GMOT-40: A Benchmark for Generic Multiple Object Tracking

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Abstract

Multiple Object Tracking (MOT) has witnessed remarkable advances in recent years. However, existing studies dominantly request prior knowledge of the tracking target (e.g., pedestrians), and hence may not generalize well to unseen categories. In contrast, Generic Multiple Object Tracking (GMOT), which requires little prior information about the target, is largely under-explored. In this paper, we make contributions to boost the study of GMOT in three aspects. First, we construct the first public GMOT dataset, dubbed GMOT-40, which contains 40 carefully annotated sequences evenly distributed among 10 object categories. In addition, two tracking protocols are adopted to evaluate different characteristics of tracking algorithms. Second, by noting the lack of devoted tracking algorithms, we have designed a series of baseline GMOT algorithms. Third, we perform a thorough evaluations on GMOT-40, involving popular MOT algorithms (with necessary modifications) and the proposed baselines. We will release the GMOT-40 benchmark, the evaluation results, as well as the baseline algorithm to the public upon the publication of the paper.

1. Introduction

Multiple Object Tracking (MOT) has long been studied in the computer vision community [13, 38], due to its wide range of applications such as in robotics, surveillance, autonomous driving, cell tracking, etc. Remarkable advances have been made recently in MOT, partly due to the progress of major components such as detection, single object tracking, association, etc. Another driving force comes from the popularization of MOT benchmarks (e.g., [20, 32, 40, 51, 61]). Despite the achievement, previous studies in MOT mostly focus on a specific object category of interest (pedestrian, car, cell, etc.) and rely on models of such objects. For example, detectors of such objects are often pre-trained offline, and motion patterns for specific objects are sometimes utilized as well. It remains unclear how well existing MOT algorithms generalize to unseen objects and hence constrains the expansion of MOT to new applications, especially those with limited data for training object detectors.

By contrast, Generic Multiple Object Tracking (GMOT), which requests no prior knowledge of the objects to be tracked, aims to deal with these issues. GMOT is however seriously under-explored, except for some early investigations [36, 37]. Comparing the progress in GMOT with that in MOT, we see a clear lack of GMOT benchmark, and the absence of GMOT baselines with effective deep learning ingredients.

Addressing the above issues, in this paper, we contribute to the study of GMOT in three aspects: dataset, baseline, and evaluation. First, we construct the first public GMOT dataset, dubbed GMOT-40, for systematical study of GMOT. GMOT-40 contains 40 carefully annotated sequences evenly distributed among 10 object categories. In addition, two tracking protocols are adopted to evaluate different characteristics of tracking algorithms. The first takes groundtruth object detection (annotation) as input and tests mainly the association component of GMOT. The second, namely one-shot GMOT [36, 37], takes as input the bounding box of one target object in the first frame, and aims to detect and track all objects of the same category and similar appearance across time. Figure 1 illustrates the one-shot GMOT Protocol.

1equal contribution
Second, we design a series of baseline tracking algorithms dedicated to one-shot GMOT. These baselines consist of a one-shot detection stage and a target association stage. The one-shot detection stage is adapted from the recently proposed GlobalTrack algorithm [27]. The target association stage comes from several typical MOT algorithms. For each baseline, the one-shot detection algorithm plays the role of public detector.

Third, we conduct thorough evaluations on GMOT-40. The evaluation involves both classic tracking algorithms (e.g., [8, 52, 53]) and recently proposed ones (e.g., [3, 12]), with necessary modifications. The results show that, as an important tracking problem, GMOT has a large room for improvement.

To summarize, we make three contributions in this paper: (1) the first public GMOT dataset, GMOT-40, which is carefully designed and annotated, along with evaluation Protocols, (2) a series of GMOT baselines adapted from modern deep-learning enhanced MOT algorithms, and (3) thorough evaluations and analysis on GMOT-40.

