PedRecNet: Multi-task deep neural network for full 3D human pose and orientation estimation

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Abstract—We present a multitask network that supports various deep neural network based pedestrian detection functions. Besides 2D and 3D human pose, it also supports body and head orientation estimation based on full body bounding box input. This eliminates the need for explicit face recognition. We show that the performance of 3D human pose estimation and orientation estimation is comparable to the state-of-the-art. Since very few data sets exist for 3D human pose and in particular body and head orientation estimation based on full body data, we further show the benefit of particular simulation data to train the network. The network architecture is relatively simple, yet powerful, and easily adaptable for further research and applications.

I. INTRODUCTION

The detection of pedestrians as well as their behavior remains a challenge in the field of autonomous driving. Previous work shows how to detect pedestrian actions using 2D pose recognition [1]. In this work, we present a new multitask network, PedRecNet, that can estimate 3D poses in addition to 2D poses. 3D poses bring in the benefit of multiple perspectives on the skeleton, enabling detection of movement changes which may not be visible in 2D projections [2]. In addition to 3D pose data, orientation information about a person’s body and head is also relevant for human recognition systems. Especially in pedestrian recognition, this information can be valuable to perform path planning or to detect if a pedestrian notices a vehicle or not. Since 3D pose recognition and body as well as head orientation estimation are related it seems beneficial to bring this tasks together in one versatile network. All tasks in the PedRecNet are based on the same input data, so all tasks should be implemented in the same network using a multitask approach. Since there are only a few real datasets available for 3D pose recognition and especially for body and head orientation estimation, we use simulation data to improve these parts of the PedRecNet and to enable training in the first place. The skeleton-based action recognition results presented by [1] and [3] support the assumption that using abstract pose information rather than just visual information enables the transfer of simulated training data to real data. We will corroborate this work hypothesis in more detail in experiments using simulated training data. In the following, we describe the developed network, the datasets used, and evaluate 3D human pose recognition as well as the body orientation estimation on several real and simulated datasets.

Our contributions in this work are:

1) A multi-task network which supports 2D and 3D human pose estimation, as well as body and head orientation estimation on cropped full body input data.
2) An approach to 3D human pose estimation in which 3D human joint positions are encoded in the skeletal coordinate system. This makes the skeleton estimation independent of the camera parameters and can thus be better used in follow-up applications, such as action recognition which uses temporal data.
3) An integrated approach to body and head orientation estimation based on whole body bounding box input. This eliminates the need for face recognition to obtain a crop of the head bounding box.
4) Simulation data that provide, in particular, accurate head and body orientation data that are not available in standard data sets.

II. RELATED WORK

Besides direct estimation of 3D human joint positions by a deep neural network [4], [5], [6], [7] alternative approaches exist that first estimate 2D poses followed by 3D pose regression [8], [9], [10], [11], [12]. Some approaches show the application of model-based approaches [13], [14], [4], [6], [12] to further improve a recognized 3D skeleton. The categorization in bottom-up [5] and top-down approaches [15], [4], [6] is also valid for 3D human pose estimation. Mehta et al. show an approach predicting three location-maps for the x, y and z position parameters per body joint [4]. Those location maps encode the distance in x, y, or z direction from the coordinate root (hip center). The location of a joint on those location maps is retrieved from 2D pose heatmaps. The results are refined using a kinematic skeleton fitting method. They have also shown how to apply location maps in a bottom-up approach which also handles occlusion better by using redundancy in so-called occlusion-robust pose-maps by representing the decomposed body as torso, limbs, and heads [5]. Luvizon et al. show a similar approach to encode depth information in a heatmap but use it only for the depth

https://github.com/noboevbo/PedRec (accessed on 2021-09-02)
estimation [7]. It is also possible to directly regress 3D poses from 2D heatmaps [10] or directly from 2D pose coordinates [16] which improves when using multiple frames as input [9]. Another approach to retrieve 3D pose information from 2D poses is 3D catalog matching [8]. Such approaches rely more heavily on the 2D human pose estimator’s output than approaches that also use visual input. Kolotouros et al. show how to reconstruct a volumetric model by estimating the parameters for the SMPL statistical body shape model [17] and further improve the model by iteratively fitting on 2D joints [12]. We present an approach similar to [7], but with a straightforward and performant method to retrieve the pose and depth heatmaps in section III.

