JRDB-Pose: A Large-scale Dataset for Multi-Person Pose Estimation and Tracking

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Abstract

Autonomous robotic systems operating in human environments must understand their surroundings to make accurate and safe decisions. In crowded human scenes with close-up human-robot interaction and robot navigation, a deep understanding of surrounding people requires reasoning about human motion and body dynamics over time with human body pose estimation and tracking. However, existing datasets captured from robot platforms either do not provide pose annotations or do not reflect the scene distribution of social robots. In this paper, we introduce JRDB-Pose, a large-scale dataset and benchmark for multi-person pose estimation and tracking. JRDB-Pose extends the existing JRDB which includes videos captured from a social navigation robot in a university campus environment, containing challenging scenes with crowded indoor and outdoor locations and a diverse range of scales and occlusion types. JRDB-Pose provides human pose annotations with per-keypoint occlusion labels and track IDs consistent across the scene and with existing annotations in JRDB. We conduct a thorough experimental study of state-of-the-art multi-person pose estimation and tracking methods on JRDB-Pose, showing that our dataset imposes new challenges for the existing methods. JRDB-Pose is available at https://jrdb.erc.monash.edu/.

1. Introduction

Visual scene understanding of human environments is a difficult and crucial task for autonomous driving, human-robot interaction, safe robotic navigation, and human action recognition. Although rough predictions of human location are sufficient for some applications, a deep understanding of crowded human scenes and close-up human-robot interaction requires reasoning about human motion and body dynamics with human body pose estimation and tracking. Developing an AI model to predict human body pose is made more difficult by the varied and highly imbalanced range of human motion found in daily living environments, including a variety of scales, occlusions, and overlapping humans, representing a long-tailed distribution of human poses which is difficult for existing methods.

Human pose estimation and tracking is an active research area with many new large-scale datasets [13, 16, 26, 46] contributing to significant recent progress; however, these datasets do not primarily target robotic perception tasks in social navigation environments, and thus rarely reflect specific challenges found in human-robot interaction and robot navigation in crowded human environments, e.g. shopping malls, university campus, etc.

JRDB [28] previously introduced a large-scale dataset and a benchmark for research in perception tasks related to robotics in human environments. The dataset was captured using a social manipulator robot with a multi-modal sensor suite including a stereo RGB 360° cylindrical video stream, 3D point clouds from two LiDAR sensors, audio and GPS positions. JRDB [28] additionally introduced annotations for 2D bounding boxes and 3D oriented cuboids. Recently, JRDB-Act [15] further introduced new annotations on the JRDB videos for individual actions, human social group

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Our contributions are:

- We introduce JRDB-Pose, a large-scale pose estimation and tracking dataset providing pose annotations and head boxes with tracking IDs and per-keypoint occlusion labels.
- In addition to adopting the popular metrics, we introduce new metrics, OSPA-Pose and OSPA\(^{(2)}\)-Pose for pose estimation and tracking, respectively.
- We conduct a comprehensive evaluation of state-of-the-art methods on JRDB-Pose and discuss the strengths and weaknesses of existing methods.

### 2. Related Datasets

We summarize the commonly used public datasets for pose estimation [3,26,26,47,54], pose tracking [13,46] and multi-object tracking [12,18,35,41] in Tab. 1.

#### Single and Multi-person Pose Estimation Datasets:

The task of 2D pose estimation involves predicting the pixel locations of human skeleton keypoints on an image. The MPII Human Pose Dataset [3] is a popular multi-person pose estimation dataset and benchmark including videos from everyday human activities, and the larger Penn Action dataset [54] provides both pose and action annotations in sports settings with a single pose per frame. MS COCO Keypoints Challenge [26] proposed a large-scale dataset including a diverse set of scenes and occlusion labels. All of these datasets label individual frames, limiting them to single-frame pose estimation. Human3.6M [20] annotates videos and single-person 3D poses from a controlled indoor scene, while 3DPW [47] provides estimated 3D human meshes in-the-wild with up to 2 people per frames. In comparison, JRDB-Pose is captured from a robotic platform in-the-wild with crowded and manually-annotated indoor and outdoor scenes, addressing a different set of challenges. JRDB-Pose also includes diverse data modalities including cylindrical video, LiDAR point clouds, and rosbags.

