Self-supervised Keypoint Correspondences for Multi-Person Pose Estimation and Tracking in Videos

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Abstract. Video annotation is expensive and time consuming. Consequently, datasets for multi-person pose estimation and tracking are less diverse and have more sparse annotations compared to large scale image datasets for human pose estimation. This makes it challenging to learn deep learning based models for associating keypoints across frames that are robust to nuisance factors such as motion blur and occlusions for the task of multi-person pose tracking. To address this issue, we propose an approach that relies on keypoint correspondences for associating persons in videos. Instead of training the network for estimating keypoint correspondences on video data, it is trained on a large scale image datasets for human pose estimation using self-supervision. Combined with a top-down framework for human pose estimation, we use keypoints correspondences to (i) recover missed pose detections (ii) associate pose detections across video frames. Our approach achieves state-of-the-art results for multi-frame pose estimation and multi-person pose tracking on the PosTrack 2017 and PoseTrack 2018 data sets.

1 Introduction

Human pose estimation is a very active research field in computer vision that is relevant for many applications like computer games, security, sports, and autonomous driving. Over the years, the human pose estimation models have been greatly improved \cite{11,31,7,22,41,3,24} due to the availability of large scale image datasets for human pose estimation \cite{26,40}. More recently, researchers started to tackle the more challenging problem of multi-person pose tracking \cite{19,18,41,37,45}.

In multi-person pose tracking, the goal is to estimate human poses in all frames of a video and associate them over time. However, video annotations are costly and time consuming. Consequently, recently proposed video datasets \cite{1} are less diverse and are sparsely annotated as compared to large scale image datasets for human pose estimation \cite{26,40}. This makes it challenging to learn deep networks for associating human keypoints across frames that are robust to

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nuisance factors such as motion blur, fast motions, and occlusions as they occur in videos.

State-of-the-art approaches [41,37,13] therefore rely on optical flow or additional networks for person re-identification [45] to boost the performance for multi-person pose tracking.

Optical flow, however, fails if a person becomes occluded which results in a lost track. While person re-identification allows to associate persons even if they disappeared for a long time. The limited annotations in pose tracking datasets requires to train the models on additional datasets for person re-identification. Moreover, it is difficult to associate partially occluded persons with person re-identification models, that operate on bounding boxes of the full person.

We therefore propose to learn a network that infers keypoint correspondences for multiple persons. The correspondence network comprises a Siamese matching module that takes a frame with estimated human poses as input and estimates the corresponding poses for a second frame. Such an approach has the advantage that it is not limited to a fixed temporal frame distance, and it allows to track persons when they are partially occluded. Our goal is to utilize keypoint correspondences to recover missed poses of a top-down human pose estimator, e.g. due to partial occlusion and to utilize keypoint correspondences for multi-person tracking.

The challenge, however, is to train such a network due to the sparsely annotated video datasets. In fact, in this work we consider the extreme case where the network is not trained on any video data or a dataset where identities of persons are annotated. Instead we show that such a network can be trained using self-supervision on an image dataset for multi-person pose estimation [26], which is anyway needed to train the human pose estimator. In order to improve the keypoint associations, we propose an additional refinement module that refines the affinity maps of the Siamese matching module.

To summarize we make following contributions:

- We propose an approach for multi-frame pose estimation and multi-person pose tracking that relies on self-supervised keypoint correspondences which are learned from a large scale image dataset.
Combined with a top-down pose estimation framework we use keypoint correspondences in two ways as illustrated in Figure 1: (i) We use keypoint correspondences to recover pose detections that have been missed by the top-down pose estimation framework and (ii) the keypoint correspondences are used to associate detected and recovered poses in different frames of a video.

We evaluate the approach on the PoseTrack 2017 and 2018 datasets for the tasks of multi-frame pose estimation and multi-person pose tracking. Our approach achieves state-of-the-art results without using any additional training data except of [26] for the proposed correspondence network.

2 Related Work

Multi-person pose estimation is an actively researched area.

Multi-person pose estimation can be categorized into top-down and bottom-up approaches, where former are superior over bottom-up methods as shown in the MS-COCO benchmark [26]. In recent years, researchers tackle the problem of multi-person pose estimation and tracking in video datasets such as PoseTrack [1]. This task comes with a set of additional challenges.

**Multi-Person Pose Estimation** Bottom-up based methods [22,29,15,31] first detect all person keypoints simultaneously and then associate body parts with their corresponding person instances. [7] is one of the most popular works that predicts part affinity fields (PAF) which preserve location and orientation information of limbs. These PAFs are used with a greedy part association algorithm. More recently, [22] propose to detect bounding boxes and pose keypoints within the same neural network. Bounding box predictions are used to crop from predicted keypoint heatmaps. As a second stage, the authors propose a pose residual module which regresses the respective keypoint locations of each person instance.

Top-Down methods [43,24,8,28,41,43,30] utilize person detectors and estimate the pose on each image crop individually. In contrast to bottom-up methods, top-down approaches do not suffer from scale variations. [41] propose to replace the last fully connected layer of a ResNet152 [16] by three transposed convolutions and achieve state-of-the-art performance. In contrast [24] proposes an information propagation procedure within a multi-stage architecture with coarse-to-fine supervision. This method achieves top-scoring results on the MS-COCO keypoints challenge.

