as tracking by detection paradigm. Moreover, it leverages the prediction for tracking from previous detection knowledge utilizing transformer query key mechanism. Tim et al. have done a similar thing by introducing TrackFormer [7], excluding some implementation details.

In [18], the patches of images were at first detected, then they took help from probabilistic concepts to get expected tracks and cropped the frames according to the bounding boxes to get the patches. Then using those patches, the tracks of current frames are predicted.

Later on, En et al. have proposed a method of combining the attention model with a Transformer encoder to make the ViT model more lightweight. The paper [19] and [20] focus more on the computation cost for running the architecture in real-time. In [20], the transformer layer has been built upon an exemplar attention module which reduces the dimension of input by giving global information. Thus the layer can work in real-time. In [21], Daitao et al. have improved the computation time by using a lightweight attention layer applied by transformer model which is inserted in a pyramid network.

In [22] Zhou et al. introduce the concept of global tracking. Instead of processing frame by frame, they take a window of 32 frames and track within them. It utilizes the transformer’s cross-attention mechanism more efficiently. According to the authors, if an object is lost within a window and reborn again, then their tracker can successfully track it, which makes their tracker lower ID switching which is one of the main challenges of MOT.

In [23] Zhu et al. extend DETR [24], which is an object detection transformer. They introduce Query Interaction Module to filter out the output of the decoder of DETR before adding a detection to the tracklet.

In [25] Zhu et al. use uses encoder of the transformer to generate a feature map and then they use three tracing heads to predict bounding box classification, regression, and embedding. In most of the cases, we show others use convolutional layer to extract features, some use popular CNN architecture to extract features from a frame, but it adds an extra load to the main architecture. This ViT utilized relatively lightweight transformers encoders compared to others. Moreover, the tracking heads are simple feed-forward networks. Consequently, they produce a lightweight architecture.

B. Graph Model

Graph Convolutional Network (GCN) is a special kind of convolutional network where the neural network is applied in a graph fashion [27] instead of a linear form. Also, a recent trend has been seen in using Graph models in solving MOT problems where a set of detected objects from consecutive frames are considered as a node, and the link between two nodes is considered as an edge. Normally data association is done in this domain by applying the Hungarian algorithm [28]. An overview of solving MOT problems using graph models is given in Table II.

Guillem et al. detect and track objects globally by using a message passing network (MPN) combined with a graph to extract deep features throughout the graph [29]. Later on, [30] and [31] have done something similar. Gaang et al. have taken the same approach, [32] but they removed the appearance information because according to them, appearance features can
cause more occlusion. Also, they have followed an advanced embedding strategy to design the ticklets.

But Jiahe et al. use two graphs: Appearance Graph Network and Motion Graph Network, to identify the similarity of appearance and motion from among the frames respectively [33].

Peng et al. have also used two graph modules to solve the MOT problem, but one of the modules is for generating the proposal, and the other one is for scoring the proposal [34]. In the case of proposal generation, they considered small tracklets or detected objects as nodes, and each node is connected with all the others. But for the next module, they have trained a GCN to rank the proposals according to their scores as can be seen in Figure 4.

In [35], Jiawei et al. have solved two problems: association problem and assignment problem. To solve the association problem, they focused more on matching features within the same frame across the graph rather than finding relationships between two frames. But for the assignment problem, they have integrated a quadratic programming layer to learn more robust features.

So far, the papers have worked with the single-camera MOT problem. But in the next year, in 2022, Kha et al. have worked on multi-camera MOT problem [36]. They have established a dynamic graph to accumulate the new feature information instead of a static graph like the other papers.

C. Detection and Target Association

In such kind of approach, detection is done by any deep learning model. But the main challenge is to associate target, i.e. to keep track of the trajectory of the object of interest [37]. Different papers follow different approaches in this regard.

Margret et al. have picked both the bottom-up approach and the top-down approach [38]. In bottom-up approach, point trajectories are determined. But in top-down approach, bounding boxes are determined. Then by combining these two, a full track of objects can be found.

In [39], to solve the association problem, Hasith et al. have simply detected the objects and used the famous Hungarian Algorithm to associate the information. In the same year 2019, Paul et al. proposed Track-RCNN [40] which is an extension of R-CNN and obviously a revolutionary task in the field of MOT. Track-RCNN is a 3-D convolutional network that can do both detection and tracking along with segmentation.

But in the year 2020, Yifu et al. have done object detection and re-identification in two separate branches [54]. The
branches are similar in architecture and they both used center to extract features to detect and re-identify respectively. They claim that they have focused equally on the two tasks, that’s why they have named their approach FairMOT.

In the year 2021, we find two papers to improve data association using LSTM. Bisheng et al. propose Detection Refinement for Tracking (DRT), which has done the detection task by semi-supervised learning which produces heatmap to localize the objects more correctly [42]. The architecture has two branches where the secondary branch, it can recover occluded objects. Also, the paper has solved the data association problem by LSTM [55]. Chanho et al. also used bilinear LSTM in this regard [43].

Besides in [44], Qiang et al. have done data association by proposing CorrTracker, which is a correlational network that is able to propagate information across the associations. They have done the part of object detection by self-supervised learning. But Jiangmiao et al. have detected objects by Faster-RCNN extended with residual networks and have combined it with similarity learning and ultimately have proposed Quasi Dense Tracking model (QDTrack) [45].

In the same year, Yaoye et al. have introduced D2LA network [41] which is based on FairMOT as introduced in [54] to keep a balance between the trade-off of accuracy and complexity. To avoid occlusion, they have taken measures namely strip attention module. On the other hand, Norman et al. estimate the geometry of each detected object and make a mapping of each object to its corresponding pose so that they can identify the object after occlusion [56].

Ramana et al. have proposed their own dataset with their own architecture namely HeadHunter for detection and HeadHunter-T for tracking [46]. There are two stages in HeadHunter. In the first stage, they have used FPN and Resnet-50 to extract features. In the second stage, they have used Faster-RCNN and RPN to generate object proposals.