Body and head orientation estimation approaches are usually handled as separate problems. The estimation of body orientation often originate in pedestrian-related works. Classical approaches often used classification of body parts, for example, by using a part descriptor in a sliding window fashion to classify position, scale, and orientation of body parts [18]. Another approach focuses on combining pedestrian orientation and classification by clustering pedestrians in the four categories front, back, left, and right and train classification networks on those clusters, which combined scores serve as the full pedestrian classification [19]. Another approach uses specific detectors for head and body orientation which are converted to a full continuous probability density function and stabilized over time by particle filtering [20], [21]. The authors also discretized the orientation space to 45-degree bins and used a HOG/linSVM based classification system [20]. There is a lot of recent head orientation work using deep learning [22], [23], [24], [25], [26], [27], which usually takes a head bounding box as input and thus is an additional step in the recognition pipeline. Such methods require a head bounding box with a reasonable resolution and thus high-resolution sensors or people not at distance from the camera sensor. Work on body orientation or combined body and head orientation estimation has not yet transitioned well to deep learning approaches. One possible reason could be the lack of appropriate datasets. There are not many standard datasets, and the existing ones are rather small and thus not suitable to train deep neural networks. Heo et al. try to overcome this issue on body orientation estimation by using a teacher-student learning framework in which they train a teacher network with labeled data and use this network to generate labels for an unlabeled dataset with which the student network is trained [28]. They have also discretized the output orientation in 45-degree bins, turning the problem into a classification problem [28]. Another work uses CNNs in a random forest that focuses on different body and head parts to recognize the human body and head orientation, with a focus on head orientation [29]. Steinhoff and Göhring propose the usage of IMUs to generate more labeled training data for body and head orientation tasks, but IMU-based approaches are usually hard to sync, suffer from error accumulation, and do not contain global reference points [30]. Wu et al. propose the application of 3D human pose estimation approaches as a basis for body and head pose estimation using a 3D pose estimation network as a backbone for a classification header which classifies the input in 72 orientation bins [31]. We propose a regression approach which is based on full human 3D pose information, described in section III. Regressed orientation estimation offer various benefits, for example in time-dependent fine-grained actions like the head movement during looking for traffic. We show how to train such a network with simulated data to overcome the deficient number of labeled data in this field.

III. Method

The overall network architecture is shown in Figure 1. The PedRecNet expands the 2D human pose estimation approach proposed by Xiao et al. [32]. The PedRecNet architecture is based on a ResNet50 backbone for feature extraction but other backbones could be used as well. The ResNet50 architecture was chosen as a compromise between accuracy and performance. The inputs I are always images cropped to the size of certain bounding boxes. First features I are extracted using the feature extraction part of the network. Next, the 2D human pose estimation part is based on three transpose convolution blocks with which joint heatmaps are generated from the extracted features [32].

In PedRecNet, the 2D human pose estimation architecture was extended to include 3D human pose estimation. For this purpose, two transpose convolution blocks are used as a common basis and then split into a 2D and a 3D path. These have basically the same structure. The output in the 2D path corresponds to 2D image coordinates. The 3D path, leading to $L_{y,3d}$, corresponds to the estimation of the $x$ and $y$ coordinates of a joint relative to the hip and additional depth estimation of the $z$ coordinate using a sigmoid map. Another change from the previous 2D pose estimation approach is the post-processing of the heatmaps. In the approach shown in [1], the heatmaps were output from the network, and a
and head orientations, are only available in the simulated labels, especially orientation estimation labels are only available in the simulated datasets. The datasets support different poses for 3D pose recognition.

### A. Datasets

The training and validation datasets of the PedRec network are composed of the COCO [34], the H36M [35], and self-generated simulated datasets. The datasets support different labels, especially orientation estimation labels are only available in the simulation data (cf. Table I).

Whole-body data, including the θ and ϕ angle of the body and head orientations, are only available in the simulated datasets. Therefore, the validation of the orientation estimation on real data can be performed with these datasets only for the azimuthal angle ϕ of the body. All simulated datasets are created using motions, captured in a motion capture laboratory.

1) **SIM-ROM**: In the SIM-ROM dataset, a person was recorded performing an extended range of motions that should include as many poses as possible. The idea behind this dataset is to provide data from various performable body poses for 3D pose recognition.

2) **SIM-C01**: The SIM-C01 dataset is a large scale pedestrian action dataset containing actions ranging from simple walking, to hitchhiking, to tripping and falling. This dataset is used in this work for validation (SIM-C01V) only.