**Multi-Frame Pose Estimation** In video data, such as PoseTrack [1], related works [42,13,4] leverage temporal information of neighboring frames to increase robustness against fast motions, occlusion and motion blur. [42] and [13] utilize optical flow to warp preceding frames into the current frame. On the other hand, [4] propose a feature warping method to warp pose heatmaps from preceding and subsequent frames into the current frame achieving state-of-the-art results.
Table 1. Overview of related works on multi-person pose tracking and theirs respective contributions.

| Method      | Detection Improvement | Tracking                  |
|-------------|-----------------------|---------------------------|
| Ours        | Correspondences       | Keypoint Correspondences  |
| HRNet [37]  | Temporal OKS          | Optical Flow              |
| POINet [35] | -                     | Ovonic Insight Net        |
| MDPN [13]   | Ensemble              | Optical FLow              |
| LightTrack [32] | Ensemble / BBox Prop. | GCN                       |
| ProTracker [12] | -                   | IoU                       |
| STAF [34]   | -                     | STFields                  |
| STEEmbeddings [20] | -               | STEEmbeddings             |
| JointFlow [10] | -                   | Flow Fields               |

Multi-person pose tracking
Recent success in multi-person pose estimation in still images has led researchers to work on the challenging problem of multi-person pose tracking. Early works [19,18] build spatio-temporal graphs which are solved by integer linear programming. Such approaches are computationally heavy and come with a long runtime.

For that reason, researchers reduced the task to bipartite graphs which are solved in a greedy fashion [37,35,13,32,12,10,34,42,20]. In contrast to [12], [10,34,17] leverage temporal information of past frames to assign poses in consecutive frames. More recent works [41,37,13,45] incorporate temporal information by using optical flow. In [41] the authors rely on optical flow to recover missed person detections and propose an optical-flow based similarity metric for tracking. In contrast, [45] builds on [12] and proposes an adopted MaskRCNN [15] with a greedy bounding box generation strategy. Further optical flow and a person re-ID module is utilized to enhance the tracking procedure. Jin et al. [20] perform multi-person pose estimation and tracking within a unified framework based on human pose embeddings. Table 1 provides a summary of the contributions of recent related works.

Sparse Video Annotations
Recent work [4] propose a Pose Wrapper framework to learn from sparse video annotations for the task of multi-frame pose estimation. Our approach, in contrast, uses large scale single images annotations for the task of multi-person pose tracking.

Correspondences
In recent years, deep learning has been successfully applied to the task of correspondence matching [9,12,14], including the task of visual object tracking (VOT) [5,23,46,47]. All of the above approaches establish correspondences at object level. In contrast, our approach establishes correspondences at instance level. Moreover, VOT tasks assume a ground truth object location for the first frame, which is in contrast to the task of PoseTracking.

Self-Supervised learning.
Self supervised learning approaches [39,25] have been proposed for establishing correspondences at patch and keypoints level from
videos. However, these approaches use videos for learning and process a single set of keypoints or patch at a time. In contrast, our approach establishes correspondences for multiple instances and is trained on single images.

3 Method Overview

![Figure 2](image)

**Fig. 2.** Given a sequence of frames, we detect a set of person bounding boxes and perform top-down pose estimation. Our proposed method uses keypoint correspondences to (i) recover missed detections and (ii) to associate detected and recovered poses to perform tracking. The entire framework does not require any video data for training since the network for estimating keypoint correspondences is trained on single images using self-supervision.

In this work, we propose a multi-person pose tracking framework that is robust to motion blur and severe occlusions, although it does not need any video data for training. As it is illustrated in Figure 2, we first estimate for each frame the human poses and then track the human poses.

For multi-person human pose estimation, we utilize an off-the-shelf object detector [6] to obtain a set of bounding boxes for the persons in each frame. For each bounding box, we then perform multi-person pose estimation in a top-down fashion by training an adapted Google-Net [38], which we will discuss in Section 6.1.

In order to be robust to motion blur and severe occlusions, we do not use optical flow in contrast to previous works like [41]. Instead we propose a network that estimates for a given frame with estimated keypoints the locations of the keypoints in another frame. We use this network for recovering human poses that have been missed by the top-down pose estimation framework as described in Section 5.1 and for associating detected and recovered poses across the video as described in Section 5.2.

The main challenge for the keypoint correspondence network is the handling of occluded keypoints and the limited amount of densely annotated video data. In order to address these issues, we do not train the network on video data, but
on single images using self-supervision. In this way, we can simulate disappearing keypoints by truncation and leverage large scale image dataset like MS-COCO \cite{26} for tracking. We will first describe the keypoint correspondence network in Section 4 and then discuss the tracking framework in Section 5.

![Keypoint correspondence framework](image)

**Fig. 3.** Keypoint correspondence framework. The Siamese network takes images $I_1$ and $I_2$ and keypoints $\{j^p\}_{1:N_p}$ for all persons $p$ in image $I_1$ as input and generates the feature maps $F_1$ and $F_2$, respectively. The keypoints of the different persons are shown in green and yellow colors, respectively. For each keypoint, a descriptor $d^p_j$ is extracted from $F_1$ and convolved with the feature map $F_2$ to generate an affinity map $S^p_j$. In order to improve the affinity maps for each person, the refinement network takes $F_1$, $F_2$ and the affinity maps $S^p_j$ for person $p$ as input and generates refined affinity maps $C^p_j$.