We will release the benchmark, evaluation results and the baseline algorithm to public upon publication of the paper.

### 2. Related Work

#### 2.1. MOT Algorithms

Multiple object tracking (MOT) has been an active research area for decades [13, 38]. Based on whether the target priors are presumed to the tracker, MOT approaches can be roughly categorized as model-based and model-free methods. In the context of model-based methods, the most popular framework is the tracking-by-detection one where a category-aware detector is employed for generating candidate proposals, and the tracker itself primarily focuses on solving the data association problem. Many methods have been investigated under this framework, such as Hungarian algorithm [6, 17, 25], network flow [15, 55, 57], graph multicut [24, 29, 49], multiple hypotheses tracking [11, 31] and multi-dimensional assignment [14, 46] using various of affinity estimation schemes. With recent advances in deep learning, deep neural networks are also learned to solve the data association problem [10, 12, 41].

Model-based MOT methods can automatically handle the entering and exiting events of targets. However, it heavily depends on using target priors by employing a category detector or the Re-identification (ReID) based affinity estimator. Therefore, most recent MOT methods in this category focus on pedestrian and vehicle tracking. For example, there is an increasing popularity in the community to leverage such as ReID dataset [33, 44, 59] or pose estimation dataset [2] to improve association robustness during tracking [10, 23, 28, 56], while others adopt the state-of-the-art person detection techniques, such as [3, 21, 42, 43, 45]. These detection and ReID networks are trained and hence limited by the available datasets, therefore, the generic targets will not be handled and tracked successfully by methods in this category.

Despite the dominant effort on the person and vehicle tracking, there are a number of works that have focused on other target categories. Cell tracking [7, 39, 50, 54] is a popular topic in this section. Detecting and tracking multiple objects, such as ants [30], bats [5], birds [37], bees [9] and fish [19, 47, 48] are also investigated. Methods proposed in those works also need special modeling of target appearance or motion pattern thus cannot be applied generally in generic targets either.

Model-free methods contribute another category of solutions to MOT. Tracking without target prior is primarily proposed for solving Single Object Tracking (SOT) where only one bounding box of target is given at the first frame and no category prior is known to the tracker. It is an emerging topic to extend the idea of model-free to the context of
MOT. However there is no unified framework so far. In [58], structure information is used to help the tracking of multiple appearance-wise similar objects. Appearance and motion models are learned in [35] to tackle sudden appearance change and occlusion. Both the two methods need the manual initialization of all targets. In [60], a generic category independent object proposal module is used to generate target candidates. Luo et al. [37] propose to use clustered Multiple Task Learning for generic object detection. All these works are evaluated on datasets that either have a limited number of sequences and target categories or are specially picked and adapted from other tracking tasks.

2.2. MOT Benchmarks

There are multiple benchmark datasets for model-based MOT. One of the oldest benchmarks is the PETS benchmark [18] which contains three sequences for single camera MOT while all of them are on pedestrians. Later on, a benchmark mainly for autonomous driving is KITTI [20] which contains two categories of pedestrian and vehicle. After that, a benchmark dataset solely on pedestrian tracking was proposed by Alahi et al. [1]. Although this benchmark contains 42 million pedestrian trajectories, yet its annotation is not high-quality (i.e., not annotated by human). Then a MOT benchmark dataset on just vehicle tracking was released with the name UA-DETRAC [51] which contains 100 sequences. In the same year MOT15 was released [32] which organized the publicly available MOT data by then and became one of the most popular MOT benchmarks. Yet it is worth noting that there are just two categories: people and vehicle in this benchmark, and only 22 sequences are included. Later, MOT16 [40] was published with 14 sequences, devoted to people and vehicle tracking. Recently, VisDrone [61] was released with 96 sequences and yet still focused on vehicle and people.