Jialian et al. have proposed two modules [47]: cost volume
TABLE III
SUMMARY OF DETECTION AND TARGET ASSOCIATION RELATED PAPERS

| Reference | Year | Detection | Association | Dataset | MOTA (%) |
|-----------|------|-----------|-------------|---------|----------|
| [38]      | 2018 | Faster R-CNN | Correlation Co-Clustering | MOT15, MOT16, MOT17 | 35.6, 47.1, 51.2 |
| [39]      | 2019 | DPM, F-RCNN, SDP, RRC | Hungarian Algorithm | MOT17, KITTI | 46.9, 85.04 |
| [40]      | 2019 | Mask R-CNN | Distance Measurement | MOT15, MOT16, MOT17, MOTSChallenge | 65.1, KITTI MOTS (MOTSA) |
| [41]      | 2021 | CenterNet | Hungarian Algorithm | MOT17, MOT20 | 60.6, 74.9, 73.7, 61.8 |
| [42]      | 2021 | ResNet50 | LSTM-based Motion Model | MOT16, MOT17 | 76.3, 76.4 |
| [43]      | 2021 | CenterNet | Bilinear LSTM | MOT16, MOT17 | 48.3, 51.5 |
| [44]      | 2021 | CenterNet | Correlation Learning | MOT15, MOT16, MOT17, MOT20 | 62.3, 76.6, 76.5, 65.2 |
| [45]      | 2021 | Faster R-CNN | Quasi-dense Similarity Matching | MOT16, MOT17, BDD100K, Waymo | 69.8, 68.7, 64.3, 51.18 |
| [46]      | 2021 | HeadHunter | HeadHunter-T | CroHD | 70.1, 69.1, 5.9 |
| [47]      | 2021 | CenterNet | CVA (Cost Volume based Association) | MOT17, nuScenes, MOTS (AMOTA), MOTS (MOTSA) | 65.5 |
| [48]      | 2022 | Mask-RCNN | Hungarian Algorithm | MOT17, MOT20, NTU-MOTD | 43.21, 57.70, 92.12 |
| [49]      | 2022 | YOLOv4 | Hungarian Algorithm | TAMU2015V, UGA2015V, UGA2018V | 79.0%, 65.5%, 73.4% |
| [50]      | 2022 | DLA-34 | Hungarian Algorithm | MOT15, MOT16, MOT17, MOT20 | 55.8, 73.8, 74.0, 60.2 |
| [51]      | 2022 | DPM and YOLOv5 with detection modifier (DM) | Global and Partial Feature Matching | MOT16 | 46.5 |
| [52]      | 2022 | YOLO X with later NMS | Kalman Filtering, Bicubic Interpolation and ReID Model | MOT17, MOT20 | 78.3, 75.7 |
| [53]      | 2022 | T-ReDet module | ReID-NMS Model | MOT16, MOT17, MOT20 | 63.9, 62.5, 57.4 |

Based association (CVA) module and motion-guided feature warper (MF) module to extract object localization offset information and to transmit the information from frame to frame respectively. They have named the integration of the whole process as TraDeS (TRACK to DETect and Segment). Changzhi et al. have made ParallelMOT [57] which have two different branches for detection and re-identification similar to [54].

In 2022, we can see diversity in the problem statements of MOT. [48] is an exceptional paper where Cheng-Jen et al. have introduced indoor multiple object tracking. They have proposed depth-enhanced tracker (DET) to improve the tracking-by-detection strategy along with an indoor MOT dataset. We can again see a different kind of problem statement in [49], which is to track crop seedlings. In this paper, Chenjiao et al. have used YOLOv4 as an object detector and tracked the bounding boxes got from the detector by optical flow.

Oluwafunmilola et al. have done object tracking along with object forecasting [50]. They have detected bounding boxes using FairMOT [54] and then have stacked a forecasting network and have made Joint Learning Architecture (JLE). Zhihong et al. have extracted new features of each frame to get the information globally and have accumulated partial features for occlusion handling [51]. They have merged these two kinds of features to detect the pedestrian accurately.

No paper has taken any measure to preserve the significant bounding boxes so that they are not eliminated in the data association stage except [52]. After detecting, Hong et al. applied Non-Maskable Suppression (NMS) in the tracking phase to reduce the probability of the important bounding boxes being removed [53]. Jian et al. also have used NMS to reduce redundant bounding boxes from the detector. They have re-detected trajectory location by comparing features and re-identified bounding boxes with the help of IoU. The ultimate outcome is a joint re-detection and re-identification tracker (JDI).

D. Attention Module

To re-identify the occluded objects, attention is needed. Attention means we only consider the objects of interest by nullifying the background so that their features are remembered for long, even after occlusion. The summary of using attention module in MOT field is given in Table IV.

In [41], Yaoye et al. have incorporated a strip attention module to re-identify the pedestrians occluded with the background. This module is actually a pooling layer that includes max and mean pooling which extracts features from the pedestrians more fruitfully so that when they are blocked, the model does not forget them and can re-identify further. Song et al. have wanted to use information from object localization in data association and also the information from data association in object localization. To link up between the two, they have used two attention modules, one for target and one for distraction [59]. Then they finally applied a memory aggregation to make strong attention.

Tianyi et al. have proposed spatial-attention mechanism [60] by implementing Spatial Transformation Network (STN) in an appearance model to force the model to only focus on the foreground. On the other hand, Lei et al. have at first proposed Prototypical Cross-Attention Module (PCAM) to
extract relevant features from past frames. Then they have used Prototypical Cross-Attention Network (PCAN) to transmit the contrasting feature of foreground and background throughout the frames [61].

Huiyuan et al. have proposed self-attention mechanism to detect vehicles [62]. The paper [36] also has a self-attention module applied in the dynamic graph to combine internal and external information of cameras.

JiaXu et al. have used both cross and self-attention in a lightweight fashion [58]. In Figure 5, we can see the cross-attention head of that architecture. The self-attention module is used to extract robust features decreasing background occlusion. Then the data is passed to the cross-attention module for instance association.

E. Motion Model

Motion is an inevitable property of objects. So this feature can be used in the area of multi-object tracking, be it for detection or association. Motion of an object can be calculated by the difference in position of the object between two frames. And based on this measure, different decisions can be taken as we have seen going through the papers. An overview is given in Table V.