#### Multi-Person and Multi-Object Tracking Datasets:

Multi-Person Pose Tracking (MPPT) and Multi-Object Tracking (MOT) are crucial tasks in robotic perception and navigation, where the challenge is to track, across a video, the body keypoints of individuals or the locations of objects,
Various statistic for JRDB-Pose, which provides visibility labels and track ids consistent across long periods of occlusion. From left to right: 1) The distribution of track lengths, with the long tail truncated. 2) A log-scaled distribution showing all track lengths. JRDB-Pose track lengths are varied and as high as 1700 frames long. 3) Number of pose annotations in each panoramic frame. 4) Number of keypoints in each pose annotated as visible.

Respectively. MOT has attracted significant attention from the community with large-scale challenges [12, 25, 30], and MPPT is increasingly becoming recognized for its significance in human activity understanding and human-object interaction. Despite high performance on easy scenes, current MPPT methods struggle in crowded environments with occlusions and scale fluctuations.

Posetrack 2018 [2] introduced a benchmark for pose estimation and tracking using annotated video sequences featuring a variety of in-the-wild scenarios such as sports and dancing. Since PoseTrack was not densely labeled in crowded scenes, it required large “ignore regions” containing regions of images and videos lacking annotations. More recently, Posetrack21 [13] used the videos from PoseTrack 2018 to provide dense annotations of crowded scenes. Both datasets target diverse pose tracking scenarios, containing videos such as surveillance-like footage that are different from typical robotic navigation and human-robot interaction scenarios. Additionally, each video sequence is limited to five seconds, while sequences in JRDB-Pose are up to 2 minutes long. JRDB-Pose is a challenging dataset and benchmark for real-world tracking tasks, containing videos captured in crowded environments with humans fading into and emerging from the crowd.

Autonomous Driving Datasets: Recently, autonomous vehicle datasets have been released featuring large-scale and detailed annotations of the surrounding environment, posing difficult MOT and MPPT challenges. H3D [35] annotates human detections and tracks. More recently, the Waymo Open Dataset [46] filled the gap by providing 172.6K human pose annotations from their autonomous vehicle navigating outdoor road and highway environments. While the data is valuable for driving applications, the dataset contains exclusively outdoor road and highway environments making it unsuitable for non-driving robotic tasks, e.g. navigating a crowded shopping mall.

Robotic Navigation: Robotics operating in a social environment must learn to navigate in a socially-compliant manner by detecting and reacting to other agents in the environment. Existing datasets for robotic navigation [23, 28, 41] provide relatively few annotations and are often created in limited environment. The THOR dataset provides human trajectories on a ground plane, and is filmed in a controlled indoor environment. SCAND [23] captures a variety of crowded indoor and outdoor environments without annotations for human detection or tracking. In human environments with complex interactions, it is crucial to understand human motion more deeply than a bounding box. To this end, JRDB-Pose is one of the first datasets providing large-scale pose annotations in a robotic navigation environment.

Synthetic Datasets: Several recent works have proposed large synthetic datasets for human pose estimation and tracking by generating data using a video game engine. The Joint Track Auto (JTA) [17] dataset generates 10M annotated human body poses, which MotSynth [16] extends to 40M human poses with associated track IDs. While synthetic datasets have been shown to be helpful to the existing frameworks’ performance boost when combined with the real-world datasets [16], they may not reflect underlying biases and distributions in real-world data, preventing them from being the only training data resources for evaluating approaches in real-world applications.

State-of-the-art Frameworks: Multi-person pose estimation involves predicting body keypoint locations for all people in an image and identifying which keypoints belong to which individuals. There are two common types of approaches to this problem: top-down methods first detect all people and then execute pose estimation for each individual [24, 34, 49, 53], while bottom-up methods first identify
keypoints and then group them into individual people [7], including disentangled representations [19], associative embedding [32], HGG [22], YOLO-Pose [27], and CID [48].

Multi-person pose tracking approaches [7, 34, 44, 53] often identify keypoints or poses using a pose estimation method, and then predict tracks using the estimated keypoints. Top-down techniques like openSVAI [34] and PGG [21] decompose the task into three discrete stages: human detection, pose estimation, and then pose tracking. Recently, UniTrack [50] proposed a unified framework for multiple object and keypoint tracking utilizing shared general-purpose appearance models.

