Estimating Egocentric 3D Human Pose in the Wild with External Weak Supervision

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Abstract

Egocentric 3D human pose estimation with a single fisheye camera has drawn a significant amount of attention recently. However, existing methods struggle with pose estimation from in-the-wild images, because they can only be trained on synthetic data due to the unavailability of large-scale in-the-wild egocentric datasets. Furthermore, these methods easily fail when the body parts are occluded by or interacting with the surrounding scene. To address the shortage of in-the-wild data, we collect a large-scale in-the-wild egocentric dataset called Egocentric Poses in the Wild (EgoPW). This dataset is captured by a head-mounted fisheye camera and an auxiliary external camera, which provides an additional observation of the human body from a third-person perspective during training. We present a new egocentric pose estimation method, which can be trained on the new dataset with weak external supervision. Specifically, we first generate pseudo labels for the EgoPW dataset with a spatio-temporal optimization method by incorporating the external-view supervision. The pseudo labels are then used to train an egocentric pose estimation network. To facilitate the network training, we propose a novel learning strategy to supervise the egocentric features with the high-quality features extracted by a pretrained external-view pose estimation model. The experiments show that our method predicts accurate 3D poses from a single in-the-wild egocentric image and outperforms the state-of-the-art methods both quantitatively and qualitatively.

1. Introduction

Egocentric motion capture using head- or body-mounted cameras has recently become popular because traditional motion capture systems with outside-in cameras have limitations when the person is moving around in a large space and thus restrict the scope of applications. Different from traditional systems, the egocentric motion capture system is mobile, flexible, and has no requirements on recording space, which enables capturing a wide range of human activities for many applications, such as wearable medical monitoring, sports analysis, and xR.

In this work, we focus on estimating the full 3D body pose from a single head-mounted fisheye camera. The most related works are Mo\textsuperscript{2}Cap\textsuperscript{2} [44] and xR-egopose [35]. While these methods have produced compelling results, they are only trained on synthetic images as limited real data exists and, therefore, suffer from significant performance drop on real-world scenarios. Furthermore, these methods often struggle with the cases when parts of the human body are occluded by or interacting with the surrounding scene (see the Mo\textsuperscript{2}Cap\textsuperscript{2} results in Fig. 1). This is due to the domain gap between synthetic and real data, but also due to their limited capability of handling occlusions.

To address the issue of the limited real egocentric data,
we capture a large-scale in-the-wild egocentric dataset called **Egocentric Poses in the Wild (EgoPW)**. This is currently the largest egocentric in-the-wild dataset, containing more than 312k frames and covering 20 different daily activities in 8 everyday scenes. To obtain the supervision for the network training, one possibility is using a multi-view camera setup to capture training data with ground truth 3D body poses or apply multi-view weak supervision. However, this setup is impractical for recording in an environment with limited space (e.g. in the small kitchen shown in Fig. 3), which is a common recording scenario. Therefore, considering a trade-off between flexibility and 3D accuracy, we use a new device setup consisting of an egocentric camera and a single auxiliary external camera. We demonstrate that the external view can provide additional supervision during training, especially for the highly occluded regions in the egocentric view (e.g. the lower body part).

To handle occlusions and estimate accurate poses, we propose a new egocentric pose estimation method for training on the EgoPW dataset in a weakly supervised way. Specifically, we propose a spatio-temporal optimization method to generate accurate 3D poses for each frame in the EgoPW dataset. The generated poses are further used as pseudo labels for training an egocentric pose estimation network [44]. To improve the network performance, we facilitate the training of the egocentric pose estimation network with the extracted features from the external pose estimation network which has been trained on a large in-the-wild body pose dataset. Specifically, we enforce the feature extracted from these two views to be similar by fooling a discriminator not being able to detect which view the features are from. To further improve the performance of the pose estimation network, besides the EgoPW dataset, we also use a synthetic dataset [44] to train the network and adopt a domain adaptation strategy to minimize the domain gap between synthetic and real data.