Hasith et al. and Oluwafunmilola et al. have used motion to compute dissimilarity cost in [39] and [63] respectively. Motion is calculated by the difference between actual location and predicted location. To predict the location of an occluded object, Bisheng et al. used motion model based on LSTM [42]. Wenyuan et al. incorporated motion model with Deep Affinity Network (DAN) [64] to optimize data association by eliminating the locations where it is not possible for an object to situate [65].

Qian et al. also have calculated motion by measuring distance from consecutive satellite frames with Accumulative Multi-Frame Differencing (AMFD) and low-rank matrix completion (LRMC) [66] and have formed a motion model baseline (MMB) to detect and to reduce the amount of false alarms. Hang et al. have used motion features to identify foreground objects in the field of vehicle driving [67]. They have detected relevant objects by comparing motion features with GLV model. Gaoang et al. have proposed a local-global motion (LGM) tracker that finds out the consistencies of the motion and thus associates the tracklets [32]. Apart from these, Ramana et al. have used motion model to predict the motion of the object rather than data association which has three modules: Integrated Motion Localization (IML), Dynamic Reconnection Context (DRC), 3D Integral Image (3DII) [46].

In the year 2022, Shoudong et al. have used motion model for both motion prediction and association by proposing Motion-Aware Tracker (MAT) [68]. Zhibo et al. have proposed compensation tracker (CT), which can obtain the lost objects having a motion compensation module [69]. But Xiaotong et
al. have used motion model to predict the bounding boxes of objects [18] so as done in [67] but to make image patches as discussed in III-A.

F. Siamese Network

Similarity information between two frames helps a lot in object tracking. Thus the Siamese network tries to learn the similarities and differentiate the inputs. This network has two parallel sub networks sharing the same weight and parameter space. Finally, the parameters between the twin networks are tied up and then trained on a certain loss function to measure the semantic similarity between them. The summary of applying Siamese network in MOT task is given in Table VI.

Daitao et al. have proposed a pyramid network that embeds a lightweight transformer attention layer. Their proposed Siamese Transformer Pyramid Network has augmented the target features with lateral cross attention between pyramid features. Thus it has produced robust target-specific appearance representation [22]. Bing et al. have tried to uplift the region based multi object tracking network by incorporating motion modeling [70]. They have embedded the Siamese network tracking framework into Faster-RCNN to achieve fast tracking by lightweight tracking and shared network parameters.

Cong et al. have proposed a Cleaving Network using Siamese Bi-directional GRU (SiaBiGRU) in post-processing the trajectories to eliminate corrupted tracklets. Then they have established Re-connection Network to link up those tracklets and make a trajectory [31].

In a typical MOT network, there are prediction and detection modules. The prediction module tries to predict the appearance of an object in the next frame, and the detection module detects the objects. The result of these two modules is used in matching the features and updating the trajectory of objects. Xinwen et al. have proposed Siamese RPN (Region Proposal Network) structure as the predictor. They have also proposed an adaptive threshold determination method for the data association module [71]. Thus overall stability of a Siamese network has been improved.

In contrast to transformer models III-A, JiaXu et al. have proposed a lightweight attention-based tracking head under the structure of a Siamese network that enhances the localization of foreground objects within a box [58]. On the other hand, Philippe et al. have incorporated their efficient transformer layer into a Siamese Tracking network. They have replaced the convolutional layer with the exemplar transformer layer [21].

G. Tracklet Association

A group of consecutive frames of objects of interest is called a tracklet. In detecting and tracking objects, tracklets are first identified using different algorithms. Then they are associated together to establish a trajectory. Tracklet association is obviously a challenging task in MOT problems. Some papers specifically focus on this issue. Different papers have taken different approaches. Such an overview is as presented in Table VII.

Jinlong et al. have proposed Tracklet-Plane Matching (TPM), [72] where at first short tracklets are created from the detected objects, and they are aligned in a tracklet-plane where each tracklet is assigned with a hyperplane according to their start and end time. Thus large trajectories are formed. This process also can handle non-neighboring and overlapping tracklets. To mitigate the performance, they have also proposed two schemes.

Duy et al. have at first made tracklet by a 3D geometric algorithm [73]. They have formed trajectories from multiple cameras and due to this, they have optimized the association globally by formulating spatial and temporal information.

In [31], Cong et al. have proposed Position Projection Network (PPN) to transfer the trajectories from local to global context. Daniel et al. re-identifies occluded objects by assigning the new-coming object to the previously found occluded object depending on motion. Then they have implemented already found tracks further for regression, thus have taken

| Reference | Year | Motion Mechanism | Dataset | MOTA (%) |
|-----------|------|------------------|---------|----------|
| [39]      | 2019 | Dissimilarity Distance between Detected and Predicted Object | MOT17, KITTI | 46.9, 85.04 |
| [63]      | 2021 | Dissimilarity Distance between Detected and Predicted object | MOT15, MOT16, MOT17, MOT20 | 55.8, 73.8, 74.0, 60.2 |
| [42]      | 2021 | LSTM-based Model on Consecutive Frames | MOT16, MOT17 | 76.3, 76.4 |
| [65]      | 2021 | Kalman Filtering | MOT17 | 44.3 |
| [66]      | 2021 | Accumulative Multi-Frame Differencing and Low-Rank Matrix Completion | VISO | 73.6 |
| [67]      | 2021 | Distance of Motion Feature and Mean Vector of Gaussian Local Velocity Model | NJDOT | 100 (Anomaly Detection Accuracy) |
| [32]      | 2021 | Box and Tracklet Motion Embedding | MOT17, KITTI, UA-Detrac | 56.0, 87.6, 22.5 |
| [46]      | 2021 | Particle Filtering and Enhanced Correlation Coefficient Maximization | CroHD | 63.6 |
| [68]      | 2022 | Combination of Camera Motion and Pedestrian Motion (IML), Dynamic Motion-based Reconnection (DRC) | MOT16, MOT17 | 70.5, 69.5 |
| [69]      | 2022 | Motion Compensation with Basic Tracker | MOT16, MOT17, MOT20 | 69.8, 68.8, 66.0 |
| [18]      | 2022 | Kalman Filtering | MOT16, MOT17 | 73.3, 73.6 |
In [75], we can see a different strategy from the formers. En et al have considered each trajectory as a center vector and made a trajectory-center memory bank (TMB) which is updated dynamically and calculates cost. The whole process is named multi-view trajectory contrastive learning (MTCL). Additionally, they have created learnable view sampling (LVS), which notices each detection as key point which helps to view the trajectory in a global context. They have also proposed similarity-guided feature fusion (SGFF) approach to avoid vague features.