In addition to the popular MOT benchmark dataset mentioned above on people and vehicle tracking, there are some other benchmark datasets on special classes such as honey bees and cells. For example, the multiple cell tracking dataset [50] has 52 sequences with a focus on cell, the honey-bee tracking dataset [9] has 60 sequences of the honey bee.

Datasets dedicated for model-free MOT are rare. In [58], Zhang et al. collect a dataset with nine video sequences, each for a different type of target. Among the videos, three are adapted from a SOT dataset, while the rest videos are collected from YouTube. The dataset contains average of 3 targets per frame. Videos here have average of 842 frames in length. Targets in the dataset are present all-time in the video, which relieves the tracker of handling the entering and exiting event of targets. Luo et al. collected datasets with four and eight videos in [36] and [37] respectively for an early study of GMOT. Recent works [60, 35] tend to use mixed sequences picked from other SOT or multiple pedestrian tracking datasets.

Compared with the data used in previous studies, our proposed GMOT-40 dataset provides the first public dataset carefully designed and annotated for GMOT. GMOT-40 contains not only much more sequences than used in previous studies, but also involves more categories. Moreover, the target density in GMOT-40 is much higher than existing datasets, and the sequences involve many real-world challenges such as entering and exiting events, fast motion, occlusion, etc. As a result, the release of GMOT-40 is expected to largely facilitate future research in GMOT.

3. The Generic MOT Dataset GMOT-40

In this section, we will present the GMOT-40 dataset and the associated evaluation Protocols. As described in the related work, a serious GMOT dataset/benchmark is in great need for advancing the study of GMOT. By investigating the data issues in previous papers and borrowing ideas from recently popularized tracking benchmarks, we aim to construct a high-quality dataset in the following aspects:

- **Diversity in target category.** To address the generalizability concern in previous MOT studies, GMOT-40 is designed to contain 40 sequences from 10 different categories, which is larger than all previously studied datasets (typically less than 3 categories). The four sequences in each category are designed with further diversity. For example, the “person” category in GMOT-40 covers both normal “person” as in PASCAL-VOC and an unseen type “wingsuit”; the “insect” category covers “ant” and “bee”, both of which are unseen in MS-COCO or PASCAL-VOC; etc. Some sample frames in GMOT-40 are shown in Figure 2.

- **Real world challenges.** During sequence selection, we pay special attention to include sequences with various real-world challenges such as occlusion, target enter/exiting, fast motion, blur, etc. Moreover, the target density ranges from 3 to 100 targets per frame, with the average around 22. All these properties make GMOT-40 cover a wide range of scenarios.

- **High-quality annotation.** For high quality annotation, all the groundtruth bounding boxes and cross-frame association need to be done by hand, followed by careful validation and revision if needed.

It is worth noting that, while more sequences would likely further improve the data usability, the additional non-trivial efforts in manual annotation may postpone the timely release of the dataset. In fact, as shown in Table 1, GMOT-40 brings comprehensive improvements over previously used GMOT data, and is thus expected to facilitate the GMOT research in the future.
3.1. Data Collection

With the guidance mentioned above, we start by deciding 10 categories of objects that are highly possible to be dense and crowded. When selecting video sequences, we request that at least 90% of the frames in a sequence to have more than 10 targets. Moreover, these targets are selected to have a reasonably similar appearance and shape. The minimum length of the sequence is set to 100 frames.

After classes and requirements are determined, we started searching the YouTube with possible candidate videos. About 1000 sequences are initially picked as candidates. After scrutiny, we select 40 sequences out of them for better quality and more challenging task. Yet it does not mean that these 40 sequences are ready for annotation. Some of the sequences contain a large part that is irrelevant to our task. For example, in “balloon” category, there are starting and ending sections focusing on the stage or the crowd of the celebration in the festival, which are hence removed. In such a way, we carefully edit the video and select the best clips with minimum of 100 frames.

Finally, GMOT-40 contains 45 trajectories per sequence on average. The whole dataset includes 10,002 frames in total, and each sequence has an average length of 250 frames. 94.16% of the frames have more than 10 targets.