We evaluate our method on the test data provided by Wang et al. [42] and Xu et al. [44]. Our method significantly outperforms the state-of-the-art methods both quantitatively and qualitatively. We also show qualitative results on various in-the-wild images, demonstrating that our method can predict accurate 3D poses on very challenging scenes, especially when the body joints are seriously occluded (see our results in Fig. 1). To summarize, our contributions are presented as follows:

- A new method to estimate egocentric human pose with weak supervision from an external view, which significantly outperforms existing methods on in-the-wild data, especially when severe occlusions exist;
- A large in-the-wild egocentric dataset (EgoPW) captured with a head-mounted fisheye camera and an external camera. It is publicly available in [https://people.mpi-inf.mpg.de/~jianwang/projects/egopw](https://people.mpi-inf.mpg.de/~jianwang/projects/egopw);

- A new optimization method to generating pseudo labels for the in-the-wild egocentric dataset by incorporating the supervision from an external view;
- An adversarial method for training the network by learning the feature representation of egocentric images with external feature representation.

2. Related Work

**Egocentric 3D full body pose estimation.** Rhodin et al. [30] developed the first method to estimate the full-body pose from a helmet-mounted stereo fisheye camera. Cha et al. [4] presented an RNN-based method to estimate body pose with two pinhole cameras mounted on the head. Xu et al. [44] introduced a single wide-view fisheye camera setup and proposed a single-frame based egocentric motion capture system. With the same setup, Tome et al. [35] captured the egocentric pose with an auto-encoder network which captures the uncertainty in the predicted heatmaps. In order to further mitigate the effect of image distortions, Zhang et al. [46] proposed an automatic calibration module. Hwang et al. [14] put an ultra-wide fisheye camera on the user’s chest and estimate body pose, camera rotation and head pose simultaneously. Jiang et al. [16] mounted a front-looking fisheye camera on the user’s head and estimated the body and head pose by leveraging the motion of the environment and extremity of the human body. Wang et al. [42] proposed an optimization algorithm to obtain temporally stable egocentric poses with motion prior learned from MoCap datasets. However, these methods are all trained on synthetic datasets, thus suffering from the performance drop on the real images due to the domain gap and lack of external supervision. Our method, on the contrary, achieves better performance on the in-the-wild scenes.

**Pseudo label generation.** The task of pseudo-labeling [20,34,45] is a semi-supervised learning technique that generates pseudo labels for unlabeled data and uses the generated labels to train a new model. This has been applied in the areas of segmentation [8,22,47,48], pose estimation [2,21,23,25] and image classification [1,13,29]. Since the pseudo labels may be inaccurate, some methods have been proposed to filter inaccurate labels to increase the labeling stability. Shi et al. [34] set confidence levels on unlabeled samples by measuring the sample density. Chen et al. [5] enforced the stability of pseudo labels by adopting an easy-to-hard transfer strategy. Wang and Wu [41] introduced a repetitive re-prediction strategy to update the pseudo labels, while Rizve et al. [32] proposed an uncertainty-aware pseudo-label selection framework that selects pseudo labels. Morerio et al. [24] used a conditional
GAN to filter the noise in the pseudo labels. Different from previous pseudo-labeling works which generate the labels from network predictions or clustering, we design an optimization framework to generate labels with supervision from egocentric and external views simultaneously.

Weakly Supervised 3D Human Pose Estimation. Recently, there is a growing interest in developing weakly-supervised 3D pose estimation methods. Weakly-supervised methods do not require datasets with paired images and 3D annotations. Some works [27, 40] leverages the non-rigid SFM to get 3D joint positions from 2D keypoint annotations in unconstrained images. Some works [6, 7, 10, 28, 38] present an unsupervised learning approach to train the 3D pose estimation network with the supervision from 2D reprojections. The closest to our work are the approaches of [15, 19, 31, 39] in that they leverage the weak supervision from multi-view images for training. Iqbal et al. [15] and Rhodin et al. [31] supervise the network training process by calculating the differences between Procrustes-aligned 3D poses from different views. Wandt et al. [39] predict the camera poses and 3D body poses in a canonical form, and then supervise the training with the multi-view consistency. Kocabas et al. [19] obtain the pseudo labels with epipolar geometry between different views and use the pseudo labels to train the 3D pose lifting network. Different from previous works [15, 19, 31, 39], our method uses spatio-temporal optimization framework that takes egocentric and external view as input to obtain robust 3D pseudo labels for training the network. This optimization method ensures the stability of the network training process when the 2D pose estimations are inaccurate.