Et al have developed tracklet booster (TBooster) [76] to alleviate the errors which occur during association. TBooster has two components: Splitter and Connector. In the first module, the tracklets are split where the ID switching occurs. Thus the problem of assigning the same ID to multiple objects can be resolved. In the second module, the tracklets of the same object are linked. By doing this, assigning the same ID to multiple tracklets can be avoided. Tracklet embedding can be done by Connector.

IV. MOT BENCHMARKS

A typical MOT dataset contains video sequences. In those sequences, every object is identified by a unique id until it goes out of the frame. Once a new object comes into the frame, it gets a new unique id. MOT has a good number of benchmarks. Among them, MOT challenge benchmarks have several versions. Since 2015, in almost every year, they publish a new benchmark with more variations. There are also some popular benchmarks such as PETS, KITTI, STEPS, and DanceTrack.

As of now, the MOT challenge has 17 datasets for object tracking, which include MOT15 [81], MOT16 [82], MOT20, [6] and others. The MOT15 benchmark contains Venice, KITTI, ADL-Rundle, ETH-Pescross, ETH-Sunnyday, PETs, TUD-Crossing datasets. This benchmark is filmed in an unconstrained environment with both static and moving cameras. MOT16 and MOT17 are basically more updated benchmarks from MOT15 with high accuracy of ground truth and strictly followed protocols. MOT20 is a pedestrian detection challenge. This benchmark has 8 challenging video sequences (4 train, 4 test) in unconstrained environments [6]. In addition to object tracking, MOTS dataset has segmentation tasks too [40]. In general, the tracking dataset has a bounding box with a unique identifier for objects in a frame. But in MOTS, every

| Reference | Year | Method | Dataset | MOTA (%) |
|-----------|------|--------|---------|----------|
| [22]      | 2020 | CNN for Appearance extraction, LSTM and RNN for Motion modelling | Duke-MTMCT, MOT16 | 73.5, 55.0 |
| [70]      | 2021 | Implicit and Explicit motion modelling | MOT17, TAO-person, HiEve | 65.9, 44.3 (TAP@0.5), 53.2 |
| [71]      | 2021 | Siamese Network with Region Proposal Network | MOT16, MOT17, MOT20 | 65.8, 67.2, 62.3 |
| [21]      | 2021 | Single instance level attention | TrackingNet | 70.55 (Precision) |
| [58]      | 2022 | Dynamic search region refine and attention based tracking | MOT17, MOT20 | 67.2, 70.4 |
| [22]      | 2022 | Transformer based appearance similarity | UAV123 | 85.83 (Precision) |
TABLE VII
SUMMARY OF TRACKLET ASSOCIATION RELATED PAPERS

| Reference | Year | Method                                                                 | Dataset                                      | MOTA (%) |
|-----------|------|------------------------------------------------------------------------|----------------------------------------------|----------|
| [72]      | 2020 | Tracklet-plane matching process to resolve confusing short tracklets    | MOT16, MOT17                                 | 50.9, 52.4 |
| [77]      | 2021 | CenterTrack [78] and DG-Net [79] as tracking graph and GAEC*KLj         | WILDTRACK, PETS-09, Campus                    | 97.1, 74.2, 77.5 |
| [31]      | 2020 | CNN for appearance extraction, LSTM and RNN for motion modelling        | Duke-MTMC, MOT16                             | 73.5, 55.0 |
| [74]      | 2021 | Regression based two stage tracking                                     | MOT16, MOT17, MOT20                         | 66.8, 65.1, 61.2 |
| [76]      | 2021 | Tracklet splitter splits potential false ids and connector connects pure tracks to trajectory | MOT17, MOT20                                 | 61.5, 54.6 |
| [75]      | 2022 | Learnable view sampling for similarity-guided feature fusion and Trajectory-center memory bank for re-identification | MOT15, MOT16, MOT17, MOT20                 | 62.1, 74.3, 73.5, 63.2 |

object has a segmentation mask also. TAO [83] dataset has a huge size due to tracking each and every object in a frame. There is a dataset called Head Tracking 21. The task for this benchmark is to track the head of every pedestrian. STEP dataset has segmented and tracked every pixel. There are some other datasets; those are included in table VIII. Frequency of the datasets used in the papers those we review is shown in Chart 7. From the chart, we can see that MOT17 dataset is used more frequently than other datasets.

TABLE VIII
STATISTICS OF PUBLICLY AVAILABLE DATASETS

| Dataset          | No. of Frames | Size (Bytes) | Published year | Reference |
|------------------|---------------|--------------|----------------|-----------|
| DanceTrack       | 105000        | 16.5G        | 2022           | [84]      |
| TAO VOS          | -             | 2.4G         | 2021           | [85]      |
| Head Tracking 21 | 11464         | 4.1G         | 2021           | [46]      |
| STEP-ICCV21      | 2075          | 380M         | 2021           | [86]      |
| MOTS CVPR22      | 1381119       | -            | 2021           | [87]      |
| MOTS CVPR22      | 1378244       | -            | 2021           | [87]      |
| MOT20            | 13410         | 5.0G         | 2020           | [6]       |
| 3D-ZeF20         | 14398         | 14.0G        | 2020           | [88]      |
| TAO              | 4447038       | 347G         | 2020           | [83]      |
| CTMC-v1          | 152498        | 768M         | 2020           | [89]      |
| OWTB             | 4447038       | 350G         | 2020           | [83]      |
| MOTS             | 5906          | 783.5M       | 2019           | [40]      |
| MOT16            | 11235         | 1.9G         | 2016           | [82]      |
| MOT17            | 33705         | 5.5G         | 2016           | [82]      |
| PETS 2016        | -             | -            | 2016           | [90]      |
| MOT15            | 11283         | 1.3G         | 2015           | [81]      |
| KITTI Tracking   | -             | 15G          | 2012           | [91]      |
| TUD Multiview    | 179           | 387M         | 2010           | [92]      |
| Pedestrians      | -             | 4.9G         | 2009           | [93]      |
| TUD Campus, Crossing | 272    | 100M         | 2008           | [94]      |

*This dataset has scenes indoors only.