The multi-object tracking task can be categorized into tracking by detection (TBD) [8, 14, 42, 51, 55] and joint detection and tracking (JDT) [5, 11, 29, 45, 52, 56, 57]. SORT-based [6] approaches [8, 14, 51] have gained popularity with methods including DeepSORT [51] and StrongSORT [14]. In addition, OC-Sort [8] improved these methods by proposing an enhanced filter and recovery strategy suitable for tracking non-linearly moving and frequently occluded objects. Recently, ByteTrack [55] achieved efficient and precise tracking results using a general association technique that utilizes nearly every detection box. Popular JDT methods include Traktor++ [5] which uses integrated detection-tracking modules and CenterTrack [56] which employs two-frames tracking algorithm for real-time and accurate tracking. Overall, since significant research in multi-person pose and multi-object tracking focuses on refining track consistency, occlusion recovery, and missing and false detection handling, JRDB-Pose is a useful and challenging benchmark for existing and future works.

3. The JRDB-Pose Dataset

We create JRDB-Pose using all videos from the JRDB dataset [28], including 64 minutes of sensory data consisting of 54 sequences captured from indoor and outdoor locations in a university campus environment. JRDB-Pose includes 57,687 annotated panoramic (3760 x 480) frames, containing total of 636k annotated pose instances with 11 million labeled keypoints with occlusion labels for each keypoint. We annotate 17 keypoints for each body pose including head, eyes, neck, shoulders, center-shoulder, elbows, wrists, hips, center-hips, knees and ankles. Each pose includes a tracking ID which is consistent for each person across the entire scene, including across long periods of full occlusion (see Fig. 4), and is also consistent with person IDs for existing 2D and 3D bounding box annotations from JRDB. Fig. 2 shows the distribution of track lengths present in JRDB-Pose. In total, JRDB-Pose provides 5022 pose tracks with an average length of 124 frames and some tracks as long as 1700 frames.

We started our annotation process using the JRDB bounding boxes and tracking IDs for each person in the scene. Annotators manually label human poses, and all the annotations were carefully quality-assessed to ensure high-quality and temporally consistent annotations. Details on our annotation protocol can be found in Appendix A.

We annotated all persons from the 5 camera views of the 360° cylindrical video stream that had either a large enough bounding box (area $\geq 6000$ pixels) or clear keypoint locations. For researchers interested in panoramic views, we merge the annotations from the 5 camera views into a single panoramic image. Note that this means not all visible people are labeled, especially those far away from the robot. Poses were annotated at 7.5 Hz and finally upsampled to 15 Hz, providing accurate high-frequency annotations without significant jitter.

JRDB-Pose labels poses for a wide range of scales, as shown in Fig. 6. We visualize the pose scales for each training and validation scene in Fig. 5, showing that the distribution of scales also varies significantly by scene as the types human motions and activities vary. Details on testing scenes

| Annotations                  | Quantity | Track IDs |
|------------------------------|----------|-----------|
| 2D Body Bounding Box [28]    | 2,400,000 | ✓         |
| 3D Body Bounding Box [28]    | 1,800,000 | ✓         |
| Atomic Action [15]           | 2,800,000 | N/A       |
| Social Group [15]            | 600,000   | N/A       |
| 2D Head Bounding Box         | 600,000   | ✓         |
| 2D Body Pose                 | 600,000   | ✓         |

Table 2. A summary of annotations in JRDB [28], JRDB-Act [15], and JRDB-Pose, which together provide a unique multi-modal dataset suitable for multi-person detection, pose estimation tracking, and activity recognition. Bolded annotations are introduced in this paper.
Figure 5. Distribution of bounding box scales in the train and validation scenes. JRDB-Pose contains a wide distribution of pose scale that is different for each scene.

Figure 6. Bounding box distribution of the train/validation and test splits. JRDB-Pose contains a wide distribution of pose scales. are not shown because test data is held out.

JRDB [28] and JRDB-Act [15] previously introduced annotations including 2D and 3D bounding boxes with tracking IDs, atomic action labels, and social groups. Together with JRDB and JRDB-Act annotations, JRDB-Pose is a multi-task learning dataset for human detection/tracking, pose estimation/tracking, individual action, social group, and social activity detection. Tab. 2 summarizes all annotations now available on videos from JRDB.