3. Method

We propose a new approach to train a neural network on the in-the-wild dataset with weak supervision from egocentric and external views. The overview of our approach is illustrated in Fig. 2. We first capture a large-scale egocentric in-the-wild dataset, called EgoPW, which contains synchronized egocentric and external image sequences (Sec. 3.1). Next, we generate pseudo labels for the EgoPW dataset with an optimization-based framework. This framework takes as input a sequence in a time window with $B$ frames of egocentric images $\mathcal{I}_{\text{ego}}^\text{seq} = \{\mathcal{I}_1^\text{ego}, \ldots, \mathcal{I}_B^\text{ego}\}$ and external images $\mathcal{I}_{\text{ext}}^\text{seq} = \{\mathcal{I}_1^\text{ext}, \ldots, \mathcal{I}_B^\text{ext}\}$ and outputs egocentric 3D poses $\mathcal{P}_{\text{ego}}^\text{seq} = \{\mathcal{P}^1, \ldots, \mathcal{P}^B\}$ as the pseudo labels (Sec. 3.2). Next, we train the egocentric pose estimation network on the synthetic data from Mo2Cap2 [44] and on the EgoPW dataset with pseudo labels $\mathcal{P}_{\text{ego}}^\text{seq}$. In the training process, we leverage the feature representation from an off-the-shelf external pose estimation network [43] to enforce our egocentric network to learn a better feature representation in an adversarial way (Sec. 3.3.2). We also use an adversarial domain adaptation strategy to mitigate the domain gap between synthetic and real datasets (Sec. 3.3.1).

3.1. EgoPW Dataset

We first describe the newly collected EgoPW dataset, which is the first large-scale in-the-wild human performance dataset captured by an egocentric camera and an
In this objective function, \( \mathbf{P} \) denotes the external poses, \( \mathbf{E} \) the egocentric poses, \( \mathbf{K} \) is the intrinsic matrix of the external camera; \( \mathbf{R}_1, \ldots, \mathbf{R}_B \) and \( t_1, \ldots, t_B \) are the rotations and translations of the external camera pose for each frame, i.e. the rotations \( \mathbf{R}_{seq} = \mathbf{R}_1, \ldots, \mathbf{R}_B \) and translations \( t_{seq} = t_1, \ldots, t_B \).

**External Reprojection Term.** In order to supervise the optimization process with the external 2D pose, we designed the external reprojection term which minimizes the difference between the projected 3D pose with the external 2D joints. The energy term is defined as:

\[
E^\text{ext}_R(\mathbf{P}_{seq}^{ego}, \mathbf{R}_{seq}, t_{seq}) = \sum_{i=1}^{B} \left\| \mathbf{J}^\text{ext}_i - K \left[ \mathbf{R}_i \mid t_i \right] \mathbf{P}^\text{ego}_i \right\|^2_2,
\]

where \( K \) is the intrinsic matrix of the external camera; \( [\mathbf{R}_i \mid t_i] \) is the pose of the egocentric camera in the \( i \) th frame w.r.t the external camera position. In Eq. 2, we first project the egocentric body pose \( \mathbf{P}^\text{ego} \) to the 2D body pose in the external view with the egocentric camera pose \( [\mathbf{R}_i \mid t_i] \) and the intrinsic matrix \( K \), and then compare the projected body pose with the 2D joints estimated by the openpose [3]. Since the relative pose between the external camera and egocentric camera are unknown at the beginning of the optimization, we optimize the egocentric camera pose \( [\mathbf{R}_i \mid t_i] \) simultaneously while optimizing the egocentric body pose \( \mathbf{P}^\text{ego} \). In order to make the optimization process converge faster, we initialize the egocentric camera pose \( [\mathbf{R}_i \mid t_i] \) with the Perspective-in-N-Point algorithm [11].