V. MOT METRICS

A. MOTP

Multiple Object Tracking Precision. It is a score given based on how precise the tracker is in finding the position of the object [95] regardless of the tracker’s ability to recognize object configuration and maintain consistent trajectories. As MOTP can only provide localization accuracy, it is often used in conjunction with MOTA (Multiple Object Tracking Accuracy), as MOTA alone can not account for localization errors. Localization is one of the outputs of an MOT task. It lets us know where the object is in a frame. Alone it can not provide a thorough idea of the tracker’s performance in object tracking.

\[
MOTP = \sum_t d_t^i / \sum_t c_t
\]

\(d_t^i\): The distance between the actual object and its respective hypothesis at time \(t\), within a single frame for each object \(o_i\) from the set a tracker assigns a hypothesis \(h_i\).
\(c_t\): Number of matches between object and hypothesis made at time \(t\).

B. MOTA

Multiple Object Tracking Accuracy. This metric measures how well the tracker detects objects and predicts trajectories without taking precision into account. The metric takes into account three types of error [95].

\[
MOTA = 1 - \frac{\sum_t (m_t + fp_t + mme_t)}{\sum_t g_t}
\]

\(m_t\): The number of misses at time \(t\)
\(fp_t\): The number of false positives
\(mme_t\): The number of identity switches
\(g_t\): The number of objects present at time \(t\)

MOTA has several drawbacks. MOTA overemphasizes the effect of accurate detection. It focuses on matches between...
predictions to ground truths at the detection level and does not consider association. When we consider MOTA without identity-switching, the metric is more heavily affected by poor precision than it is by re-call. The aforementioned limitations could lead researchers to tune their trackers towards better precision and accuracy at detection level whilst ignoring other important aspects of tracking. MOTA can only take into account the short-term associations. It can only evaluate how well an algorithm can perform first-order association and not how well it associates throughout the whole trajectory. But, it doesn’t take into account association precision/ID transfer at all. In fact, if a tracker is able to correct any association mistake, it punishes it instead of rewarding it. While the highest score in MOTA is 1 the is no fixed minimum value for the score, which can lead to a negative MOTA score.

C. IDF1

The Identification Metric. It tries to map predicted trajectories with actual trajectories, in contrast to metrics like MOTA which perform bijective mapping at the detection level. It was designed for measuring ‘identification’ which, unlike detection and association, has to do with what trajectories are there [96].

\[
ID - \text{Recall} = \frac{|IDTP|}{|IDTP| + |IDFN|}
\]

\[
ID - \text{Precision} = \frac{|IDTP|}{|IDTP| + |IDFP|}
\]

\[
IDF1 = \frac{|IDTP|}{|IDTP| + 0.5|IDFP| + 0.5|IDFN|}
\]

IDTP: Identity True Positive. The predicted object trajectory and ground truth object trajectory match.
IDFN: Identify False Negative. Any ground truth detection that went undetected and has an unmatched trajectory.
IDFP: Identity False Positive. Any predicted detection that is false.

Due to MOTA’s heavy reliance on detection accuracy, some prefer IDF1 as this metric puts more focus on association. However, IDF1 has some flaws as well. In IDF1, the best unique bijective mapping does not lead to the best alignment between predicted and actual trajectories. The end result would leave room for better matches. IDF1 score can decrease even if there are correct detections. The score could also decrease if there are a lot of un-matched trajectories. This incentives researchers to increase the total number of unique and not focus on making decent detections and associations.

D. Track-mAP

This metric matches the ground truth trajectory and predicted trajectory. Such a match is made between trajectories when the trajectory similarity score, \(S_{tr}\), between the pair is greater than or equal to the threshold \(\alpha_{tr}\). Also, the predicted trajectory must have the highest confidence score [96].

\[
Pr_n = \frac{|TPTn|}{n}
\]

\(n\): The total number of predicted trajectories. Predicted trajectories are arranged according to their confidence score in descending order.

\(Pr_n\): Calculates the precision of the tracker.

\(TPTn\): True Positive Trajectories. Any predicted trajectory that has found a match.

\(TPTr\): Number of true positive trajectories among n predicted trajectories.

\(Re_n\): Measures Re-call

\(gtTraj\): Ground Truth Object Trajectory using the equation for precision and recall further calculation is done to obtain the final Track − mAP score.

\[
InterpPr_n = \max(Pr_m)
\]

We first interpolate the precision values and obtain \(InterpPr\) for each value of \(n\). Then we plot a graph of \(InterpPr\) against \(Re_n\) for each value of \(n\). We now have the precision-recall curve. The integral from this curve will give us the Track − mAP score. There are some demerits to track mAP as well. It is difficult to visualize the tracking result for Track − mAP. It has several outputs for a single trajectory. The effect of the trajectories with low confidence scores on the final score is obscured. There is a way to ‘hack’ the metric. Researchers can get a higher score by creating several predictions that have a low confidence score. This would increase the chances of getting a decent match and thus increases the score. However, it is not an indicator of good tracking. Track − mAP can not indicate if trackers have better detection and association.

E. HOTA

Higher Order Tracking Accuracy. The source paper [96] describes HOTA as, “HOTA measures how well the trajectories of matching detections align, and averages this overall matching detection, while also penalizing detections that don’t match.” HOTA is supposed to be a single score that can cover all the elements of tracking evaluation. It is also supposed to be decomposed into sub-metrics. HOTA compensates for the shortcomings of the other commonly used metrics. While metrics like MOTA ignore association and heavily depend on detection(MOTA) or vice versa (IDF1), novel concepts such as TPAs, FPAs and FNFAs are developed so that association can be measured just like how TPs, FNs, and FPs are used to measure detection.

\[
HOTA_n = \sqrt{\frac{\sum_{c \in TP} A(c)}{|TP| + |FN| + |FP|}}
\]

\[A(c) = \frac{|TPA(c)|}{|TPA(c)| + |FNA(c)| + |FP(c)|}
\]

\(A(c)\): Measures how similar predicted trajectory and ground-truth trajectory are.