## 4 Keypoint Correspondence Network

Given two images $I_1$ and $I_2$ with keypoints $\{j^p\}_{1:N_p}$ for all persons $p$ in image $I_1$, our goal is to find the corresponding keypoints in $I_2$. Towards this end, we use a Siamese network as shown in Figure 3 which estimates for each keypoint an affinity map. The affinity maps are further improved by the refinement module, which is described in Section 4.2.

### 4.1 Siamese Matching Module

The keypoint correspondence network consists of a Siamese network. Each branch in the Siamese network is a batch normalised Google-Net up to layer 17 with shared parameters. The Siamese network takes an image pair $(I_1, I_2)$ and keypoints $\{j^p\}_{1:N_p}$ for persons $p \in \{1, \ldots, P\}$ in the image $I_1$ as input. During
training, \( I_2 \) is generated by applying a randomly sampled affine warp to \( I_1 \). In this way, we do not need any annotated correspondences during training or pairs of images, but train the network on single images with annotated poses. We use an image resolution of 256 \( \times \) 256 for both images.

The Siamese network generates features \( F_1 \in \mathbb{R}^{32 \times 64 \times 64} \) and \( F_2 \in \mathbb{R}^{32 \times 64 \times 64} \) for images \( I_1 \) and \( I_2 \), respectively. The features are then pixel-wise \( l_2 \) normalised and local descriptors \( d^p_j \in \mathbb{R}^{32 \times 3 \times 3} \) are generated for each keypoint \( j^p \) by extracting squared patches around the spatial position of a keypoint in the feature maps \( F_1 \).

Given a local descriptor \( d^p_j \), we compute its affinity map \( A^p_j \) over all \( x, y \), where \( x = \{1, \ldots, 64\} \) and \( y = \{1, \ldots, 64\} \), in \( F_2 \) as:

\[
A^p_j = d^p_j \ast F_2
\]

where \( \ast \) denotes the convolution operation. Finally, a softmax operation is applied to the affinity map \( A^p_j \), i.e.,

\[
S^p_j(x, y) = \frac{\exp(A^p_j(x, y))}{\sum_{x', y'} \exp(A^p_j(x', y'))}.
\]

We refine the affinity maps \( S^p_j \) further using a refinement module.

### 4.2 Refinement Module

We append a second module to the keypoint correspondence network to improve the affinity maps generated by the Siamese matching module. For the refinement module, we use a batch normalised Google-Net from layer 3 till layer 17. The refinement module concatenates \( F_1 \), \( F_2 \) and the affinity maps \( \{ S^p_j \}_{1:N_p} \) for a single person \( p \) and refines the affinity maps, which we denote by \( C^p_j \in \mathbb{R}^{64 \times 64} \). The refinement module is therefore applied to the affinity maps for all persons \( p \in \{1, \ldots, P\} \). Before we describe in Section 5 how we will use the affinity maps for tracking \( C^p_j \), we describe how the keypoint correspondence network is trained.

### 4.3 Training

Since we train our network using self-supervision, we train it using a single image \( I_1 \) with annotated poses. We generate a second image \( I_2 \) by applying a randomly sampled affine warp to \( I_1 \). We then generate the ground-truth affinity map \( G^p_j \) for a keypoint \( j^p \) belonging to person \( p \) as:

\[
G^p_j(x, y) = \begin{cases} 
1 & \text{if } x = \hat{x}^p_j \text{ and } y = \hat{y}^p_j, \\
0 & \text{otherwise},
\end{cases}
\]

where \( (\hat{x}^p_j, \hat{y}^p_j) \) is the spatial position of the ground-truth correspondence for keypoint \( j^p \) in image \( I_2 \), which we know from the affine transformation. As
Fig. 4. Recovering missed detections. (a) Person detected by the top down pose estimation framework in frame $f-1$. (b) Person missed by the top down pose estimation framework in frame $f$ due to occlusions. (c) Keypoints affinity maps of the missed person from frame $f-1$ to frame $f$. (d) Corresponding keypoints in frame $f$. (e) Estimated bounding box from correspondence keypoints with recovered poses.

illustrated in Figure 3, not all corresponding keypoints are present in image $I_2$. In this case, the ground-truth affinity map is zero and predicting a corresponding keypoint is therefore penalized.

During training, we minimize the binary cross entropy loss between the predicted affinity maps $S^p_j$ and $C^p_j$ and the ground-truth $G^p_j$ affinity:

$$\min_\theta \sum_{x,y} - (G^p_j \log(S^p_j) + (1 - G^p_j)(1 - \log(S^p_j)))$$

(4)

$$\min_\theta \sum_{x,y} - (G^p_j \log(C^p_j) + (1 - G^p_j)(1 - \log(C^p_j)))$$

(5)

where $\theta$ are the parameters of the keypoint correspondence framework.

5 Multi-Person Pose Tracking

We use the keypoint correspondence network in two ways. We use it to recover human poses that have been missed by the frame-wise top down multi-person pose estimation step, which will be described in Section 5.1. Given the set of detected and recovered poses, we use keypoint correspondences for tracking poses across frames of the video as described in Section 5.2.
5.1 Recover Missed Detections

For a given frame $f$, we first detect the human poses in the frame using the top-down multi-person pose estimator described in Section 6.1. While the person detector [6] performs well, it fails in situations with overlapping persons and motion blur. Consequently, the human pose is not estimated in these cases. Examples are shown in Figure 4(b).