3) **SIM-CIRCLE**: The SIM-Circle dataset resulted from an analysis of the other datasets. As highlighted in Figure 3 there is a substantial difference in the distribution of the azimuthal angle ϕ of the body pose.

![Fig. 2: Visualization of the orientation estimation for each, the body and the head. The orange dot shows an example point on a 3D sphere, visualizing an orientation. We use the standard notation from ISO 80000-2:2019[33] for spherical coordinates. As we only need the polar angle θ and azimuthal angle ϕ we use a unit sphere and with r = 1.](image)

| Dataset   | Pose2D | Pose3D | Orientation |
|-----------|--------|--------|-------------|
| COCO      | ✓      | X      | O           |
| H36M      | ✓      | ✓      |             |
| TUD [36]  | X      | X      | O           |
| SIM-ROM   | ✓      | ✓      | ✓           |
| SIM-Circle| ✓      | ✓      | ✓           |

**TABLE I**: Overview of used datasets and the supported labels. COCO (MEBOW [31]) and TUD [36] orientation annotations provide only body ϕ labels. The 2D and 3D pose estimation labels differ in the available labels as COCO, H36M and SIM use different skeleton structures. Legend: ✓ data is available, X data is not available, O data is partially available.

![Fig. 3: Distribution of body θ orientations [°] in the datasets used in this work. The plots show the distribution of the samples in a polar plot. The small peaks in SIM-CIRCLE are due to overlapping start and end frames.](image)

The same could be observed for the distribution of the azimuthal angle ϕ of the head poses. In order to generate further data with a uniform distribution, the SIM-Circle...
dataset was created, in which 3D models walk clock- and counterclockwise in a circle at a uniform speed (see Fig. 3d). Table I provides an overview over the datasets used.

| Data       | COCO [34] | H36M [35] | TUD [36] | SIM-ROM | SIM-CIRCLE |
|------------|-----------|-----------|----------|---------|------------|
| \( n \)    | 149,814   | 1,559,752 | 8,322    | 147,729 | 39,484     |
| \( L_{\|d\|} \) [px] | 229       | 855       | 193      | 503     | 222        |
| \( \sigma_{d} \) [px]  | 148       | 81        | 44       | 502     | 153        |
| \( \min \|b\| \) [px] | 28        | 585       | 45       | 33      | 43         |
| \( \max \|b\| \) [px]  | 1,002     | 1,339     | 462      | 2,022   | 830        |
| \( \theta_{d} \) [mm]  | 1,712     | 1,416     | 1,885    |         |            |
| \( \sigma_{\theta_{d}} \) [mm] | 197       | 403       | 194      |         |            |
| \( \min \|b\| \) [mm]  | 859       | 169       | 1,202    |         |            |
| \( \max \|b\| \) [mm]  | 2,769     | 2,840     | 2,194    |         |            |
| \( \min \|d\| \) [px]  | 5,170     | 7,205     | 10,609   |         |            |
| \( \max \|d\| \) [px]  | 7,690     | 21,289    | 25,754   |         |            |

TABLE II: Statistics of datasets used in the PedRec experiments. \( b \) represents the 2D or 3D bounding box size and \( d \) the distance to the camera. The number of samples is notated as \( n \), the mean of bounding boxes and the distances to the camera as \( b/d \), and the standard deviation values are notated with \( \sigma \).

This overview shows that the H36M dataset was recorded in a lab with limited space, which is why the bounding boxes are always relatively large. Comparing the 2D bounding box diameters of COCO, TUD, and SIM-CIRCLE, the distribution is similar, as each of the datasets contains individuals at various distances.

B. Training procedure

The network was trained step by step in the following order:

1) 2D human pose estimation
2) 3D human pose estimation
3) Joint visibility
4) Head and body orientation

The training was performed on real data (COCO+H36M) and then on simulation data in the same order.