\(TP\): True Positive. A ground truth detection and predicted
detection are matched together given that $S \geq \alpha$. $S$ is the localization similarity and $\alpha$ is the threshold.

- **FN**: False Negative. A ground truth detection that was missed.
- **FP**: False Positive. A predicted detection with no respective ground truth detection.

**TPA**: True Positive Association. The set of True Positives that have the same ground truth IDs and the same prediction ID as a given $TP_c$.

$$TPA(c) = \{k\},$$

$$k \in \{TP|prID(k) = prID(c) \land gtID(c) = gtID(c)\}$$

**FNA**: The set of ground truth detections with the same ground truth ID as a given $TP_c$. However, these detections were assigned a prediction ID different from $c$ or none at all.

$$FNA(c) = \{k\},$$

$$k \in \{TP|prID(k) \neq prID(c) \land gtID(c) = gtID(c)\} \cup \{FN|gtID(k) = gtID(c)\}$$

**FPA**: The set of predicted detections with the same prediction ID as a given $TP_c$. However, these detections were assigned a ground-truth ID different from $c$ or none at all.

$$FPA(c) = \{k\},$$

$$k \in \{TP|prID(k) = prID(c) \land gtID(k) \neq gtID(c)\} \cup \{FP|prID(k) = prID(c)\}$$

$HOTA_\alpha$ means that this is HOTA calculated for a particular value of $\alpha$. Further calculation needs to be done to get the final HOTA score. We find the value of $HOTA$ for different values of $\alpha$, ranging from 0 to 1 and then calculate their average.

$$HOTA = \int_0^1 HOTA_\alpha \, d\alpha \approx \frac{1}{19} \sum_{\alpha \in \{0.05, 0.1, \ldots, 0.9, 0.95\}} HOTA_\alpha$$

We are able to break down $HOTA$ into several sub-metrics. This is useful to us because we can take different elements of the tracking evaluation and use them for comparison. We can get a better idea of the kind of errors our tracker is making. There are five types of errors commonly found in tracking, false negatives, false positives, fragmentations, mergers and deviations. These can be measured through detection recall, detection precision, association recall, association precision, and localization, respectively.

**F. LocA**

Localization Accuracy

$$LocA = \int_0^1 \frac{1}{TPA} \sum_{c \in \{TPA\}} S(c) \, d\alpha$$

$S(c)$: The spatial similarity score between the predicted detection and ground truth detection. This sub-metric deals with the error type deviation or localization errors. Localization errors are caused when the predicted detections and ground truth detections are not aligned. This is similar to but unlike $MOTP$ as it includes several localization thresholds. Commonly used metrics like $MOTA$ and $IDF1$ do not take localization into account despite the importance of object localization in tracking.

**G. AssA: Association Accuracy Score**

According to MOT Benchmark: "The average of the association jaccard index over all matching detections and then averaged over localization threshold” [96]. Association is part of the result of an MOT task that lets us know if objects in different frames belong to the same or different objects. The objects have the same ID and are part of the same trajectories. Association Accuracy gives us the average alignment between match trajectories. It focuses on association errors. These are caused when a single object in ground truth is given two different predicted detections, or a single predicted detection is given two different ground truth objects.

$$AssA_\alpha = \frac{1}{|TP|} \sum_{c \in \{TP\}} A(c)$$

**H. DetA: Detection Accuracy**

According to MOT Benchmark: "Detection Jaccard Index averaged over localization threshold” [96]. Detection is another output of an MOT task. It is simply what objects are within the frame. The detection accuracy is the portion of correct detections. Detection errors exist when ground truth detections are missed or when there are false detections.

$$DetA_\alpha = \frac{|TP|}{|TP| + |FN| + |FP|}$$

**I. DetRe: Detection Recall**

The equation is given for one localization threshold. We need to average over all localization thresholds [96].

$$DetRe_\alpha = \frac{|TP|}{|TP| + |FN|}$$

Detection recall errors are false negatives. They happen when the tracker misses an object that exists in the ground truth. Detection accuracy can be broken down into Detection recall and Detection precision.

**J. DetPr: Detection Precision**

The equation is given for one localization threshold. We need to average over all localization thresholds [96].

$$DetPr_\alpha = \frac{|TP|}{|TP| + |FP|}$$

As mentioned previously, detection precision is part of detection accuracy. Detection precision errors are false positives. They happen when the tracker makes predictions that does not exist in the ground truth.
K. AssRe: Association Recall

We need to calculate the equation below and then average over all matching detections. Finally, average the result over the localization threshold [96].

\[
AssRe_\alpha = \frac{1}{|TP|} \sum_{c \in \{TP\}} \frac{|TPA(c)|}{|TPA(c)| + |FNA(c)|}
\]

Association Recall errors happen when the tracker assigns different predicted trajectories to the same ground-truth trajectory. Association Accuracy can be broken down into Association Recall and Association Precision.

L. AssPr: Association Precision

We need to calculate the equation below and then average over all matching detections. Finally, average the result over the localization threshold [96].

\[
AssPr_\alpha = \frac{1}{|TP|} \sum_{c \in \{TP\}} \frac{|TPA(c)|}{|TPA(c)| + |FP\alpha(c)|}
\]

Association precision makes up part of association accuracy. Association errors occur when two different ground truth trajectories are given the same prediction Identity.

M. MOTSA: Multi Object Tracking and Segmentation Accuracy

This is a variation of the MOTA metric, so that the trackers performance of segmentation tasks can also be evaluated.

\[
MOTSA = 1 - \frac{|FN| + |FP| + |IDS|}{|M|}
\]

\[
= \frac{|TP| - |FP| - |IDS|}{|M|}
\]

Here \(M\) is a set of \(N\) non-empty ground truth masks. Each mask is assigned a ground truth track Id. \(TP\) is a set of true positives. A true positive occurs when a hypothesized mask is mapped to a ground truth mask. \(FP\) is false negatives, the set of hypothesized maps without any ground truth maps and \(FN\), false negatives are the ground truth maps without any corresponding hypothesized maps. The \(IDS\), ID switches are ground truth masks belonging to the same track but have been assigned different ID’s.