Occlusion: Occlusion is a key problem for human pose estimation and tracking because it causes incomplete information for predicting keypoints, leading to major errors in pose estimation tasks [33]. Significant research in the field of pose estimation has focused on occlusion-aware methods for improving pose estimation [1, 9, 10], but may be limited by lack of quantity and diversity in the existing data [9]. JRDB-Pose advances this research by providing large-scale data including occluded scenarios, as well as detailed occlusion labels for every keypoint which we hope will be useful for quantifying and improving performance under occlusion. In particular, we assign each keypoint a label in \{0, 1, 2\} defining its occlusion type, where for every pose we annotate the position and occlusion of each keypoint:

Figure 7 shows that the training scenes of JRDB-Pose contain varied distributions of keypoint visibility, from densely populated indoor to dynamic outdoor scenes in which the robot navigates and interacts with oncoming pedestrians.

3.1. Benchmark and Metrics

JRDB-Pose Splits: We follow the splits of JRDB [28] to create training, validation, and testing splits from the 54 captured sequences, with each split containing an equal proportion of indoor and outdoor scenes as well as scenes captured using a stationary or moving robot. All frames from a scene appear strictly in one split.

3.1.1 Pose estimation

OKS. We define the ground-truth and a corresponding predicted human body keypoints as \(x_i \in \mathbb{R}^{2 \times J}\) and \(y_j \in \mathbb{R}^{2 \times J}\), respectively, where \(J\) represents the number of the keypoints. We measure a similarity score between \(x_i\) and \(y_j\) via Object Keypoint Similarity (OKS) [26] as:

\[
OKS(x_i, y_j) = \exp \left( -\frac{d_E(x_i, y_j)^2}{2\sigma^2 k^2} \right)
\]

where \(d_E(x_i, y_j)\) is the mean Euclidean distance between two set of keypoints normalized by the product of ground-truth box area \(s\) and a sigma constants \(k\). While this metric is commonly used for single-person pose estimation, in multi-person settings the assignment between ground-truth and predicted poses is not known, so it is unclear which pose pairs to use without a matching mechanism.
Average Precision. Average Precision (AP) and mean AP (mAP) [36] are among the most common multi-person pose estimation metrics. Similarity between predicted and ground-truth poses are calculated via OKS [26], and poses are matched via a non-optimal greedy assignment strategy that matches poses with higher confidence scores first. True and false positive predictions are determined by a threshold on the OKS score. Since the resulting AP score corresponds to the performance at a specific OKS threshold rather than on the OKS score, we apply OKS (as defined in Eq. (1)) to obtain a similarity score between keypoint sets, with any keypoint pair of OKS above a threshold of 0.5 considered a positive prediction.

OSPA-Pose. Inspired by [38] extending the OSPA metric for evaluating two sets of trajectories, we propose a new metric for evaluating two sets of human body pose tracks, namely OSPA-Pose ($O_{\text{pose}}^2$).

Let $X = \{X_1^D, X_2^D, \ldots, X_m^D\}$ and $Y = \{Y_1^D, Y_2^D, \ldots, Y_n^D\}$ to be two sets of body keypoint trajectories for ground-truth and predicted body poses, respectively. Note $D_i$ represents the time indices which track $i$ exists (having a state-value). Then, we calculate the time average distance of every pair of tracks $X_i^D$ and $Y_j^D$:

$$d(X_i^D, Y_j^D) = \sum_{t \in D_i \cup D_j} \frac{d_O(\{X_i^t\}, \{Y_j^t\})}{|D_i \cup D_j|}, \quad (3)$$

where $t \in D_i \cup D_j$ is the time-step when either or both track presents. Note that $\{X_i^t\}$ and $\{Y_j^t\}$ are singleton sets, i.e. $\{X_i^t\} = \emptyset$ or $\{X_i^t\} = x_i^t \in \mathbb{R}^{2 \times J}$ and $\{Y_j^t\} = \emptyset$ or $\{Y_j^t\} = y_j^t \in \mathbb{R}^{2 \times J}$. Therefore, inspired by the OSPA set distance, $d_O(\{X_i^t\}, \{Y_j^t\})$ can be simplified into the following distance function:

$$d_O(\{X_i^t\}, \{Y_j^t\}) = \begin{cases} d_K(x_i^t, y_j^t) & \text{if } ||\{X_i^t\}|| \cup ||\{Y_j^t\}|| = 1, \\ 1 & \text{if } ||\{X_i^t\}|| \oplus ||\{Y_j^t\}|| = 1, \\ 0 & \text{Otherwise,} \end{cases} \quad (4)$$

where $\wedge$ and $\oplus$ are boolean operators AND and OR, $d_K(x_i^t, y_j^t) = 1 - OKS(x_i^t, y_j^t) \in [0, 1]$.