a) Loss Functions: We used the \( L_{1} \) loss function for the 2D and 3D human joint coordinate regression losses \( L_{2d} \) and \( L_{3d} \). The joint visibility loss \( L_{\text{conf}} \) is the standard binary cross-entropy loss. In the orientation regression task, we represent circular data in a one-dimensional map. Thus we cannot use the standard \( L_{1} \) or \( L_{2} \) loss; for example, a prediction of 359° with a ground truth of 0° results in an error of 359°. This applies only for the azimuthal angle \( \varphi \), the polar angle \( \theta \) is defined between 0° and 180°, and thus the standard distance metrics can be used. As such, we applied the following loss functions:

\[
L_{\varphi} = \frac{\sum_{i=1}^{N} \min(1 - |\hat{m}_{\varphi} - m_{\varphi}|, |\hat{m}_{\varphi} - m_{\varphi}|)}{N} \tag{1}
\]

\[
L_{\theta} = \frac{\sum_{i=1}^{N} |\hat{m}_{\theta} - m_{\theta}|}{N} \tag{2}
\]

\[
L_{o} = \frac{L_{\varphi} + L_{\theta}}{2} \tag{3}
\]

where \( N \) is the number of samples and \( m_{\varphi} \) and \( m_{\theta} \) are the softargmax outputs for the azimuthal angle \( \varphi \) and the polar angle \( \theta \) normalized between zero and one. As shown in equation (1) and (2), the \( L_{1} \) loss is applied. For training data which only provides labels for the azimuthal angle \( \varphi \) only equation (1) is used.

In our experiments, \( N \) may be a subset of the entire training set, as various datasets with different supported labels (see Table I) were combined. As such, each loss function contains a sample selection step before the actual calculation of the loss.

To weight the loss functions, we applied uncertainty loss, described by Kendall et al. [37], to balance the different loss outputs. The final loss function is:

\[
L = \frac{1}{\sigma_{1}^{2}} L_{2d} + \frac{1}{\sigma_{2}^{2}} L_{3d} + \frac{1}{\sigma_{o}^{2}} L_{o} + \frac{1}{\sigma_{\text{conf}}^{2}} + \log (1 + \sum_{i=1}^{4} \sigma_{i}) \tag{4}
\]

where \( \sigma_{1-4} \) are learnable parameters. We use \( \log (1 + \sigma) \) instead of \( \log (\sigma) \) to ensure a positive loss value.

b) Optimizer: For optimization we used the AdamW optimizer [38] which is an slightly modified variant of the Adam optimizer [39]. We applied the learning rate range test [40] to get an initial learning rate of \( 4e^{-3} \). We used a standard weight decay of \( 1e^{-2} \). We also applied the 1cycle policy [41] with which the learning rate is updated during the training process from a minimum learning rate of \( 2e^{-3} \) to the maximum of \( 4e^{-3} \) and afterward back to a minimum using cosine annealing. Smith showed that this approach results in faster convergence and usually better results [40]. The network was trained with a training cycle of 15 epochs, from which 10 epochs were trained with frozen weights in the feature extractor. For the last five epochs with the feature extractor unfrozen, we reduced the learning rate for the feature extraction to \( 2e^{-4} \) and for the other layers to \( 4e^{-4} \). The training cycle was repeated five times, which improved the performance slightly.

c) Datasets: We used the training datasets of COCO [34], H36M [35], SIM-ROM, and SIM-Circle to train the PedRecNet. The validation is done on the validation parts of COCO, H36M, and the SIM-C01 dataset. We subsampled the H36M training dataset by ten, all samples from the other datasets were used. For the orientation estimation part, we used only labels from SIM-ROM and SIM-Circle during the initial training. COCO labels were used in an additional training step during orientation experiments (see section IV-B). The dataset names are abbreviated in the results as follows: \( C \) stands for COCO, \( M \) for COCO (MEBOW [31]), \( H \) for H36M and \( S \) for SIM-Circle and SIM-ROM combined. COCO is always the base dataset of PedRecNet and is therefore used as one of the training dataset in every experiment.

d) Augmentations: We augmented the data by scaling the input by up to \( \pm 25\% \). We rotate the input by up to \( \pm 30\° \) in 50% of the cases, but only when no orientation labels were used. The image is flipped in 50% of the cases.