The statistics of GMOT-40 in comparison with other data used in GMOT studies are summarized in Table 1. Note that we use the category definition of GMOT-40 here since categories in other benchmarks are not general enough. As an example, both “sky diving” and “basketball” classes in [35] belong to the “person” class of GMOT-40.

3.2. Annotation

The annotation format follows that of MOT15 [32] where the detailed description is in the Supplementary Material. The only difference is that there is no out-of-view value and hence all bounding box in the groundtruth file should be considered for trackers.

Furthermore, only targets sharing similar appearance in the same sequence are annotated. This is because, for generic object tracking where no prior knowledge (e.g., about the appearance variation) of the target category is known, it is often unreasonable to treat two objects with very different appearances as from the same category. For this reason, when there exist objects from the same category but have very different appearances, e.g., balloons of totally different colors, only those with similar color will be treated as the targets to be tracked. Note that, this is also practically plausible: In the case where a task does request tracking multiple objects with two (or more) types of appearance, then all we need to do is to provide the target bounding boxes for the two types in the first frame.

The most important parts for building a high-quality GMOT dataset are manual labeling, double-checking, and error-correction. To ensure this, a group of experts such as Ph.D. students are included in the annotation team. For each video, it is first sent to the labeler to decide the group of instances sharing a similar appearance. Then an expert will...
review the target group to see whether it reaches our requirement. After approval by experts, the labeler will start working on the annotation. The completed annotation will again be sent to experts for review and possible revision.

3.3. Video Attributes

As shown in the Figure 2, diverse scenarios and hence more comprehensive attributes are included in GMOT-40 compared with other data used in previous GMOT papers. As an example, all of the “person”, “ball” and “insect” classes have the properties of motion-blur and fast motion. Besides, the viewpoint significantly affects the appearance in “boat” category. Furthermore, low resolution and camera motion appear in “ball” and “livestock” respectively.

A detailed histogram on various attributes are presented in Figure 3. The abbreviation of attributes have the following meaning: CM – camera motion; ROT – targets rotate; DEF – target deforms in the tracking; VC – significant viewpoint change that affects the appearance of target; MB – target is blurred due to camera or target motion; FM – fast motion of the targets with displacements larger than the bounding box; LR – target bounding box is smaller than 1024 pixel for at least 30% of the targets in the whole sequences.

Although some of the attributes above are present in previous studies of GMOT [35, 36, 37, 58, 60], yet GMOT-40 is the most comprehensive one since it is collected from various natural scenes. These miscellaneous attributes of GMOT-40 can help the community to evaluate their trackers from every aspect.

4. GMOT Protocols and Tracking Baselines

4.1. Protocols

Associated with the GMOT-40 dataset, we design two evaluation protocols: one resembles the classical design as in [32] and the other follows the one-shot setting in [37] for GMOT.

4.1.1 Protocol 1: Generic Object Association

In Protocol 1, we focus on evaluating the ability of trackers to successfully associate dense generic objects with similar appearance, as in some previous studies like [32]. Hence the groundtruth locations of all targets in each frame are provided. Both online and offline trackers are able to solve the association problem without being interfered by missing or fake target candidates. Besides, as a generic tracker, an algorithm is expected to work for the unseen categories and sequences in GMOT-40. Hence all 40 sequences are used to test the performance of the tracker. Researchers are encouraged to train their trackers on any datasets except GMOT-40.

4.1.2 Protocol 2: One-Shot GMOT

Protocol 2 is to comprehensively evaluate the GMOT trackers in real-world application settings. As claimed in [37], a practical generic tracker is model-free thus is able to track multiple generic objects knowing only a template of targets. By adopting this Protocol, only one bounding box in the first frame of each video is provided to indicate the objects of interest. Trackers are supposed to use the object in that bounding box as a template and leverage the information of that object to detect and track all the targets in the video with a similar appearance. All sequences in GMOT-40 are used to test the tracker for their performance on unseen category for the one-shot GMOT Protocol. For comparison, we also design several new baselines (see Section 4.2) to generate the public detection for the whole sequence using the only one sample given in the first frame. Trackers can be trained at any other benchmarks except GMOT-40.

