Abstract

Despite significant progress, we show that state-of-the-art 3D human pose and shape estimation methods remain sensitive to partial occlusion and can produce dramatically wrong predictions although much of the body is observable. To address this, we introduce a soft attention mechanism, called the Part Attention REgessor (PARE), that learns to predict body-part-guided attention masks. We observe that state-of-the-art methods rely on global feature representations, making them sensitive to even small occlusions. In contrast, PARE’s part-guided attention mechanism overcomes these issues by exploiting information about the visibility of individual body parts while leveraging information from neighboring body-parts to predict occluded parts. We show qualitatively that PARE learns sensible attention masks, and quantitative evaluation confirms that PARE achieves more accurate and robust reconstruction results than existing approaches on both occlusion-specific and standard benchmarks. The code and data are available for research purposes at https://pare.is.tue.mpg.de/
and why such methods fail. This indicates that, for state-of-the-art (SOTA) methods, relatively small occlusions, even of only a single joint, can lead to entirely implausible pose predictions. This is illustrated in Fig. 1, where we slide an occluder over the image, regress body pose, and compute the average 3D joint error with respect to ground truth. The heatmaps in Fig. 1 (d,g) illustrate a method’s sensitivity to a square occluder centered at each pixel location (shown in white). The visualization reveals that methods like SPIN [41] are highly sensitive to localized part occlusion. To address this issue, we propose a method, based on a novel part-guided attention mechanism, making direct regression approaches more robust to occlusion.

The proposed method is called Part Attention REgressor (PARE). It has two tasks: the primary one is learning to regress 3D body parameters in an end-to-end fashion, and the auxiliary task is learning attention weights per body part. Each task has its own pixel-aligned feature extraction branch. We guide the attention branch with part segmentation labels in the early stages of training and continue without them for the later stages, thus we call it body-part-driven attention. Our key insight is that, to be robust to occlusions, the network should leverage pixel-aligned image features of visible parts to reason about occluded parts.

Given the success of attention-based methods on other tasks [11, 18, 34, 57], we exploit insights gained from the occlusion sensitivity analysis to focus attention on body parts. Therefore, we supervise the attention mask with part segmentation labels in the early stages of training and continue without them for the later stages, thus we call it body-part-driven attention. Our key insight is that, to be robust to occlusions, the network should leverage pixel-aligned image features of visible parts to reason about occluded parts.

The above methods are typically sensitive to occlusion. In summary, our key contributions are: (1) We apply a visualization technique [60] to study how local part occlusion can influence global pose; we call this occlusion sensitivity analysis. (2) This analysis motivates a novel body-part-driven attention framework for 3D HPS regression that leverages pixel-aligned localized features to regress body pose and shape. (3) The network uses part visibility cues to reason about occluded joints by aggregating features from the attended regions, and by doing so, achieves robustness to occlusions. (4) We achieve SOTA results on a 3D pose estimation benchmark featuring occluded bodies, as well as a standard benchmark.

2. Related Work

We focus on 3D human shape and pose estimation from RGB images and discuss how previous approaches handle occlusions in various scenarios, e.g. self occlusion, camera frame occlusion, and scene object occlusion.

3D pose and shape from a single image. In estimating human shape and pose, many methods output the parameters of 3D human body models [3, 33, 40]. Initial work predicts the 3D body using keypoint locations and silhouettes [1, 4, 5, 15, 48]. These approaches are fragile, need manual input, use additional data, e.g. multi-view images, or do not generalize well to in-the-wild images. SMPLify [7] was the first automated method to fit the SMPL model to the output of a 2D keypoint detector [42]. Lassner et al. [31] employ silhouettes together with keypoints during fitting. In contrast, deep neural networks regress SMPL parameters directly from pixels [16, 24, 39, 41, 52, 53]. In order to deal with the lack of in-the-wild 3D ground-truth, methods use a 2D keypoint re-projection loss as weak supervision [24, 52, 53], use intermediate 2D representations, e.g. body/part segmentation [39, 41, 59], 2D sparse keypoints [47, 59], or leverage a human in the loop [31]. Note that the use of part segmentation in [31, 39, 59] is very different from our approach, in which part segmentations are used to facilitate soft attention. Kolotouros et al. [29] combine HMR [24] and SMPLify [7] in a training loop. At each step, HMR initializes SMPLify, which fits the body model to 2D joints, resulting in better supervision for the network. The above methods are typically sensitive to occlusion.

Implicit occlusion handling (data augmentation). Ideally, the regressed 3D body should be the same with or without occlusion. Current SOTA pose and shape estimation methods [24, 27, 29] directly encode the entire input region as one CNN feature after global average pooling, followed by body model parameter regression. The lack of pixel-aligned structure makes it hard for networks to explicitly reason about the locations and visibility of body parts. A common way to achieve robustness to occlusion in these frameworks is through data augmentation. For example, frame occlusion is often simulated by cropping [6, 23, 44], whereas object occlusion is approximated by overlaying object patches on the image [13, 45]. Instead of applying augmentation to input images, Cheng et al. [8] apply augmentations to heatmaps that contain richer semantic information and hence occlusions can be simulated in a more intelligent way. While helpful, these synthetic occlusions do not fully capture the complexity of occlusions in realistic images, nor do they provide insight into how to improve the network architecture to be inherently more robust to occlusion.