**Camera Pose Consistency.** We cannot get the accurate 3D pose only with the external reprojection term because the egocentric camera pose and the optimized body pose can be arbitrarily changed without violating the external reprojection constraint. To alleviate this ambiguity, we introduce the camera consistency term \( E_C \) as follows:

\[
E_C(\mathbf{R}_{seq}, t_{seq}) = \sum_{i=1}^{B-1} \left\| \begin{bmatrix} \mathbf{R}_i & t_i & 1 \\ 0 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix} ^{-1} \begin{bmatrix} \mathbf{R}_{i+1} & t_{i+1} & 1 \\ 0 & 0 & 1 \end{bmatrix} \right\| _2.
\]

It enforces the egocentric camera pose at \((i + 1)\) th frame \([\mathbf{R}_{i+1} \mid t_{i+1}]\) to be consistent with the pose obtained by transforming the egocentric camera pose at the \( i \) th frame \([\mathbf{R}_i \mid t_i]\) with the relative pose between the \( i \) th and \((i + 1)\) th frame.

**External 3D Body Pose Regularization.** Besides the external reprojection term, we also use the external 3D body poses to supervise the optimization of the egocentric 3D body pose. We define the external 3D pose term which measures the difference between the external and the egocentric body poses after a rigid alignment:

\[
E_J(\mathbf{P}_{seq}^{ego}, \mathbf{P}_{seq}^{ext}) = \sum_{i=1}^{B} \left\| \mathbf{P}^\text{ext}_i - \left[ \mathbf{R}^\text{ego}_i \mid t^\text{ego}_i \right] \mathbf{P}^\text{ego}_i \right\|^2_2.
\]
where $[R^p_i | t^p_i]$ is the transformation matrix calculated with Procrustes analysis, which rigidly aligns the external 3D pose $P^{ext}_i$ and the egocentric 3D pose $P^{ego}_i$.

By combining the body poses estimated from the egocentric view and external view, we can reconstruct more accurate pseudo labels. As shown in Fig. 3, the hands of the person are occluded in the external view, resulting in the tracking of the hands failing in the external view (Fig. 3, b), however, the hands can be clearly seen and tracked in the egocentric view (Fig. 3, d); on the other hand, the feet cannot be observed in the egocentric view and thus fail to be tracked in this view (Fig. 3, b), but can be easily viewed and tracked in the external view (Fig. 3, d). By joining the information from both views, we can successfully predict accurate 3D poses as the pseudo labels (Fig. 3, c). We note that the external camera is only used for generating the pseudo labels but at test time, only the egocentric camera is used.

**Camera Matrix Regularization.** We constrain the camera rotation matrix $R_i$ to be orthogonal:

$$E_J(R_{seq}) = \sum_{i=1}^{B} \|R_i^{T}R_i - I\|_2^2. \quad (5)$$

Different from previous single-view pose estimation methods which leverages the weak supervision from multiple views \([15, 19, 31, 39]\), our spatio-temporal optimization method generates the pseudo labels under the guidance of learned motion prior, making it robust to noisy and inaccurate 2D pose estimations which is common for the 2D pose estimation results from the egocentric view.

### 3.3. Training Egocentric Pose Estimation Network

Through the optimization framework in Sec. 3.2, we can get accurate 3D pose pseudo labels $P^{ego}_i$ for each egocentric frame in the EgoPW dataset, which is further processed into the 2D heatmap $H_E$ and the distance between joints and egocentric camera $D_E$ with the fisheye camera model \([33]\) described in supplementary materials.