To choose the initial target of one sequence, we extract features for all labeled targets on the first frame with ResNet [22]. Then we ranked the targets based on their Euclidean distance to the center of the feature space cluster and return the top five. After that, we carefully pick the best one out of the five by hand to ensure it is representative and robust as the one-shot sample.

4.2. Baselines for One-shot GMOT

For one-shot GMOT protocol, we propose a series of two-stage baselines by adapting existing tracking algorithms. Each baseline consists of a one-shot detection stage, which gets detection results for all frames in sequence, and a target association stage, which associates detected targets and gets the final tracking results.

4.2.1 One-Shot Detection Stage

In our implementation, we adopt a recently proposed SOT method, GlobalTrack [27], to create a one-shot detection
4.2.2 Target Association Stage

With these detection results, we now transform the one-shot GMOT task to a traditional MOT task with public detection. Most existing MOT algorithms can be adapted here to get association. In particular, we adopt the same MOT trackers used in Protocol 1 for consistency and comparison.

Combining the one-shot detection method with different target association methods, we get a series of baselines for the one-shot GMOT task. We evaluate their tracking performances comprehensively, as well as one-shot detection performances in Section 5.4.

5. Experiment

5.1. Evaluation Metrics

A group of metrics on MOT have been proposed to fairly compare the tracker and reveal the performance. Among them the most widely used ones are CLEAR MOT metrics [4] and ID metrics [44]. The former stresses the number of incorrect predictions while the latter focus on the longest time of following targets. Combining them will provide a comprehensive evaluation of the performance in GMOT-40.

Algorithm 1: One-shot Detection Process.

**Data:**
\{I_1, \ldots, I_m\}: images in a sequence;
\(x_{gt}\): initial detection (groundtruth box) in \(I_1\);
\(s_{th}\): threshold for detection similarity score.

**Model:**
\(\phi_R\): target-guided region proposal module;
\(\phi_M\): target-guided matching module.

**Output:**
\(\{x^k_i\}_{i=1}^{n_k}\): \(n_k\) detected targets for \(I_k\), \(1 \leq k \leq m\).

1. Extract features for the initial target;  
2. \(F_{g} = \phi_R(I_1, x_{gt})\);
3. for \(k = 1, \ldots, m\) do
4. \quad Use \(F_{g}\), \(\phi_R\) to produce \(r_k\) regions \(R\) that may contain targets on image \(I_k\);
5. \quad \(R = \{x^1_k, \ldots, x^n_k\} = \phi_R(F_{g}, I_k)\);
6. \quad Use \(\phi_M\) to extract features \(F_R\) from \(R\);
7. \quad \(F_R = \{f^1_k, \ldots, f^n_k\} = \phi_M(R)\);
8. Compute similarity scores \(S\) between \(F_R\) and \(F_{g}\), and produce targets \(T\) with refined positions;
9. \quad \(S = \{s^1_k, \ldots, s^n_k\} = \phi_M(F_{g}, F_R)\);
10. \quad \(T = \{\hat{x}^1_k, \ldots, \hat{x}^n_k\} = \phi_M(F_{g}, F_R)\);
11. Filter \(T\) by comparing \(S\) with \(s_{th}\), and then get the final \(n_k\) targets \(T^k\);
12. \quad \(T^k = \{x^1_k, \ldots, x^n_k\} = C(T, S, s_{th})\);
13. where \(C\) denotes the comparison process;
14. end

5.2. Evaluated Trackers

We focus on the trackers that are built on public detection and have publicly available code. Both classical and more recent trackers are included to provide a comprehensive review. Among them, there are FAMnet [12], Deep SORT [52], MDP [53], IOU tracker [8]. For the other recent SOTA (State Of The Art) papers, they are either excluded due to the code availability or the algorithms heavily relying on the other tracker for pre-processing [10].