Explicit occlusion handling. To reason more explicitly about occlusions, previous work exploits visibility information. For example, Cheng et al. [9] avoid including occluded joints when computing losses during training. Such visi-
Occlusion sensitivity analysis. Heatmaps illustrate the error of SPIN [29] in individual joints caused by an occluder placed at each image location. Image size: 224 × 224; occluding patch: 40 × 40. The title of each heatmap names the joint and notes the range of the 3D error in mm visualized in the heatmap. See Section 3 for analysis.

3. Occlusion Sensitivity Analysis

To extract features from the input image region \( I \), current direct regression approaches [24, 29] use a ResNet-50 [17] backbone and take the features after global average pooling (GAP), followed by an MLP that regresses and refines the parameters iteratively. In this section, we investigate the impact of occlusions on this type of architecture. Our analysis is inspired by Zeiler et al. [60] who systematically cover different portions of the image with a gray square to analyze how feature maps and classifier output changes. In contrast, we slide a gray occlusion patch over the image and regress body poses using SPIN [29]. Instead of computing a classification score as in [60], we measure the joint Euclidean distance between ground truth and predicted joints. We create an error heatmap, in which each pixel indicates how much error the model creates for joint \( j \) when the occluder is centered on this pixel. In addition to per-joint heatmaps, we compute an aggregate occlusion sensitivity map, that shows how the average joint error is influenced by an occlusion; this is visualized in Fig. 1(d) and in greater detail in the Sup. Mat.

The per-joint error heatmaps for SPIN are visualized in Fig. 2 for a sample image from the 3DPW dataset [54]. Each sub-image corresponds to a particular joint and hot regions are locations where occlusion causes high error in this joint. This visualization allows us to make several observations. (1) Errors are low in the background and high on the body. This shows that SPIN has learned to attend to meaningful regions. (2) Joints visible in the original image have high errors when they are occluded by the square, as expected. (3) For joints that are naturally occluded, the network relies on other regions to reason about the occluded poses. For example, in the top row of Fig. 2, we observe high errors for the left/right ankles (which are occluded) when we occlude the thigh region. Since the network has no image features for the occluded parts, it must look elsewhere in the image for evidence. (4) Such dependencies happen not only between neighboring parts; occlusion can have long-range effects (e.g. occluding the pelvis causes errors in the head).
4. Method

Given the observations above, PARE is designed with the following insights. First, as shown in Fig. 2, SOTA networks \([24, 27, 29]\) learn to attend to meaningful regions implicitly, despite limited spatial information after global average pooling. To better understand whether body parts are visible or not, and to know if their locations are occluded, PARE exploits a pixel-aligned structure, where each pixel corresponds to a region in the image and stores a pixel-level representation, namely, a feature volume. Second, since estimating attention weights and learning end-to-end trainable features for 3D poses are two different tasks, PARE is equipped with two feature volumes: one from the 2D part branch that estimates attention weights and one from the 3D body branch that performs SMPL parameter regression. Finally, to model the body part dependencies observed above, PARE exploits part segmentations as soft attention masks to adjust the contribution of each feature in the 3D body branch differently for each joint.

**Preliminaries: Body Model.** SMPL \([33]\) represents the body pose and shape by \(\Theta\), which consists of the pose \(\theta \in \mathbb{R}^{72}\) and shape \(\beta \in \mathbb{R}^{10}\) parameters. Here we use the gender-neutral shape model as in previous work \([24, 29]\). Given these parameters, the SMPL model is a differentiable function that outputs a posed 3D mesh \(M(\theta, \beta) \in \mathbb{R}^{6890 \times 3}\). The 3D joint locations \(J_{3D} = W\mathcal{M} \in \mathbb{R}^{J \times 3}\), \(J = 24\), are computed with a pretrained linear regressor \(W\).

![Diagram of PARE model architecture](image)

**Figure 4:** PARE model architecture. Given an input image, PARE extracts two pixel-level features \(P\) and \(F\), which are fused by part attention (green box) leading to the final feature \(F'\) for camera and SMPL body regression.

### 4.1. Model Architecture and Losses

The overall framework of PARE is depicted in Fig. 4. Our architecture works as follows: given an image \(I\), we first run a CNN backbone to extract \(H\times W\times C\) features, e.g. before the global average pooling layer for ResNet-50, followed by two separate feature extraction branches to obtain two volumetric image features. We denote the 2D part branch as \(P \in \mathbb{R}^{H \times W \times (J+1)}\), modelling \(J\) part attention and 1 background masks, where \(H\) and \(W\) are the height and width of the feature volume and each pixel \((h, w)\) stores the likelihood of belonging to a body part \(j\). The other branch, denoted by \(F \in \mathbb{R}^{H \times W \times C}\), is used for 3D body parameter estimation. It has the same spatial dimensions \(H \times W\) as \(P\) but a different number of channels, \(C\).