Afterward, we train a single-image based egocentric pose estimation network on both the synthetic dataset from Mo2Cap$^2$ and the EgoPW dataset, as shown in the right part of Fig. 2. The pose estimation network contains a feature extractor $\Theta$ which encodes an image into a feature vector and a pose estimator $\Psi$ which decodes the feature vector to 2D heatmaps and a distance vector. The 3D pose can be reconstructed from them with the fisheye camera model. Here, we note the synthetic dataset $S = \{I_S, H_S, D_S\}$ including synthetic images $I_S$ along with their corresponding heatmaps $H_S$ and distance labels $D_S$ from Mo2Cap$^2$ dataset, and the EgoPW dataset $E = \{I^E_ego, H_E, D_E, I^E_ext\}$ including egocentric in-the-wild images $I^E_ego$ along with pseudo heatmaps $H_E$, distance labels $D_E$ and corresponding external images $I^E_ext$. During the training process, we train the egocentric pose estimation network with two reconstruction loss terms and two adversarial loss terms. The reconstruction losses are defined as the mean squared error (MSE) between the predicted heatmaps/distances and heatmaps/distances from labels:

$$L_S = \text{mse}(\hat{H}_S, H_S) + \text{mse}(\hat{D}_S, D_S)$$

$$L_E = \text{mse}(\hat{H}_E, H_E) + \text{mse}(\hat{D}_E, D_E), \quad (6)$$

where

$$\hat{H}_S, \hat{D}_S = \Psi(F_S), F_S = \Theta(I_S);$$

$$\hat{H}_E, \hat{D}_E = \Psi(F^{ego}_E), F^{ego}_E = \Theta(I^{ego}_E). \quad (7)$$

Two adversarial losses are separately designed for learning egocentric feature representation and bridging the domain gap between synthetic and real datasets. These two losses are described as follows.

#### 3.3.1 Adversarial Domain Adaptation

To bridge the domain gap between the synthetic and real data domains, following Tzeng et al. \([36]\), we introduce an adversarial discriminator $\Gamma$ which takes as input the feature vectors extracted from a synthetic image and an in-the-wild image, and determines if the feature is extracted from an in-the-wild image. The adversarial discriminator $\Gamma$ is trained with a cross-entropy loss:

$$L_D = -E[\log(\Gamma(F_S))] - E[\log(1 - \Gamma(F^{ego}_E))]. \quad (8)$$

Once the discriminator $\Gamma$ has been trained, the feature extractor $\Theta$ maps the images from different domains to the same feature space such that the classifier $\Gamma$ cannot tell if the features are extracted from synthetic images or real images. Therefore, the pose estimator $\Psi$ can predict more accurate poses for the in-the-wild data.
3.3.2 Supervising Egocentric Feature Representation with External View

Although our new training dataset is large, the variation of identities in the dataset is still relatively limited (20 identities) compared with the existing large-scale external-view human datasets (thousands of identities). Generally speaking, the representations learned with these external-view datasets are of higher quality due to the large diversity of the datasets. To further improve the generalizability of our network and prevent overfitting to the training identities, we propose to supervise our egocentric representation by leveraging the high-quality third-person-view features. From a transfer learning perspective, although following Mo²Cap² [44], our egocentric network is pretrained on the third-person-view datasets, it can easily “forget” the learned knowledge while being finetuned on the synthetic dataset. The supervision from third-person-view features can prevent the egocentric features from deviating too much from those learned from large-scale real human images.

However, directly minimizing the distance between egocentric features $F_{E}^{ego}$ and external features $F_{E}^{ext}$ will not enhance the performance since the intermediate features of the egocentric and external view should be different from each other due to significant difference on the view direction and camera distortions. To tackle this issue, we use the adversarial training strategy to align the feature representation from egocentric and external networks. Specifically, we use an adversarial discriminator $\Lambda$ which takes the feature vectors extracted from an egocentric image and the corresponding in-the-wild images and predicts if the feature is from egocentric or external images. The adversarial discriminator $\Lambda$ is trained with a cross-entropy loss:

$$L_V = -\mathbb{E}[\log(\Lambda(F_{E}^{ego}))] - \mathbb{E}[\log(1 - \Lambda(F_{E}^{ext}))], \quad (9)$$

where $F_{E}^{ext} = \Theta^{ext}(I_{E}^{ext})$ and $\Theta^{ext}$ is the feature extractor of external pose estimation network that shares exactly the same architecture as the egocentric pose estimation network. The parameters of the features extractor $\Theta^{ext}$ and the pose estimator $\Psi^{ext}$ of the external pose estimation network are obtained from the pretrained model in Xiao et al.’s work [43] and keep fixed during the training process.

Note that the deep layers of the pose estimation network usually represent the global semantic information of the human body [9], we use the output feature of the 4th res-block of ResNet-50 network [12] as the input to the discriminator $\Lambda$. Furthermore, the spatial position of the joints is quite different in the egocentric view and the external view, which will make the discriminator $\Lambda$ easily learn the difference between egocentric and external features. To solve this, we use an average pooling layer in the discriminator $\Lambda$ to spatially aggregate features, thus further eliminating the influence of spatial distribution between egocentric and external images. Please refer to the suppl. mat. for further details.

During the training process, the egocentric pose estimation network is trained to produce the features $F_{E}^{ego}$ to fool the domain classifier $\Lambda$ such that it cannot distinguish whether the feature is from an egocentric or external image. To achieve this, the egocentric network learns to pay more attention to the relevant parts of the input image, i.e., the human body, which is demonstrated in Fig. 4.

4. Experiments

4.1. Datasets

We quantitatively evaluate our finetuned network on the real-world dataset from Mo²Cap² [44] and Wang et al. [42]. The real-world dataset in Mo²Cap² [44] contains 2.7k frames of two people captured in indoor and outdoor scenes, and that in Wang et al. [42] contains 12k frames of two people captured in the studio. To measure the accuracy of our pseudo labels, we evaluate our optimization method (Sec. 3.2) only on the dataset from Wang et al. [42] since the Mo²Cap² dataset does not include the external view.

To evaluate our method on the in-the-wild data, we also conduct a qualitative evaluation on the test set of the EgoPW dataset. The EgoPW dataset will be made publicly available, and more details and comparisons to other datasets are included in the supplementary materials.

4.2. Evaluation Metrics

We measure the results of our method as well as other baseline methods with two metrics, PA-MPJPE and BA-MPJPE, which estimate the accuracy of a single body pose. For PA-MPJPE, we rigidly align the estimated pose $\hat{P}$ of each frame to the ground truth pose $P$ using Procrustes analysis [17]. In order to eliminate the influence of the body scale, we also report the BA-MPJPE scores. In this metric, we first resize the bone length of each predicted body pose $\hat{P}$ and ground truth body pose $P$ to the bone length of a standard skeleton. Then, we calculate the PA-MPJPE between the two resulting poses.

4.3. Pseudo Label Generation

In this paper, we first generate the pseudo labels with the optimization framework (Sec. 3.2) and use them to train our
Figure 5. Qualitative comparison between our method and the state-of-the-art methods. From left to right: input image, \(\text{Mo}^2\text{Cap}^2\) result, \(xR\text{-egopose}\) result, our result, and external image. The ground truth pose is shown in red. Note that the external images are not used during inference. The input images in the left part are from the test dataset in [42], while those in the right part come from EgoPW test sequences.

<table>
<thead>
<tr>
<th>Method</th>
<th>PA-MPJPE</th>
<th>BA-MPJPE</th>
</tr>
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<tbody>
<tr>
<td>(\text{Mo}^2\text{Cap}^2)</td>
<td>102.3</td>
<td>74.46</td>
</tr>
<tr>
<td>(xR\text{-egopose})</td>
<td>112.0</td>
<td>87.20</td>
</tr>
<tr>
<td>Wang et al. [42]</td>
<td>83.40</td>
<td>63.88</td>
</tr>
<tr>
<td>VIBE [18]</td>
<td>68.13</td>
<td>52.99</td>
</tr>
<tr>
<td><strong>Our Optimizer</strong></td>
<td><strong>57.19</strong></td>
<td><strong>46.14</strong></td>
</tr>
</tbody>
</table>

Table 1. The accuracy of pseudo labels on Wang et al.’s dataset. Utilizing both egocentric and external view, the body poses from our optimization method (Sec. 3.2) are more accurate and can serve as better pseudo labels.