5.3. Protocol 1 Evaluation

In Protocol 1, each tracker is used in its initial setting with the pre-trained model without any further modification. The groundtruth detections are provided for the tracker. The result is presented in Table 2. Note that our benchmark contains many categories that are unseen for the tracker during their training. Hence the benchmark would favor the association based on Intersection Over Union (IOU) of targets across frames rather than appearance features. As a result, the simple IOU tracker has the 2nd best IDF1 and MOTA of 0.825 and 0.824, respectively. While using both motion and appearance information, Deep SORT has the best MOTA and IDF1 score by maintaining a reasonable balance between them. For MDP, its performance is not as good as Deep SORT and IOU tracker. The reason may be its superfluous processing on detection since we di-
Protocol 1

Figure 4. Results visualization of trackers on hard, medium and easy sequences using different protocols.

Table 2. Comparison of trackers using Protocol 1.

| Tracker                | MOTA | IDF1 | IDP  | IDR  | Rcll | Prcn | MT  | PT  | ML↓ | FP↓ | FN↓ | IDS↓ | FM↓ |
|------------------------|------|------|------|------|------|------|-----|-----|-----|-----|-----|------|-----|
| MDP [53]               | 70.10% | 75.10% | 79.40% | 71.20% | 80.30% | 89.60% | 931 | 278 | 211 | 10  | 4443 | 1845 | 4976 |
| DeepSORT [52]          | 88.60% | 82.90% | 84.60% | 81.20% | 97.10% | 1326  | 347 | 91  | 6191| 347 | 1543 | 1326 | 3045 |
| IOU [8]                | 82.40% | 82.50% | 85.10% | 80.20% | 88.60% | 94.00% | 1228| 259 | 1264| 840 | 1323 | 741  | 845 |
| FAMnet [12]            | 45.20% | 56.90% | 90.80% | 41.40% | 45.60% | 99.90% | 434 | 91  | 4976| 347 | 1226 | 1323 | 3769 |

Table 2. Comparison of trackers using Protocol 1.

rectly provide groundtruth detection here. For FAMnet [12], its mediocre performance is mainly due to processing on detection noise. Although groundtruth detections are provided here, FAMnet drops too many detection and hence causes many false negatives. A qualitative result of the 4 trackers is visualized in the first row of Figure 4 and different color represents a different trajectory. More qualitative analysis are provided in Supplementary Materials.

Furthermore, we include Figure 5 to compare the performance under different categories. The average scores are calculated for all 5 trackers in each category. We can see that in average all trackers achieve the best performance in “car” but not so good in others. This suggests that our GMOT-40 is more challenging than traditional vehicle tracking datasets dedicated to only the “car” class. Besides, the difference int performance among the categories emphasizes the importance of releasing a GMOT benchmark to better evaluate trackers.
|                  | MOTA   | IDF1  | IDP    | IDR    | Rcll   | Prcn | MT      | PT      | ML↓    | FP↓   | FN↓   | IDs↓  | FM↓  |
|------------------|--------|-------|--------|--------|--------|------|--------|--------|-------|-------|-------|-------|------|
| MDP [53]         | 18.10% | 35.10%| 51.30% | 26.70% | 35.60% | 68.40%| 155    | 694    | 915   | 37157 | 145329| 2229 | 3876 |
| DeepSORT [52]    | 14.20% | 34.80%| 47.30% | 27.50% | 36.90% | 63.40%| 166    | 741    | 857   | 48002 | 142382| 3254 | 4065 |
| IOU [8]          | 10.60% | 23.20%| 49.50% | 15.10% | 20.80% | 68.00%| 58     | 468    | 1238  | 22051 | 178645| 1085 | 2652 |
| FAMnet [12]      | 14.40% | 30.60%| 57.50% | 21.10% | 26.60% | 69.60%| 105    | 636    | 1023  | 26266 | 165512| 1281 | 4916 |

Table 3. Comparison of trackers using Protocol 2.