Given the detected human poses $J^p_{f-1} = \{j^p_{f-1}\}$ for persons $p \in \{1, \ldots, P\}$ in frame $f-1$, we compute the corresponding refined affinity maps $C^p = \{C^p_j\}$ by using the keypoint correspondence network. For each keypoint $j^p_{f-1}$, we then get the corresponding keypoint $\bar{j}^p_f$ in frame $f$ by taking the argmax of $C^p_j$ and mapping it to the image resolution. Since the resolution of the affinity maps is lower than the image resolution and since the frame $f$ might contain a keypoint that was occluded in the previous frame, we reestimate the propagated poses. This is done by computing for each person $p$ a bounding box that encloses all keypoints $\bar{J}^p_f = \{\bar{j}^p_f\}$ and using the human pose estimation network described in Section 6.1 to get a new pose for this bounding box. We denote the newly estimated poses by $\hat{J}^p_f$. The overall procedure is shown in Figure 4. We apply OKS based non-maximum suppression [41] to discard redundant recovered poses.

5.2 Tracking

Given detected and recovered poses, we need to link them across video frames to obtain tracks of human poses. Tracking can be seen as a data association problem over estimated poses. Previously, the problem has been approached using bipartite graph matching [12] or greedy approaches [41,37,10]. In this work, we greedily associate estimated poses over time by using the keypoint correspondences. We initialise tracks on the first frame and then associate new candidate poses to initial tracks one frame at a time.

Formally, our goal is to assign pose instances $B^p_f = \{J^p_f\} \cup \{\hat{J}^p_f\}$ in frame $f$ for persons $p \in \{1, \ldots, P\}$ to tracks $T^q_{f-1}$ till frame $f-1$ for persons $q \in \{1, \ldots, Q\}$. Towards this end, we measure the similarity between a pose instance $B^p_f$ and a track $T^q_{f-1}$ as:
\[ S(T^q_{f-1}, B^p_f) = \frac{\sum_{j=1}^{N_q} C^q_j(j^p_f) \cdot \mathbb{I}_{C^q_j(j^p_f) > \tau_{corr}}}{\sum_{j=1}^{N_q} \mathbb{I}_{C^q_j(j^p_f) > \tau_{corr}}}, \]  

where \( C^q_j \) is the affinity map of the keypoint \( j \) in track \( T^q_{f-1} \) for frame \( f \). The affinity map is computed using the procedure described in Section 4. \( C^q_j(j^p_f) \) is the confidence value in the affinity map \( C^q_j \) at the location of the joint \( j^p_f \) for person \( p \) in frame \( f \). \( N_q \) is the number of detected joints. An example is shown in Figure 5. We only consider \( j^p_f \) if its affinity is above \( \tau_{corr} \). If a pose \( B^p_f \) cannot be matched to a track \( T^q_{f-1} \), a new track is initiated.

6 Experiments and Results

We evaluate our approach on the Posetrack 2017 and Posetrack 2018 datasets [1]. The datasets have 292 and 593 videos for training and 214 and 375 videos for evaluation, respectively. We evaluate multi-frame pose estimation and tracking results using the mAP and MOTA evaluation metrics.

6.1 Implementation Details

We provide implementation details for our top-down pose estimation and key-point correspondences framework below.

**Top down Pose Estimation.** We use a top down framework for frame level pose estimation. We use cascaded RCNN [6] for people detection. We extract crops of size \( 384 \times 288 \) around detected people as input to our pose estimation framework. Our pose estimation framework is a 2 stage framework. Each stage uses GoogleNet [38] as a backbone followed by a pose decoder. Both stages predict pose heatmaps for the cropped person. We use the pose heatmaps from the 2nd stage as our pose detections.

We train the pose estimation framework on the MS-COCO dataset [26] for 260 epochs with a base learning rate of \( 1e^{-3} \). The learning rate is reduced to \( 1e^{-4} \) after 200 epochs. During training we apply random flippings and rotations to input crops. We finetune the pose estimation framework on the PoseTrack 2017 dataset [1] for 12 epochs. The learning rate is further reduced to \( 1e^{-5} \) after epoch 7.

**Keypoint Correspondence framework.** The keypoint correspondence framework is trained on the MS-COCO dataset [26] only. We perform module-wise training. We first train the Siamese module. We then fix the Siamese module and then train the refinement module. Both modules are trained for 100 epochs with base learning rate of \( 1e^{-4} \) reduced to \( 1e^{-5} \) after 50 epochs. We generate a second image for the correspondence framework by applying random translations, rotations and flippings to the first image. We did not observe any improvements in our tracking results by fine-tunning the correspondence model on the PoseTrack.
Table 2. MOTA and Identity Switches (IDSW) comparison with baselines over the PoseTrack 2017 validation set. The comparison is performed using the same set of pose detections obtained with ground truth and detected boxes. Correspondence based tracking consistently improves MOTA over all the baselines and significantly reduces the number of identity switches.

| Tracking Method   | GTBoxes | IDSW | MOTA |
|-------------------|---------|------|------|
| OKS               | ✓       | 6582 | 65.9 |
| Optical Flow      | ✓       | 4419 | 68.4 |
| Re-ID             | ✓       | 4164 | 67.1 |
| Correspondences   | ✓       | 3583 | 70.5 |
| OKS               | X       | 7207 | 60.4 |
| Optical Flow      | X       | 5611 | 66.7 |
| Re-ID             | X       | 4589 | 64.1 |
| Correspondences   | X       | 3632 | 67.9 |

dataset. Training only on the PoseTrack dataset yielded sub-optimal tracking results. Unless stated otherwise all reported results are based on the keypoint correspondence model trained on MS-COCO only.