Finally, we obtain the distance, $O_{\text{pose}}^2$, between two sets of pose tracks, i.e. $X$ and $Y$ by applying another OSPA
4. Multi-Person Pose Estimation and Tracking Baselines

In this section we evaluate the performance of various state-of-the-art methods for pose estimation and tracking, verifying that JRDB-Pose is a challenging dataset for existing frameworks seeking an opportunity for a dedicated development in this domain. All methods are evaluated on our individual images and annotations.

4.1. Multi-Person Pose Estimation

We evaluate several popular or recent state-of-the-art methods for multi-person pose estimation models [19, 27, 48, 49]. We evaluate one top-down method using HRNet backbone [49]. The top-down method uses a Faster R-CNN [37] detector to predict all humans in the scene, from which the high-confidence (score > 0.95) predictions are kept. We use a heatmap size of 192x256, and the HRNet backbone with a high-resolution convolution width of 48. We further evaluate three recent bottom-up models, which regress joint locations directly without the need for human detections: DEKR [19], CID [48], an YoloPose [27]. All methods are trained from their respective initializations without COCO pre-training. To help address training difficulties associated with wide panoramic images, we train on individual camera images, and then combine them together to form stitched view predictions. Duplicate poses in the stitched annotation set are eliminated using NMS on the predicted boxes. 

Tab. 3 summarises the pose estimation results for each method. To highlight the large number of occluded and invisible labels in our dataset, we include the total contribution of joints of each visibility type to the overall OSPA-Pose as well as average contribution for joints of each visibility. We also include cardinality and localization errors of OSPA-Pose. We find that Yolo-Pose is the best performing baseline, outperforming the other methods in O_pose and AP. DEKR achieves the lowest O_pose localization error but a higher cardinality error as a result of a high number of missed detections. In Tab. 4 we see the contributions to the localization error based on keypoint visibility. DEKR achieves the lower metrics due to its low localization error, besides which Yolo-Pose again performs best. Although visible joints contribute the most to localization error due to their higher overall frequency, on a per-keypoint average the predictions on occluded and invisible joints showed significantly higher errors for all models, confirming that occlusion poses a difficult challenge for existing methods. JRDB-Pose contains a significant number of occluded joints which we hope will be useful for researchers to improve the robustness of pose estimation methods to occlusions. We also find that all methods achieve lower AP as compared to their results on common large-scale benchmarks [26], showing that JRDB-Pose presents a reasonable and difficult challenge for multi-person pose estimation.

4.2. Multi-Person Pose Tracking

We evaluate three recent state-of-the-art methods, such as ByteTrack [55], Unitrack [50], and OC-SORT [5], in our tracking benchmark. All these methods are from the tracking-by-detection category and predict tracks based on predictions from a pose estimation method. We use the estimates from Yolo-Pose, as our highest-performing baseline, to initialize the predictions for all pose tracking methods. In Tab. 5 we provide our pose tracking results for all trackers and training strategies. OC-Sort achieves the best results by a wide margin. Since OC-SORT targets improving tracking robustness for objects in non-linear mo-
tion with the improved Kalman-filter and recovery strategy, we believe it is better suited for JRDB-Pose which includes occluded periods during which people are often not moving linearly with respect to the robot’s perspective (e.g., sequences where both the robot and nearby people are turning or moving simultaneously), thus better recovering from occlusions. This method’s lower \(O^2_{pose}\) cardinality error further confirms that it can better find accurate tracks. Compared to their performance in other large-scale tracking benchmarks [12, 13], these methods achieve relatively lower overall performance in the same reported metrics, reflecting the unique challenges in our dataset, which we hope will motivate further work within the research community.

### 4.3. Study on Pre-training Methods

Using our highest performing pose estimation method, we further study how pre-training strategies affect our final model performance. We try inference-only with a COCO-pretrained model, finetuning a COCO-pretrained model, and training from scratch. Tab. 6 and Tab. 5 show pose estimation and tracking performance of our highest performing model across the different training strategies. For pose estimation we find that finetuning from COCO generally performs better than training from scratch in both pose estimation and tracking tasks with an improvement of 1.7% in \(O^2_{pose}\), while running inference from a COCO model without finetune shows much weaker results especially in \(O^2_{pose}\). The relatively small improvement also suggests that JRDB-Pose contains a varied distribution of scenes and poses suitable for model training.