IV. EXPERIMENTS

a) 3D pose estimation: For 3D human pose estimation, we first consider the performance compared to other methods.

\[
\phi = \frac{\sum_{i=1}^{N} \min(1 - |\hat{m}_{\varphi} - m_{\varphi}|, |\hat{m}_{\varphi} - m_{\varphi}|)}{N} \tag{1}
\]

\[
L_{\theta} = \frac{\sum_{i=1}^{N} |\hat{m}_{\theta} - m_{\theta}|}{N} \tag{2}
\]

\[
L_{o} = \frac{L_{\varphi} + L_{\theta}}{2} \tag{3}
\]
on the H36M validation dataset. The results of 3D pose estimation are shown in Table III. It summarizes various approaches, which differ in the methods used, input data, and test methods. Some approaches use test-time augmentations like flip-testing. Others use temporal information to improve the results. Our novel PedRecNet is based on single-frame estimation. For better comparability, we also show results using flip-testing in addition to the results without any form of test-time augmentation. The performance of our method with an average MPJPE of 52.7mm is comparable to current SOTA approaches such as Gong et al. [45] with 50.2mm and Luvison et al. [7] with 48.6mm. The use of temporal information leads to noticeable better results in this benchmark. This becomes clear when comparing the two results of Pavllo et al. [9]. An improvement of 4.7mm could be achieved by using temporal information. The performance from PedRecNet, depending on the datasets used, is very similar but decreases slightly when simulation data is added. However, this may also be because the simulation data is partly very different from the H36M data in terms of distances and body size of the persons.

Figure 4 shows some examples on ‘in the wild’ real data. The examples are from various sources and include different cameras, focal lengths, exposures and perspectives. Examples [40][41] show that even in challenging situations a good 3D pose can be predicted. In contrast, we have reported some error cases in Figure 5. Figure 5a shows an extreme corner case where the pose detection fails completely. Note that the corner case dataset from our work [46] was not used during training. In Figure 5b the pose is correct in principle, but the outstretched left arm is not correctly recognized. From the pose only, it is not clear that the person is just operating a traffic light switch. Example 5c shows a false recognition due to self occlusion. The body occludes the left arm, but the 3D pose recognition estimates it to be hidden behind the right arm and displays it stretched out accordingly. These false detections by occlusion could possibly be improved by further training data or the use of temporal context.

b) Body orientation estimation: As described in the related work section, there are only few datasets in the area of body and head orientation estimation for full-body inputs.

For a state-of-the-art comparison, we found the relatively new dataset [31], which provides body orientation labels for the COCO dataset. However, it only contains the azimuthal angle $\phi$ and labels for the head pose are not included. We also used the TUD [36] dataset in the analysis, although it only contains 309 samples in the validation dataset. Accordingly, the significance of the results here is relatively low. Table IV gives an overview on the results on these datasets. It is to notice that with the PedRecNet we already achieve an Acc. $(22.5^\circ)$ of 75.4% on the TUD [36] dataset and 80.2% on the MEBOW dataset. For Acc. $(45^\circ)$, which is often sufficient for real-world applications, we even achieve 98.1% on the TUD [36] dataset and 94.7% on the MEBOW dataset. These are surprising results for not using any training data from the corresponding training datasets. Especially when compared to the earlier approaches of Hara et al. [47] and Yu et al. [48], the PedRecNet gives better results without ever having seen any data from the TUD [36] dataset. We are accordingly able to provide a solid baseline here purely with simulated data. It should be noted, however, that 3D pose data is also used for orientation estimation and the training for this has included real data from the H36M dataset. When the MEBOW training data are used in addition to the simulation data, the Acc. $(22.5^\circ)$ and Acc. $(45^\circ)$ improve by 11.5% and 2.3%, respectively, and are 2.2% and 1.2% worse than the results reported by Wu et al.

In total, 159 body orientations were predicted with an error above $45^\circ$. We analyzed these misclassifications further and detected erroneous ground truth labels for 37 images, some of which are shown in Figure 6.

c) Head orientation estimation: For the head orientation ($\phi$) estimation, we use the SIM-C01V dataset. We consider only the $\phi$ estimate at this point because $\theta$ is underrepresented in the SIM-C01 dataset; the head orientations are relatively horizontal in the pedestrian actions in almost all cases. Accordingly, for the estimation of $\theta$, further targeted experiments and new data recordings are needed in the future. The results for the estimation of the head $\phi$ orientation are shown in Table V.