4.4. Comparisons on 3D Pose Estimation

In this section, we compare the egocentric pose estimation network trained in Sec. 3.3 with previous single-frame-based methods on the test dataset from [42] under the “Wang et al.’s test dataset” in Table 2. Since the code or the predictions of \(xR\text{-egopose}\) are not publicly available, we use our reimplementation of \(xR\text{-egopose}\) instead. On this dataset, our method outperforms \(\text{Mo}^2\text{Cap}^2\) by 20.1% and \(xR\text{-egopose}\) by 27.0% respectively. We also compared with previous methods on the \(\text{Mo}^2\text{Cap}^2\) test dataset and show the results under the “\(\text{Mo}^2\text{Cap}^2\) test dataset” in Table 2. On the \(\text{Mo}^2\text{Cap}^2\) test dataset, our method performs better than \(\text{Mo}^2\text{Cap}^2\) and \(xR\text{-egopose}\) by 8.8% and 4.2%, respectively.

From the results in Table 2, we can see that our approach outperforms all previous methods on the single-frame egocentric pose estimation task. More quantitative results on each type of motion are available in the supplementary material. For the qualitative comparison, we show the results of our method on the studio dataset and in-the-wild dataset in Fig. 5. Our method performs much better compared with \(\text{Mo}^2\text{Cap}^2\) and \(xR\text{-egopose}\), especially for the in-the-wild cases where the body parts are occluded. Please refer to the supplementary materials for more qualitative results.

We also compared our method with Rhodin et al.’s method [31], which uses the weak supervision from multi-

<table>
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<tr>
<th>Method</th>
<th>PA-MPJPE</th>
<th>BA-MPJPE</th>
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<tbody>
<tr>
<td>Wang et al.’s test dataset</td>
<td></td>
<td></td>
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<tr>
<td>Rhodin et al. [31]</td>
<td>89.67</td>
<td>73.56</td>
</tr>
<tr>
<td>(\text{Mo}^2\text{Cap}^2) [44]</td>
<td>102.3</td>
<td>74.46</td>
</tr>
<tr>
<td>(xR\text{-egopose}) [35]</td>
<td>112.0</td>
<td>87.20</td>
</tr>
<tr>
<td><strong>Ours</strong></td>
<td><strong>81.71</strong></td>
<td><strong>64.87</strong></td>
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<tr>
<th>Method</th>
<th>PA-MPJPE</th>
<th>BA-MPJPE</th>
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<tbody>
<tr>
<td>(\text{Mo}^2\text{Cap}^2) test dataset</td>
<td></td>
<td></td>
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<tr>
<td>Rhodin et al. [31]</td>
<td>97.69</td>
<td>76.92</td>
</tr>
<tr>
<td>(\text{Mo}^2\text{Cap}^2) [44]</td>
<td>91.16</td>
<td>70.75</td>
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<tr>
<td>(xR\text{-egopose}) [35]</td>
<td>86.85</td>
<td>66.54</td>
</tr>
<tr>
<td><strong>Ours</strong></td>
<td><strong>83.17</strong></td>
<td><strong>64.33</strong></td>
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Table 2. Performance of our egocentric pose estimation network (Sec. 3.3) on Wang et al.’s test dataset and \(\text{Mo}^2\text{Cap}^2\) test dataset [44]. Our method outperforms the state-of-the-art methods, \(\text{Mo}^2\text{Cap}^2\) [44] and \(xR\text{-egopose}\) [35], on both metrics.
ple views to supervise the training of a single view pose estimation network. In our EgoPW dataset, we only have one egocentric and one external view. Thus, we fix the 3D pose estimation network for the external view and only train the egocentric pose estimation network. Following Rhodin et al. [31], we align the prediction from the egocentric and external view with Procrustes analysis and calculate the loss proposed by Rhodin et al. Our result in Table 2 shows our method performs better. This is mainly because our spatio-temporal optimization method predicts accurate and temporally stable 3D poses as pseudo labels, while other methods suffer from inaccurate egocentric pose estimations.