We also include results for pose tracking across the same three training strategies of YoloPose used to initialize the tracking. In Tab. 5 we find that the JRDB-Pose model outperforms the COCO model finetuned on JRDB-Pose in MOTA and IDF1 but is itself outperformed in IDSW and \(O^2_{pose}\). The COCO model without finetuning performs worse than the other models. Since the COCO model is not trained on the crowded human scenes and overall im-

| Pose Estimation Method (Training) | Tracking Method | MOTA ↑ | IDF1↑ | IDSW↓ | \(O^2_{pose}\)↑ | Components | \(O^2_{pose}\)↓ by Visibility |
|----------------------------------|----------------|--------|--------|--------|----------------|-----------|---------------------------|
| Yolo-Pose [27] (COCO only)       | ByteTrack [55] | 61.32  | 55.80  | 4236   | 0.715          | 0.519     | \(O^2_{pose}\)↓         |
|                                  | UniTrack [50]  | 60.80  | 55.01  | 2854   | 0.727          | 0.473     | \(O^2_{pose}\)↓         |
|                                  | OC-SORT [8]    | 66.09  | 59.93  | 2588   | 0.630          | 0.380     | \(O^2_{pose}\)↓         |
| Yolo-Pose [27] (JRDB-Pose only)  | ByteTrack [55] | 61.17  | 52.11  | 3203   | 0.693          | 0.429     | \(O^2_{pose}\)↓         |
|                                  | UniTrack [50]  | 69.84  | 56.06  | 2565   | 0.725          | 0.454     | \(O^2_{pose}\)↓         |
|                                  | OC-SORT [8]    | 69.22  | 60.62  | 1977   | 0.577          | 0.295     | \(O^2_{pose}\)↓         |
| Yolo-Pose [27] (COCO → JRDB-Pose)| ByteTrack [55] | 67.16  | 55.38  | 3325   | 0.690          | 0.456     | \(O^2_{pose}\)↓         |
|                                  | UniTrack [50]  | 72.82  | 57.69  | 2413   | 0.708          | 0.435     | \(O^2_{pose}\)↓         |
|                                  | OC-SORT [8]    | 71.74  | 61.15  | 2260   | 0.594          | 0.331     | \(O^2_{pose}\)↓         |

Table 5. Multi-person pose tracking baselines evaluated on JRDB-Pose individual camera images.

| Training strategy | Stitched | Per Camera |
|-------------------|----------|------------|
|                   | AP ↑     | \(O^2_{pose}\)↑ | AP ↑ | \(O^2_{pose}\)↑ |
| COCO [26]         | 48.0     | 0.460      | 60.2  | 0.320         |
| JRDB-Pose         | 48.2     | \cancel{0.357} | 61.9  | 0.280         |
| COCO → JRDB-Pose  | 49.6     | 0.385      | 63.9  | 0.273         |

Table 6. We study how training protocols affect performance of YoloPose. Finetuning from COCO achieves best results.

age distribution present in JRDB-Pose, it struggles to find keypoints and thus has a high miss-rate as indicated by a much higher \(O^2_{pose}\) cardinality component compared to the other training schemes. JRDB-Pose contains a varied distribution of scenes in human environments different from COCO. Based on the per-sequence results, the models typically demonstrate superior performance in indoor areas with no obstacles, such as hewlett-class and midia-aud. On the other hand, the models tend to perform more poorly in complex scenes containing numerous background objects, including robot hands, photocopies, coffee machines, trolleys, and so on. Such scenarios can be observed in gate-ai-lab and indoor/outdoor-coupa-caffe.

### 5. Conclusion

In this paper we have introduced JRDB-Pose, a large-scale dataset of human poses and track IDs suitable for multi-person pose estimation and tracking from videos. JRDB-Pose features high-frequency annotations for crowded indoor and outdoor scenes with heavy occlusion, diverse actions, and longer videos than existing largescale pose estimation and tracking datasets. Finally, we have introduced \(OSPA_{pose}\) and \(OSPA^1_{pose}\), new metrics for multi-person pose estimation and tracking. We believe that JRDB-Pose will help address limitations in human action understanding for human-robot interaction and navigation in human environments and advance research by proving large-scale and high-quality annotations.
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