The results are slightly inferior to the body orientation estimation by 2.6% and 2.8% for Acc. $(22.5^\circ)$ and

| Method | Prop. | Dir. | Disc. | Eat | Greet | Phone | Photo | Pose | Purch. | Sit | SitD. | Smoke | Wait | WalkD. | Walk | WalkT | Avg |
|--------|-------|------|-------|-----|-------|-------|-------|------|--------|-----|-------|-------|------|--------|------|--------|
| Chen et al. ['17 [8] | g | - | - | - | - | - | - | - | - | - | - | - | - | - | - | 82.4 |
| Martinez et al. ['17 [16] | g | 51.8 | 56.2 | 58.1 | 59.0 | 69.5 | 78.4 | 55.2 | 58.1 | 74.0 | 94.6 | 62.3 | 59.1 | 65.1 | 49.5 | 52.4 | 62.9 |
| Luvison et al. ['17 [42] | gs | 49.2 | 51.6 | 47.6 | 50.5 | 51.8 | 48.9 | 48.5 | 51.7 | 61.5 | 70.9 | 55.7 | 60.3 | 44.4 | 48.9 | 57.9 | 53.2 |
| Yang et al. ['18 [43] | - | 51.5 | 58.9 | 50.4 | 57.0 | 62.1 | 65.4 | 49.8 | 52.7 | 69.2 | 85.2 | 57.4 | 58.4 | 43.6 | 60.1 | 47.7 | 58.6 |
| Pavllo et al. ['18 [9] | agt | 45.1 | 47.4 | 42.0 | 46.0 | 49.1 | 56.7 | 44.5 | 44.4 | 57.2 | 66.1 | 47.5 | 44.8 | 49.2 | 52.6 | 34.0 | 47.1 |
| Pavllo et al. ['19 [9] | ag | 47.1 | 50.6 | 49.0 | 51.8 | 53.6 | 61.4 | 49.4 | 47.4 | 59.3 | 67.4 | 52.4 | 49.5 | 55.3 | 39.5 | 42.7 | 51.8 |
| Luvison et al. ['20 [7] | gs | 43.2 | 48.6 | 44.1 | 45.9 | 48.2 | 43.5 | 44.2 | 45.5 | 57.1 | 64.2 | 50.6 | 53.8 | 40.0 | 44.0 | 51.1 | 48.6 |
| Shan et al. ['21 [44] | at | 40.8 | 44.5 | 41.4 | 42.7 | 46.3 | 55.6 | 41.8 | 41.9 | 53.7 | 60.8 | 45.0 | 41.5 | 44.8 | 30.8 | 31.9 | 44.3 |
| Gong et al. ['21 [45] | ag | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | 50.2 |

For the 4D-4F estimate, even in challenging situations a good 3D pose can be predicted. In contrast, we have reported some error cases in Figure 5. Figure 5a shows an extreme corner case where the pose is correct in principle, but the outstretched left arm is not correctly recognized. From the pose only, it is not clear that the person is just operating a traffic light switch. Example 5c shows a false recognition due to self occlusion. The body occludes the left arm, but the 3D pose recognition estimates it to be hidden behind the right arm and displays it stretched out accordingly. These false detections by occlusion could possibly be improved by further training data or the use of temporal context.

| Method | Prop. | Dir. | Disc. | Eat | Greet | Phone | Photo | Pose | Purch. | Sit | SitD. | Smoke | Wait | WalkD. | Walk | WalkT | Avg |
|--------|-------|------|-------|-----|-------|-------|-------|------|--------|-----|-------|-------|------|--------|------|--------|
| ours C+HWM | ag | 49.2 | 51.9 | 49.6 | 50.8 | 55.4 | 60.4 | 45.4 | 48.8 | 64.3 | 75.2 | 53.0 | 47.3 | 54.0 | 39.2 | 45.5 | 52.7 |
| ours C+HWM +S+M | ag | 51.2 | 51.9 | 49.7 | 52.1 | 56.0 | 60.3 | 47.1 | 48.8 | 62.2 | 75.6 | 53.1 | 48.2 | 54.2 | 40.5 | 47.3 | 53.3 |
| ours C+HWM | g | 50.4 | 53.8 | 50.8 | 52.9 | 57.5 | 62.9 | 47.2 | 50.5 | 65.8 | 78.6 | 54.8 | 49.2 | 56.0 | 40.7 | 46.3 | 54.5 |
| ours C+HWM +S+M | g | 52.4 | 53.9 | 50.8 | 54.0 | 57.8 | 62.6 | 48.6 | 50.3 | 64.6 | 79.9 | 54.7 | 49.6 | 56.3 | 41.6 | 48.1 | 54.9 |
TABLE IV: Human body orientation ($\varphi$) test results on the MEBOW, TUD [36] and SIM-C01V datasets. The column trainset specifies the training dataset(s) used to train the specific networks. Testset specifies on which testsets the results are reported on. In addition to the accuracy in $22.5^\circ$ and $45^\circ$ intervals we report the mean average error (MAE).