6.2 Baselines

We compare our keypoint correspondence tracking to different standard tracking baselines for multi-person pose tracking as reported in Table 2. To measure the performance of each baseline, we report the number of identity switches and the MOTA score. For a fair comparison, we use the same pose detections obtained with ground truth and detected boxes.

**OKS.** OKS is an image based baseline proposed in [41]. OKS measures the similarity between two poses and is independent of their appearance. It is not robust to large motion, occlusion and large temporal offsets. This is reflected in Table 2 as this baseline achieves the lowest performance.

**Optical Flow.** Optical flow is a temporal baseline that has been proposed in [41]. We use optical flow to warp the poses from the previous frame to the current frame. We then apply OKS for associating the warped poses with candidate poses in the current frame. We use the pre-trained PWC-net [36] as done in [37] for a fair comparison. Optical flow clearly outperforms OKS and achieves superior MOTA of 68.4 and 66.7 for GT and detected boxes, respectively.

**Person Re-id.** Compared to optical flow and OKS, person re-id is more robust to larger temporal offsets and large motion. However, the achieved results indicate that bounding box level person re-id performs sub-optimally under the frequent partial occlusions in the PoseTrack datasets. For our experiments, we use the pre-train re-id model from [27]. Re-id based tracking achieves MOTA scores of 67.1 and 64.1 for GT and detected boxes, respectively.
Table 3. Effect of joint detection thresholds and missed detections on mAP and MOTA on the PoseTrack 2018 validation set. The results are shown for (i) detected poses only and (ii) detected and recovered poses. As expected, recovering missed detections improve both MOTA and mAP. A good trade-off between mAP and MOTA is achieved at joint detection threshold of 0.3.

| Joint Threshold | mAP  | MOTA |
|-----------------|------|------|
| Detected Poses Only |      |      |
| 0.0             | 80.1 | 48.1 |
| 0.1             | 79.7 | 63.3 |
| 0.2             | 78.9 | 66.1 |
| 0.3             | **77.7** | **67.6** |
| 0.4             | 75.9 | 68.0 |
| 0.5             | 73.1 | 67.1 |

| Joint Threshold | mAP  | MOTA |
|-----------------|------|------|
| Detected and Recovered Poses |      |      |
| 0.3             | 82.0 | 48.1 |
| 0.4             | 81.4 | 64.1 |
| 0.5             | 80.5 | 67.2 |

Table 4. Comparison to the state-of-the-art on the PoseTrack 2017 and 2018 validation set for multi-frame pose estimation.

| Dataset       | Method      | Head | Shoulder | Elbow | Wrist | Hip | Knee | Ankle | mAP  |
|---------------|-------------|------|----------|-------|-------|-----|------|-------|------|
| PoseTrack 17 Val Set | DetectNTrack [12] | 72.8 | 75.6 | 65.3 | 54.3 | 63.5 | 60.9 | 51.8 | 64.1 |
| PoseFlow [42] | 66.7 | 73.3 | 68.3 | 61.1 | 67.5 | 67.0 | 61.3 | 66.5 |
| FlowTrack [11] | 81.7 | 83.4 | 80.0 | 72.4 | 75.3 | 74.8 | 67.1 | 76.7 |
| HRNet [37] | 82.1 | 83.6 | 80.4 | 73.3 | 75.5 | 75.3 | 68.5 | 77.3 |
| MDPN [13] | 85.2 | 88.5 | 83.9 | 78.0 | 82.4 | 80.5 | 73.6 | 80.7 |
| PoseWarper [4] | 81.4 | 88.3 | 83.9 | 78.0 | 82.4 | 80.5 | 73.6 | **81.2** |
| Ours | 86.1 | 87.0 | 83.4 | 76.4 | 77.3 | 79.2 | 73.3 | 80.8 |

| PoseTrack 18 Val Set | PoseFlow [42] | 63.9 | 78.7 | 77.4 | 71.0 | 73.7 | 73.0 | 69.7 | 71.9 |
| MDPN [13] | 75.4 | 81.2 | 79.0 | 74.1 | 72.4 | 73.0 | 69.9 | 75.0 |
| PoseWarper [3] | 79.9 | 86.3 | 82.4 | 77.5 | 79.8 | 78.8 | 73.2 | 79.7 |
| Ours | 86.0 | 87.3 | 84.8 | 78.3 | 79.1 | 81.1 | 75.6 | **82.0** |

The results show that correspondences based tracking (1) achieves consistent improvement over the baselines both with GT and detected boxes, respectively, with MOTA scores of 70.5 and 67.9 and (2) significantly reduces the number of identity switches. The results show that, compared to optical flow, correspondences are more robust to partial occlusions, motion blur and large motions. A qualitative comparison is provided in Section 6.5.