The downsides of \(MOTSA\) include, giving more importance to detection over association and being affected greatly by the choice of matching threshold.

N. AMOTA: Average Multiple Object Tracking Precision

This is calculated by averaging the \(MOTA\) value over all recall values.

\[
AMOTA = \frac{1}{L} \sum_{r \in \{\frac{1}{L}, \frac{2}{L} \ldots 1\}} \frac{1 + FP_r + FN_r + IDS_r}{num_{gL}}
\]

The value \(num_{gL}\) is the number of ground truth objects in all the frames. For a specific recall value \(r\) the number of false positive, number of false negative and the number of identity switches are denoted as \(FP_r\), \(FN_r\) and \(IDS_r\). The number of recall values is denoted using \(L\).

VI. APPLICATIONS

There is a myriad of applications for MOT. Much work has gone into tracking various objects, including pedestrians, animals, fish, vehicles, sports players, etc. Actually, the domain of multiple object tracking can not be confined to only a few fields. But to get an idea from an application point of view, we will cover the papers depending on specific applications.

A. Autonomous Driving

Autonomous driving can be said to be the most common task in Multiple Object Tracking. In recent years, this is a very hot topic in artificial intelligence.

Gao et al. have proposed a dual-attention network for autonomous driving where they have integrated two attention modules [97]. Fu et al. have at first detected vehicles by self-attention mechanism and then used multi-dimensional information for association. They have also handled occlusion by re-tracking the missed vehicles [62]. Pang et al. have combined vehicle detection with Multiple Measurement Models filter (RFS-M3) which is based on random finite set-based (RFS) introducing 3-D MOT [98]. Luo et al. have also applied 3-D MOT by proposing SimTrack which detects and associates the vehicle from point clouds captured by LiDAR.

Mackenzie et al. have done two studies: one for self-driving cars and the other for sports [99]. They have looked into the overall performance of Multiple Object Avoidance (MOA), a tool for measuring attention for action in autonomous driving. Zou et al. have proposed a lightweight framework for the full-stack perception of traffic scenes in the 2-D domain captured by roadside cameras [100]. Cho et al. have identified and tracked the vehicles from traffic surveillance cameras by YOLOv4 and DeepSORT after projecting the images from local to global coordinate systems [101].

B. Pedestrian Tracking

Pedestrian Tracking is one of the most frequent tasks of multiple object tracking systems. As streetcam videos are easy to be captured, much work has been done regarding human or pedestrian tracking. Consequently, pedestrian tracking is considered to be an individual field of research.

Zhang et al. have proposed DROP (Deep Re-identification Occlusion Processing) which can re-identify the occluded pedestrians with the help of appearance features of the pedestrians [102]. Sundararaman et al. have proposed HeadHunter to detect pedestrians’ heads followed by a re-identification module for tracking [46]. On the other hand, Stadler et al. have proposed an occlusion handling strategy rather than a feature-based approach followed by a regression-based method [74].

Chen et al. have introduced a framework applied by Faster R-CNN, KCF trackers and Hungarian algorithm to detect vehicle-mounted far-infrared (FIR) pedestrians [103]. Ma et al. have made a multiple-stages framework for trajectory processing and Siamese Bi-directional GRU (SiaBiGRU) for post-processing them [31]. They have also used a Position Projection Network for cross-camera trajectory matching.
Later on, in [104], Wang et al. have tracked pedestrians simply by using YOLOv5 for detection and DeepSORT for tracking. Patel et al. have proposed a number of algorithms regarding different aspects [105]. At first, they have created an algorithm to localize objects, then they proposed a tracking algorithm to identify any suspicious pedestrians from the crowd. There are a couple of algorithms for measuring physical distances as well.

C. Vehicle Surveillance

Vehicle Surveillance is also a very important task along with autonomous driving. To monitor the activities of vehicles, MOT can be applied.

Shi et al. have introduced a motion based tracking method along with a Gaussian local velocity (GLV) modeling method to identify the normal movement of vehicles and also a discrimination function to detect anomalous driving [67]. Quang et al. have focused more on Vietnamese vehicles’ speed detection. They have at first detected traffic by YOLOv4 and estimated speed by back-projecting it into 3-D coordinate system with Haversine method [106].

Wang et al. have used graph convolutional neural network to associate the bounding boxes of vehicles into tracklets and proposed an embedding strategy, reconstruct-to-embed with global motion consistency to convert the tracklets into tracks [32]. Zhang et al. have proposed a convolutional network based on YOLOv5 to solve the low recognition rate accuracy problem in tracking vehicles [107]. At last, Diego et al. have published a review paper regarding the traffic environment itself discussing various works of multiple object tracking under traffic domain [108].

D. Sports Player Tracking

In the age of artificial intelligence, rigorous analysis of players in any sport is one of the most important tactics. Thus MOT is used in many ways for sports player tracking.

In [109], Kalafatić et al. have tried to solve the occlusion problem of football players tracking by typical tracking by detection approach. They have also mentioned some challenges like similar appearance, varying size of projection of players, changing illumination, which MOT researchers should keep in mind to solve besides tracking. However, Naik et al. have addressed identity switching in real-world sports videos [110]. They have proposed a novel approach DeepPlayer-Track to track players and referees while retaining the tracking identity. They have used YOLOv4 and SORT to some extent.

In [111], Zheng et al. have argued that MOT can replace the use of hardware chips for target tracking. For long term real time multicamera multi target tracking of soccer player, they utilize KCF algorithm which has shown good robustness in terms of accuracy. In [112], Cioppa et al. have proposed a novel dataset of soccer videos. In which they have annotated multiple players, referees, and ball. They have also given some baseline on that dataset. In [113], Vats et al. have introduced ice hockey video analysis. Their system can track players, identify teams, and identify individual players. Their work overcomes the challenges of camera panning, zooming of hockey broadcast video.

E. Wild Life Tracking

One of the potential use cases of MOT is wildlife tracking. It helps wildlife researchers to avoid costly sensors which are not so reliable in some cases.