| Network       | Trainset | Testset | Acc.$(22.5^\circ)$ | Acc.$(45^\circ)$ | MAE($^\circ$) |
|---------------|----------|---------|--------------------|-----------------|---------------|
| Wu et al.[31] (2020) | MEBOW    | MEBOW   | 93.9              | 98.2            | 8.4           |
| ours          | MEBOW    | MEBOW   | 92.3              | 97.0            | 9.7           |
| ours          | SIM+MEBOW| MEBOW   | 91.7              | 97.0            | 10.0          |
| ours          | SIM      | MEBOW   | 80.2              | 94.7            | 16.1          |
| Hara et al.[47] (2017) | TUD      | TUD     | 70.6              | 86.1            | 26.6          |
| Wu et al.[31] (2020) | MEBOW    | TUD     | 75.7              | 96.8            | 15.3          |
| ours          | MEBOW    | TUD     | 79.6              | 99.0            | 10.8          |
| ours          | SIM+MEBOW| TUD     | 77.3              | 98.7            | 14.3          |
| ours          | SIM      | TUD     | 75.4              | 98.1            | 16.0          |
| ours          | MEBOW    | SIM-C01 | 76.2              | 97.0            | 16.6          |
| ours          | SIM+MEBOW| SIM-C01 | 79.7              | 97.9            | 15.3          |
| ours          | SIM      | SIM-C01 | 78.7              | 96.5            | 16.0          |

TABLE V: PedRecNet: Head orientation test results for $\varphi$.

| Network | Trainset | Testset | Acc.$(22.5^\circ)$ | Acc.$(45^\circ)$ | MAE$^\circ$ |
|---------|----------|---------|--------------------|-----------------|-------------|
| PedRec  | SIM+MEBOW| SIM-C01V| 77.1               | 95.1            | 16.65       |
| PedRec  | SIM      | SIM-C01V| 76.3               | 94.8            | 17.43       |

Acc.$(45^\circ)$, respectively. In general, however, performance on the body and head orientation estimates is relatively similar. The somewhat inferior performance can be explained by the head region’s smaller image area than the body region. We are not currently aware of a larger and publicly dataset that includes head orientation images in addition to full-body images. Therefore, most approaches to head orientation estimation work with datasets that only contain cropped faces. In productive applications, face recognition can then be performed first, followed by a crop of the face, and orientation estimation can be performed based on this cropped face bounding box. In addition, most datasets only contain faces, which means that a side view or the back of
Fig. 6: MEBOW validation dataset: Examples of misclassifications. The red dotted arrow shows the annotated ground truth, the black arrow shows the prediction of PedRecNet. The misclassifications are caused by: (a) false ground truth label, (b) occlusion of the labeled person (the one in the back of the woman) and (c) PedRecNet misclassification.

the head cannot usually be used for orientation estimation. In our approach, the entire body is always considered, which enables head orientation estimation even for a side and back view of a person. However, based on subjective observation of ‘in-the-wild’ examples, we think that we can achieve similar performance on real data for head pose recognition as for body pose recognition when trained on simulation data only. We show ‘in-the-wild’ examples in Figure 7.

Figure 7a shows a typical example, where one can nicely depict the different estimates of head versus body orientation. Example 7b shows a boy in a stroller, which shows that the orientation estimation gives good results even in non-upright positions. Figure 7c shows a person who was photographed from behind. Especially the correct head pose estimation is interesting, although the person wears a hood and only a small part of the nose is visible. Another interesting example is demonstrated in Figure 7d, where the orientation estimation is based on input data of a person shot from behind and only visible in a low-resolution image section of about \(38 \times 78\) px.

V. Conclusion

With PedRecNet, we presented a simple yet efficient architecture that performs multiple tasks simultaneously and can run on consumer hardware at over 15 FPS even with multiple people. The network achieves performance that is comparable to current SOTA methods for 2D and 3D pose detection and orientation estimation. Our model combines all these tasks in a simple and extensible architecture which is straightforward to train. Thus, the introduced model is also well suited as a baseline for further research. We have further shown that we can train the orientation estimation purely with simulation data and achieve high accuracy on real data without requiring real sensor data for training.

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