6.3 Effect of Joint Detection Threshold & Missed Detections

We evaluate the impact of different joint detection thresholds on mAP and MOTA, respectively, on the PoseTrack 2018 dataset as shown in Table 3. Since mAP does not penalize false-positive keypoints, thresholding decreases the pose estimation performance by discarding low confident joints. Vice versa, joint thresholding results in cleaner tracks and improves the tracking performance, as MOTA penalizes false-positive keypoint detections. A good trade-off between mAP and MOTA is achieved for the joint detection threshold 0.3 resulting in a mAP and MOTA of 77.9 and 67.6, respectively. Table 3 shows that recovering missed detections further improves mAP and MOTA to 79.2 and 68.8, respectively.
6.4 Comparison with State-of-the-art Methods

![Comparison with State-of-the-art Methods](image)

**Fig. 6.** Qualitative comparison between optical flow and correspondences for the task of pose warping under occlusion, motion blur and large motion. (a) Query Poses in frame $f$. (b) Warped poses using optical flow. (c) Warped poses using correspondences. The correspondences warp poses correctly under occlusion and motion blur as compared to optical flow.

We compare to the state-of-the-art for multi-frame pose estimation and multi-person pose tracking on the PoseTrack 2017 and 2018 datasets.

**Multi-Frame Pose Estimation.** For the task of multi-frame pose estimation, we compare to the state-of-the-art on the PoseTrack 2017 and 2018 validation sets, respectively. Despite, our correspondences are trained without using any video data, they outperform the recently proposed PoseWrapper [4] approach on the PoseTrack 2018 validation set with mAP of 82.0 and achieves very competitive mAP on the PoseTrack 2017 validation set with a mAP of 80.8 as shown in Table 4.

**Multi-Person Pose Tracking.** We compare our tracking approach with the state-of-the-art for multi-person pose tracking on the PoseTrack 2017 and PoseTrack 2018 validation sets and leader boards. In addition, we perform a post-processing step in which we merge broken tracks similar to the recovery of missed detections procedure as introduced in Section 5.1. This further improves the tracking performance. For further details we refer to the supplementary materials.

We submitted our results to the PoseTrack 2017 and PoseTrack 2018 test servers, respectively. Our approach achieves top scoring MOTA of 60.0 on the
| PoseTrack 17 val set | Approach          | mAP  | MOTA  |
|----------------------|-------------------|------|-------|
|                      | STEmbedding [20]  | 77.0 | 71.8  |
|                      | PGPT [45]         | 76.7 | 70.1  |
|                      | Ours + Merge      | 78.0 | 68.3  |
|                      | Ours              | 78.0 | 67.9  |
|                      | POINet            | -    | 65.9  |
|                      | HRNet             | 77.3 | -     |
|                      | FlowTrack         | 76.7 | 65.4  |
| PoseTrack 17 test set| Ours + Merge     | 74.2 | 60.0  |
|                      | POINet            | 72.5 | 58.4  |
|                      | LightTrack        | 66.8 | 58.0  |
|                      | HRNet             | 75.0 | 58.0  |
|                      | FlowTrack         | 74.6 | 57.8  |
| PoseTrack 18 val set | Ours + Merge     | 79.2 | 69.1  |
|                      | MIPAL             | 74.6 | 65.7  |
|                      | LightTrack        | 71.2 | 64.9  |
|                      | Miracle + [44]    | 80.9 | 64.0  |
|                      | OpenSVAT [33]     | 69.7 | 62.4  |
|                      | STAF [31]         | 70.0 | 60.9  |
| PoseTrack 18 test set| Ours + Merge     | 74.4 | 60.7  |
|                      | MIPAL             | 70.0 | 57.4  |
|                      | CV-Human          | 67.8 | 54.9  |
|                      | MSRA              | 74.0 | 61.4  |

Our tracking performance is on-par with state-of-the-art approaches on the PoseTrack 2017 validation set.

Similarly, we achieve top scoring MOTA of 69.1 on the Pose Track 2018 validation set as shown in Table 5. Our tracking results are very competitive to the winning entries on the Pose Track 2018 leader board. However, the winning entries use additional training data.

### 6.5 Qualitative Results

We qualitatively compare the task of pose warping using optical flow and correspondences under motion blur, occlusions and large motion in Figure 6. The column on the left shows query poses in frames $f$. The column in the middle shows warped poses generated by optical flow in another frame $f + 1$. The right column shows poses warped using correspondences for frame $f + 1$. The figure shows that poses warped by correspondences are robust to occlusions and motion blur.

### 6.6 Conclusion

In this work, we have proposed a self-supervised keypoint correspondence framework for the tasks of multi-frame pose estimation and multi-person pose tracking. The proposed keypoint correspondence framework solves two tasks: (1) recovering missed detections and (2) associating human poses across video frames for the task of multi-person pose tracking. The proposed keypoint correspondences tracking approach outperforms the state-of-the-art for the tasks of multi-frame pose estimation and multi-person pose tracking on the PoseTrack 2017 and PoseTrack 2018 datasets. Currently our approach requires an extra pose estimation step during pose propagation. As future work we plan to investigate a unified approach without any bells and whistles as shown in Table 5.

3 It is mentioned in the winning entries submission that they used additional training data.
framework that simultaneously performs keypoints correspondences and pose estimation.