### 4.5. Ablation Study

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<th>Method</th>
<th>PA-MPJPE</th>
<th>BA-MPJPE</th>
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<tbody>
<tr>
<td>w/o external view</td>
<td>90.05</td>
<td>68.99</td>
</tr>
<tr>
<td>w/o learning representation</td>
<td>85.46</td>
<td>67.01</td>
</tr>
<tr>
<td>w/o domain adaptation</td>
<td>84.22</td>
<td>66.48</td>
</tr>
<tr>
<td>Unsupervised DA</td>
<td>91.56</td>
<td>69.17</td>
</tr>
<tr>
<td>Ours</td>
<td>81.71</td>
<td>64.87</td>
</tr>
</tbody>
</table>

Table 3. The quantitative results of ablation study.

**Supervision from the external view.** In our work, we introduce the external view as supervision for training the network. The external view enables generating accurate pseudo labels, especially when the human body parts are occluded in the egocentric view but can be observed in the external view. Without the external view, the obtained pseudo labels are less accurate and will further affect the network performance. In order to demonstrate this, we firstly generate the 3D poses as pseudo labels with Wang et al.’s method, *i.e.* without any external supervision, and then train the pose estimation network on these new pseudo labels. The result is shown in the “w/o external view” row of Table 3. We also show the qualitative results with and without external-view supervision in Fig. 6. Both the qualitative and quantitative results demonstrate that with the external supervision, the performance of our pose estimation network is significantly better especially on occluded cases.

**Learning egocentric feature representation and bridging the domain gap with adversarial training.** In our work, we train the pose estimation network with two adversarial components in order to learn the feature representation of the egocentric human body (Sec. 3.3.2) and bridge the domain gap between synthetic and real images (Sec. 3.3.1). In order to demonstrate the effectiveness of both modules, we removed the domain classifier $\Lambda$ in our training process and show the results in the row of “w/o learning representation” in Table 3. We also removed the domain classifier $\Gamma$, train the network without $L_D$ and show the quantitative results in the row of “w/o domain adaptation” in Table 3. After moving any of the two components, our method suffers from the performance drop, which demonstrates the effectiveness of both the feature representation learning module and the domain adaptation module.

![Figure 6](image.png)

**Comparison with only using unsupervised domain adaptation.** In this experiment, we compare our approach with the unsupervised adversarial domain adaptation method [36] which is commonly used for transfer learning tasks. We train the network only with the $L_S$ and $L_D$ in the adversarial domain adaptation module (Sec. 3.3.1) and show the results in the “Unsupervised DA” of the Table 3. Our approach outperforms the unsupervised domain adaptation method due to our high-quality pseudo labels.

### 5. Conclusions

In this paper, we have proposed a new approach to egocentric human pose estimation with a single head-mounted fisheye camera. We collected a new in-the-wild egocentric dataset (EgoPW) and designed a new optimization method to generate accurate egocentric poses as pseudo labels. Next, we supervise the egocentric pose estimation network with the pseudo labels and the features from the external network. The experiments show that our method outperforms all of the state-of-the-art methods both qualitatively and quantitatively and our method also works well under severe occlusion. As future work, we would like to develop a video-based method for estimating temporally-consistent egocentric poses from an in-the-wild video.

**Limitations.** The accuracy of pseudo labels in our method is constrained by our in-the-wild capture system, which only contains one egocentric view and one external view, and further constrains the performance of our network. One future solution is to fuse different sensors, including IMUs and depth cameras, for capturing the in-the-wild dataset.

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