In [114], Marcos et al. have developed a uav based single animal tracking system. They have used YOLOv3 with particle filter for object tracking. Furthermore, in [115] Zhang et al. have addressed the challenge of animal motion and behavior analysis for wildlife tracking. Consequently, they have proposed AnimalTrack which is a largescale benchmark dataset for multi-animal tracking. They have also provided some baseline.

In [116], Guo et al. have proposed a method to utilize MOT to detect negative behavior of animals. As analysis of the behavior of animals is very important for breeding, they have shown that using two very popular trackers FairMOT [54] and JDE [65], they tracked groups of pigs and laying hens. Which further have helped them to analyze the improvement of health and welfare. However, one of the most interesting job is done by Ju et al. In [117], they have argued that monitoring the turkey health during reproduction is very important. Thus they have proposed a method to identify the behavior of turkeys utilizing MOT. They have introduced a turkey tracker and head tracker to identify turkey behavior.

MOT is also playing a vital role in tracking underwater entities like fish. In [118], Li et al. have proposed CMFTNet, which is implemented by applying Joint Detection and Embedding for extracting and associating features. Deformable convolution is applied furthermore to sharpen the features in complex context and finally, with the help of weight counterpoised loss the fish can be tracked accurately. Also, Filip et al. have analyzed some multiple object tracking works on tracking fish accomplished in the past [119].

F. Others

We can see the real-life application of MOT in other fields, as well as MOT, is not limited to some particular tasks.

In the field of visual surveillance, Ahmed et al. have presented a collaborative robotic framework that is based on SSD and YOLO for detection and a combination of a number of tracking algorithms [120]. Urbann et al. have proposed a siamese network-based approach for online tracking under surveillance scenarios [121]. Nagrath et al. have analyzed various approaches and datasets of multiple object tracking for surveillance [122].

Robotics is a very trendy topic in today’s world. In [123], Wilson et al. have introduced audio-visual object tracking (AVOT). Peireira et al. have implemented mobile robots and tracked them by typical SORT and Deep-SORT algorithms integrated with their proposed cost matrices [124].

We can also see the implementation of MOT in agriculture. To track tomato cultivation, Ge et al. have used a combination of YOLO-based shufflenetv2 as a baseline, CBAM for
attention mechanism, BiFPN as multi-scale fusion structure, and DeepSORT for tracking [125]. Tan et al. have also used YOLOv4 as detector of cotton seedlings and an optical flow-based tracking method to track the seedlings [49].

MOT can be also utilized in various real-life applications like security monitoring, monitoring social distancing, radar tracking, activity recognition, smart elderly care, criminal tracking, person re-identification, behavior analysis, and so on.

VII. Future Directions

As MOT is a trending research topic for many years, numerous efforts have been made on it already. But still, there is a lot of scope in this field. Here we would like to point out some of the potential directions of MOT.

1) Multiple object tracking under multiple cameras is a bit challenging. The main challenge would be how to fuse the scenes. But if scenes from non-overlapping cameras are fused together and projected in a virtual world, then MOT can be utilized to track a target object in a long area continuously. A similar kind of effort can be seen in [31]. A relatively new dataset Multi-camera multiple people tracking is also available [126]. Xindi et al. have proposed a real-time online tracking system for multi-target multi-camera tracking [127].

2) Class-based tracking system can be integrated with multiple object tracking. An MOT algorithm tries to track almost all moving objects in a frame. This will be better applied in real-life scenarios if class-based tracking can be possible. For example, bird tracking MOT system can be very useful in airports, because to prevent the clash of birds with airplanes on the runway some manual preventive mechanism is currently applied. It can be totally automated using a class-based MOT system. Class-based tracking helps in surveillance in many ways. Because it helps to track a certain type of object efficiently.

3) MOT is widely applied in 2D scenes. Though it is a bit challenging task, analyzing 3D videos utilizing MOT will be a good research topic. 3D tracking can provide more accurate tracking and occlusion handling. As in 3D scene depth information is kept, thus it helps to overcome one of the main challenges on MOT which is occlusion.

4) So far in most of the papers transformer is used as a black box. But transformer can be used more specifically in solving different MOT tasks. Some approaches are totally based on detection and further regression is applied to predict the bounding box of the next frame [128]. In that case, DETR [25] can be used to detect as it has very high efficiency in detecting objects.

5) In any application lightweight architecture is very important for real-life applications. Cause lightweight architecture is resource efficient and in real-life scenarios, we have constrained on resources mostly. In MOT lightweight architecture is also very crucial if we want to deploy a model in IoT embedded devices. Also to track in real-time, lightweight architecture plays a very important role. So without decreasing accuracy, if we can achieve more fps then, it can be implemented in real-life applications, where lightweight architecture is very necessary.

6) To apply in real-life scenarios, online multiple object tracking is the only possible solution. Thus inference time plays a very crucial role. We observe the trend of acquiring more accuracy from researchers in recent times. But if we can achieve an inference time of over thirty frames per second, then we can use MOT as real-time tracking. As real-time tracking is the key to surveillance thus it is one of the major future directions for MOT researchers.

7) A trend of applying quantum computing in computer vision can be seen in recent times. Quantum computing can be used in MOT as well. Zaech et al. have published the first paper of MOT using Adiabatic Quantum Computing (AQC) with the help of Ising model [129]. They expect that AQC can speed up the N-P hard assignment problem during association in future. As quantum computing has a very high potential in the near future, this can be a very promising domain to research on.

VIII. Conclusion

In this paper, we have tried to compact a summary and review of recent trends in computer vision in MOT. We have tried to analyze the limitations and significant challenges. At the same time, we have found that besides some major challenges like occlusion handling, id switching, there are also some minor challenges that may sit in the driving position in terms of better precision. We have added them too. Brief theories related to each approach are included in this study. We have tried to focus on each approach equally. We have added some popular benchmark datasets along with their insights. We have included some possibilities for future direction based on recent MOT trends. Our observation of this study is that recently researchers have focused more on transformer-based architecture. This is because of the contextual information memorization of transformer. As transformer is resource hungry to get better accuracy with a lightweight architecture, focusing on a specific module is necessary per our study. Finally, we hope this study will serve as complementary to a researcher in the field to start the journey in the field of Multiple Object Tracking.

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