A Supplementary Material

A.1 Impact of $\tau_{\text{corr}}$

We evaluated $\tau_{\text{corr}}$ on the pose estimation and tracking performance. As shown in Table 6, the threshold has a low impact. We use $\tau_{\text{corr}} = 0.3$ for all our experiments.

| $\tau_{\text{corr}}$ | MOTA  | mAP  |
|----------------------|-------|------|
| 0.1                  | 67.9  | 77.9 |
| 0.2                  | 67.9  | 77.9 |
| **0.3**              | **67.9** | **78.0** |
| 0.4                  | 67.9  | 78.0 |
| 0.5                  | 67.8  | 78.0 |

A.2 Effect of refinement module and duplicate removal

In our experiments, we evaluated the effect of the refinement module and duplicate removal on the pose estimation and tracking performance. As shown in Table 7, omitting any of the introduced design choices results in a significant drop in MOTA of at least 1%, and increases the number of identity switches (IDSW).

Our proposed correspondence refinement module improves the generated correspondence affinity maps which results in stronger tracking results. This is reflected by the MOTA and mAP scores that drop to 66.9 and 77.7, respectively, if we disable the refinement module.

If duplicates are not removed, the mAP and the MOTA scores drop to 77.9 and 64.5, respectively.

A.3 Track Merging

We propose a post-processing step in which we merge tracks of the same pose instance at different time steps by utilizing keypoint correspondences from multiple frames. Given two tracks $T^q$ and $T^p$ as illustrated in Figure 7, we select three pose instances $\{B^q_f\}$ with $f \in \{f^q_s, f^q_c, f^q_e\}$ at the start, center and end frames of track $T^q$. For each of the pose instances $B^q_f$, we compute the pose $\tilde{B}^q_f$ for the starting frame $f^p_s$ of track $T^p$ using correspondences, as described in
Table 7. Comparison of mAP and MOTA for different design choices on the PoseTrack 2017 validation set.

| Design Choices                                      | MOTA | mAP | IDSW |
|-----------------------------------------------------|------|-----|------|
| Correspondence Tracking                             | 67.9 | 78.0| 3632 |
| Correspondence Tracking w/o refinement module       | 66.9 | 77.7| 4304 |
| Correspondence Tracking w/o duplicate removal       | 64.5 | 77.9| 8288 |

Fig. 7. Tack merging: For the start frame $f^q_s$, the center frame $f^q_c$ and the last frame $f^q_e$ of track $T^q$, we estimate poses from keypoint correspondences in the start frame $f^p_s$ of $T^p$, as illustrated by the colored dashed lines. We use an OKS-based similarity metric to measure the average pose similarity between the poses from correspondences and the pose in the starting frame $f^p_s$ of track $T^p$.

Section 5 of the paper. We then employ OKS as similarity metric and calculate the average similarity between tracks $T^q$ and $T^p$ as

$$S_{match}(T^q, T^p) = \frac{\sum_{f \in \{f_s, f_c, f_e\}} OKS(\bar{B}_f^q, B_{f_s}^p)}{3}. \quad (7)$$

We then greedily merge pairs of tracks based on the highest similarity.
Fig. 8. Qualitative results for recovering missed detections. Best seen using the zoom function of the PDF viewer.
References