![Figure 5](image-url) Average scores of all trackers for different classes in Protocol 1.

![Figure 6](image-url) Average scores of all trackers for different classes in Protocol 2.

5.4. Protocol 2 Evaluation

We first evaluate the quality of the proposed target candidates that are generated by our baseline algorithm. Since in one-shot generic setting, the difference between categories is inconsequential. Thus we directly use AP (Average Precision) as our metric to report the “detection” solely performance. We have $AP_{0.5}$ of 18.20% and $AP_{0.75}$ of 18.01% while setting the IOU threshold at 0.5 and 0.75 respectively. Note that our baseline target candidate proposal is not trained on GMOT-40, so it is consistent with Protocol 2 in Section 4.1.2. In qualitative analysis, the baseline is found out to behave badly with deformation, rotation out-of-plane, motion blur and low resolution. The reason may be that the matching module of our modified GlobalTrack produced too many false negatives while ranking the confidence in the final stage.

The detection results generated by our baseline algorithm serve as public detections in the following experiments. We test the trackers on all 40 sequences with its initial setting. The results as well as MOTA and IDF1 are listed in the Table 2. We can see from there that almost all trackers’ performances drop significantly due to the use of public detection. With the inclusion of the one-shot detector, MDP becomes the best among them all. Yet its IDF1 is just 35.10% and MOTA is just 18.10%. Deep SORT and FAMnet here behave slightly worse than MDP with the IOU tracker after them. In other words, there is correlation between their processing of detection and their performance. A sample of results is presented in the second row of Figure 4 with each color standing for a different trajectory. More qualitative analysis are included in Supplementary Materials.

Besides, we include Figure 6 to compare the performance in different classes. Each bar represents the mean of all 5 trackers. Generally speaking, the trackers perform much worse in Protocol 2 than in Protocol 1. Specically, the “balloon” class poses a challenge for all the trackers, causing a negative average score of MOTA. This again proves the necessity of diversity and hence the release of GMOT-40. A more detailed version with ablation study is included in Supplementary Material.

6. Conclusion

In this paper, we proposed the first, to the best of our knowledge, generic multiple object tracking (GMOT) benchmark named GMOT-40. By thoroughly considering major MOT factors and carefully annotating all tracking objects, GMOT-40 contains 40 sequences evenly distributed in 10 object categories. Associated with GMOT are two GMOT evaluation Protocols, one focusing on target association and the other on one-shot tracking. Several new baseline algorithms dedicated to one-shot GMOT are developed as well, and evaluated together with relevant MOT trackers to provide references for future study. The evaluation shows that there is still large room to improve for GMOT and further studies are desired. Overall, we expect the benchmark, along with the initial studies, to largely facilitate future research on GMOT, which is an important yet under-explored problem in computer vision.

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GMOT-40: A Benchmark for Generic Multiple Object Tracking
—Supplementary Material—

1. Label Format for GMOT-40

The label format for proposed GMOT-40 is shown in the Table 1. We mainly follow the format of the widely-used MOT15 dataset [4]. The only difference is, MOT15 does not take some challenging targets, like small ones, into consideration for evaluation. It uses an extra flag to indicate that these labeled targets should be ignored. On the contrary, GMOT-40 includes all of them in evaluation, no matter how challenging the targets could be, and the flag is not used here. This is consistent with our motivation, i.e., trackers need to deal with these real world challenges.

2. Qualitative Analysis

2.1. Protocol 1

We copy the visualization result figure from body part to Figure 2 here for convenience of reference, which includes top-4 tracker results. Each bounding box with a polygon line in color represents a tracked target and its trajectory. For the 2nd row of fish sequence in Protocol 1 result, Deep SORT [6] and IOU tracker [2] have tracked more targets than MDP [7] and FAMnet [3]. The reason might be Deep SORT and IOU tracker mainly adopt IOU-based tracking paradigm, and they could perform well with all ground truth detection results available. But MDP and FAMnet have superfluous pre-processing on detection which may be harmful under this protocol. Note the visualization result may not be consistent with the quantitative result in the main body for each sequence, due to the averaging process of computing metrics.

2.2. Protocol 2

The Protocol 2 visualization results are shown in the bottom three rows of Figure 2. With public detection instead of ground truth available, IOU tracker performance drops a lot. We think this is because IOU tracker can not handle errors, like false positive/negative detection results, induced by imperfect detectors. By contrast, MDP, Deep SORT and FAMnet have extra mechanisms to refine these faulty detection results during tracking process. Furthermore, unlike Deep SORT and FAMnet, MDP did not use any pre-trained CNN, which makes itself more robust against during generalization to unseen categories.

2.3. Tracking Videos

To show the real tracking process, we transform these results of these sequences into a video, including these four trackers of two protocols mentioned in Figure 2. We show the first 72 frames of each sequence with a frame rate of 24 FPS. (updated video here-combined.mp4: https://drive.google.com/drive/folders/1qO6QQq8t6YRNM2pGRz−hdWg7ACD5ZMJAJ?usp=sharing)

3. One-shot Detection Evaluation

To further understand the evaluation results of Protocol 2, we evaluate the detection performance of the one-shot detector. We compute $AP_{50}$ and $AP_{75}$ (Average Precision with IOU threshold as 0.5 and 0.75) for each class of GMOT-40. The result is shown in Figure 1.

Note that the class with higher detection score does not necessarily result to a better tracking performance. For example, the detection result of balloon class has a higher AP than the one of boat class. But the tracking performance of balloon class is worse. We think it is because balloon...
Table 1. Annotation format in GMOT.

| Position | Name                | Description                                                                 |
|----------|---------------------|-----------------------------------------------------------------------------|
| 1        | Frame number        | Starts from 0, indicates which frame the target belongs to                  |
| 2        | Identity number     | Each trajectory is identified as an unique ID. For detection, it is set to be -1. |
| 3        | Bounding box left   | Coordinates of the top-left corner of the bounding box                      |
| 4        | Bounding box top    | Coordinates of the top-left corner of the bounding box                      |
| 5        | Bounding box width  | Width of bounding box in pixels                                             |
| 6        | Bounding box height | Height of bounding box in pixels                                            |
| 7        | Confidence score    | Predicted probability of the detection being foreground. For groundtruth, it is set to be 1. |
| 8-10     | -1                  | Padding to fit MOTChallenge format                                           |

MDP [7] Deep SORT [6] IOU tracker [2] FAMnet [3]

![Figure 2. Results visualization of trackers on hard, medium and easy sequences using different protocols.](image)

class has more critical occlusion problem than boat class. Specifically, there are situations that a balloon is occluded totally by another balloon and then appears again in following frames. Such situations appear much less in the boat class.

For the overall one-shot detection performance, it is relatively lower than current detectors with full supervised training (over 50 mAP on COCO [5]), which demonstrates the difficulty and necessity of the one-shot GMOT protocol. A better one-shot GMOT tracker may require the improvement on both one-shot detection and data association stage.
Figure 3. Scores in protocol 1

Figure 4. Scores in protocol 2

4. Scores for all sequences

Figure 3 and Figure 4 present the scores for both protocols and all sequences. We can see that the sequences that are easy to handle in protocol 1 may be challenging in protocol 2. Yet the challenging sequences in protocol 1 are still difficult in protocol 2. Such difference and similarity again stress the importance and necessity of a one-shot framework in Generic MOT.
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