1. Andriluka, M., Iqbal, U., Ensafutdinov, E., Pishchulin, L., Milan, A., Gall, J., B., S.: PoseTrack: A benchmark for human pose estimation and tracking. In: CVPR (2018)
2. Andriluka, M., Pishchulin, L., Gehler, P., Schiele, B.: 2d human pose estimation: New benchmark and state of the art analysis. In: CVPR (2014)
3. Bertasius, G., Feichtenhofer, C., Tran, D., Shi, J., Torresani, L.: Learning temporal pose estimation from sparsely-labeled videos. NeurIPS (2019)
4. Bertasius, G., Feichtenhofer, C., Tran, D., Shi, J., Torresani, L.: Learning temporal pose estimation from sparsely-labeled videos. In: NeurIPS (2019)
5. Bertinetto, L., Valmadre, J., Henriques, J., Vedaldi, A., Torr, P.: Fully-convolutional siamese networks for object tracking. In: ECCV (2016)
6. Cai, Z., Vasconcelos, N.: Cascade r-cnn: Delving into high quality object detection. CVPR (2017)
7. Cao, Z., Simon, T., Wei, S.E., Sheikh, Y.: Realtime multi-person 2d pose estimation using part affinity fields. In: CVPR (2017)
8. Chen, Y., Wang, Z., Peng, Y., Zhang, Z., Yu, G., Sun, J.: Cascaded pyramid network for multi-person pose estimation. CVPR (2018)
9. Choy, C., Gwak, J., Savarese, S., Chandraker, M.: Universal correspondence network. NIPS (2016)
10. Doering, A., Iqbal, U., Gall, J.: Joint flow: Temporal flow fields for multi person tracking. BMVC (2018)
11. Felzenszwalb, P.F., Huttenlocher, D.P.: Pictorial structures for object recognition. IJCV (Jan 2005)
12. Girdhar, R., Gkioxari, G., Torresani, L., Paluri, M., Tran, D.: Detect-and-Track: Efficient Pose Estimation in Videos. In: CVPR (2018)
13. Guo, H., Tang, T., Luo, G., Chen, R., Lu, Y., Wen, L.: Multi-domain pose network for multi-person pose estimation and tracking. In: CVPR (2018)
14. Han, K., R.S.R, Ham, B., Wong, K., Cho, M., Schmid, C., Ponce., J.: Scnet: Learning-semantic correspondence. ICCV (2017)
15. He, K., Gkioxari, G., Dollár, P., Girshick, R.B.: Mask R-CNN. ICCV (2017)
16. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: CVPR (2016)
17. Hwang, J., Lee, J., Park, S., Kwak, N.: Pose estimator and tracker using temporal flow maps for limbs (2019). [https://doi.org/10.1109/IJCNN.2019.8851734]
18. Insafutdinov, E., Andriluka, M., Pishchulin, L., Tang, S., Levinkov, E., Andres, B., Schiele, B.: ArtTrack: Articulated Multi-person Tracking in the Wild. In: CVPR (2017)
19. Iqbal, U., Milan, A., Gall, J.: Posetrack: Joint multi-person pose estimation and tracking. In: CVPR (2017)
20. Jin, S., Liu, W., Ouyang, W., Qian, C.: Multi-person articulated tracking with spatial and temporal embeddings. CVPR (2019)
21. Kim, S., Min, D., Ham, B., Jeon, S., Lin, S., Sohn., K.: Fully convolutional self-similarity for dense semantic correspondence. CVPR (2017)
22. Kocabas, M., Karagoz, S., Akbas, E.: MultiPoseNet: Fast multi-person pose estimation using pose residual network. In: European Conference on Computer Vision (ECCV) (2018)
23. Li, B., Yan, J., Wu, W., Zhu, Z., Hu, X.: High performance visual tracking with siamese region proposal network. In: CVPR (2018)
24. Li, W., Wang, Z., Yin, B., Peng, Q., Du, Y., Xiao, T., Yu, G., Lu, H., Wei, Y., Sun, J.: Rethinking on multi-stage networks for human pose estimation. arXiv preprint (2019)
25. Li, X., Liu, S., Mello, S.D., Wang, X., Kautz, J., Yang, M.H.: Joint-task self-supervised learning for temporal correspondence. In: NeurIPS (2019)
26. Lin, T.Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollr, P., Zitnick, C.: Microsoft coco: Common objects in context (05 2014)
27. Luo, H., Gu, Y., Liao, X., Lai, S., Jiang, W.: Bag of tricks and a strong baseline for deep person re-identification. In: CVPRW (2019)
28. Moon, G., Chang, J.Y., Lee, K.M.: Multi-scale aggregation R-CNN for 2d multi-person pose estimation. In: CVPRW (2019)
29. Newell, A., Huang, Z., Deng, J.: Associative embedding: End-to-end learning for joint detection and grouping. In: NIPS (2017)
30. Newell, A., Yang, K., Deng, J.: Stacked hourglass networks for human pose estimation. In: ECCV (2016)
31. Nie, X., Feng, J., Xing, J., Yan, S.: Generative partition networks for multi-person pose estimation. ECCV (2018)
32. Ning, G., Huang, H.: Lighttrack: A generic framework for online top-down human pose tracking. arXiv preprint (2019)
33. Ning, G., Liu, P., Fan, X., Zhang, C.: A top-down approach to articulated human pose estimation and tracking. ArXiv-Preprint (2019)
34. Raaj, Y., Idrees, H., Hidalgo, G., Sheikh, Y.: Efficient online multi-person 2d pose tracking with recurrent spatio-temporal affinity fields. In: CVPR (2019)
35. Ruan, W., Liu, W., Bao, Q., Chen, J., Cheng, Y., Mei, T.: Poinet: Pose-guided omonic insight network for multi-person pose tracking. In: ICM (2019)
36. Sun, D., Yang, X., Liu, M.Y., Kautz, J.: PWC-Net: CNNs for optical flow using pyramid, warping, and cost volume. In: CVPR (2018)
37. Sun, K., Xiao, B., Liu, D., Wang, J.: Deep high-resolution representation learning for human pose estimation. In: CVPR (2019)
38. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., Rabinovich, A.: Going deeper with convolutions. In: CVPR (2015)
39. Wang, X., Jabri, A., Efros, A.A.: Learning correspondence from the cycle-consistency of time. In: CVPR (2019)
40. Wu, J., Zheng, H., Zhao, B., Li, Y., Yan, B., Liang, R., Wang, W., Zhou, S., Lin, G., Fu, Y., Wang, Y., Wang, Y.: AI challenger : A large-scale dataset for going deeper in image understanding. ArXiv-preprint (2017)
41. Xiao, B., Wu, H., Wei, Y.: Simple baselines for human pose estimation and tracking. In: ECCV (2018)
42. Xiu, Y., Li, J., Wang, H., Fang, Y., Lu, C.: Pose Flow: Efficient online pose tracking. BMVC (2018)
43. Yang, W., Li, S., Ouyang, W., Li, H., Wang, X.: Learning feature pyramids for human pose estimation. ICCV (2017)
44. Yu, D., Su, K., Sun, J., Wang, C.: Multi-person pose estimation for pose tracking with enhanced cascaded pyramid network. In: ECCV Workshop (2018)
45. Zhang, R., Zhu, Z., Li, P., Wu, R., Guo, C., Huang, G., Xia, H.: Exploiting offset-guided network for pose estimation and tracking. In: CVPR (2019)
46. Zhang, Z., Peng, H., Wang, Q.: Deeper and wider siamese networks for real-time visual tracking. CVPR (2019)
47. Zhu, Z., Wang, Q., Li, B., Wu, W., Yan, J., Hu, W.: Distractor-aware siamese networks for visual object tracking. ECCV (2018)