Let \(P_j \in \mathbb{R}^{H \times W}\) and \(F_c \in \mathbb{R}^{H \times W}\) denote the \(j\)-th and \(c\)-th channel of \(P\) and \(F\), respectively, and let \(F' \in \mathbb{R}^{J \times C}\) represent the final feature tensor. Each element in \(F_c\) contributes proportionally to \(F'\) according to the corresponding elements in \(P_j\) after spatial softmax normalization \(\sigma\). Formally, the element at location \((j, c)\) in \(F'\) is computed as:

\[
F'_{j,c} = \sum_{h,w} \sigma(P_{j}) \odot F_{c},
\]

where \(\odot\) is the Hadamard product. In other words, we use \(\sigma(P_j)\) as a soft attention mask to aggregate features in \(F_c\). This operation can be efficiently implemented as a dot product similar to existing attention implementations: \(F' = \sigma(P)^{T} F\), where \(\tilde{P} \in \mathbb{R}^{H \times W \times J}\) and \(F \in \mathbb{R}^{H \times W \times C}\) denote the reshaped \(P\) (omitting the background mask) and \(F\) respectively. This attention operation suggests that if a particular pixel has a higher attention weight, its corresponding feature contributes more to the final representation \(F'\). We supervise the 2D part branch \(P\) with ground-truth segmentation labels, which helps the attention maps of visible parts converge to the corresponding regions. For occluded parts, however, this encourages 0 attention weights for all pixels.
in $P_j$ because they do not exist in the ground-truth segmentation labels. An attention map with all 0 weights is undesirable and, in practice, also impossible since the spatial softmax ensures that all elements sum to 1. Therefore, we adopt a hybrid approach that supervises the 2D part branch only for the initial stage and continues training without any supervision. This allows the network to attend to other regions to estimate the poses of an occluded joint.

We take the full feature tensor $F'$ to regress body shape $\beta$ and a weak-perspective camera model with scale and translation parameters $[s, t]$, $t \in \mathbb{R}^2$, while each row, $F'_j$, is also sent to different MLPs to predict the rotation of each part, $\theta_j$, parameterized as a 6D vector following [27, 29]¹.

Overall, our total loss is:

$$L = \lambda_{3D}L_{3D} + \lambda_{2D}L_{2D} + \lambda_{SMPL}L_{SMPL} + \lambda_{P}L_{P},$$ (2)

where each term is calculated as:

$$L_{3D} = \|\mathcal{J}_{3D} - \hat{\mathcal{J}}_{3D}\|_F^2,$$

$$L_{2D} = \|\mathcal{J}_{2D} - \hat{\mathcal{J}}_{2D}\|_F^2,$$

$$L_{SMPL} = \|\Theta - \hat{\Theta}\|_2^2,$$

$$L_P = \frac{1}{HW} \sum_{h,w} \text{CrossEntropy} \left( \sigma(P_{h,w}), \hat{P}_{h,w} \right),$$

where $\hat{x}$ represents the ground truth for the corresponding variable $x$. To compute the 2D keypoint loss, we need the SMPL 3D joint locations $\mathcal{J}_{3D}(\theta, \beta) = W\mathcal{M}(\theta, \beta)$, which are computed from the body vertices with a pretrained linear regressor $W$. With the inferred weak-perspective camera, we compute the 2D projection of the 3D joints $\hat{\mathcal{J}}_{3D}$, as $\mathcal{J}_{2D} \in \mathbb{R}^{J \times 2} = s\Pi(R\mathcal{J}_{3D}) + t$, where $R \in SO(3)$ is the camera rotation matrix and $\Pi$ is the orthographic projection. $\lambda$ is a scalar coefficient to balance the loss terms. Let $P_{h,w} \in \mathbb{R}^{1 \times 1 \times (J+1)}$ denote the fiber of $P$ at the location $(h, w)$, and $\hat{P}_{h,w} \in \{0, 1\}^{J+1}$ denotes the ground-truth part label at the same location, expressed as a one-hot vector. The part segmentation loss $L_P$ is the cross-entropy loss between $P_{h,w}$ after softmax and $\hat{P}_{h,w}$, averaged over $H \times W$ elements. Note that this softmax normalizes along the fiber $P_{h,w}$ while the one in Eq. 1 normalizes over the slice $P_j$.

### 4.2. Implementation Details

As mentioned above, the body-part label supervision via $L_P$ is applied on the attention tensor $P$ only in the initial stages of training. It is later removed by setting $\lambda_P$ to zero, turning the attention mechanism into an unsupervised pure soft-attention. The absence of body-parts due to occlusion is the main motivation for this training scheme. Setting $\lambda_P$

¹With slight abuse of notations, $\theta$ is in axis-angle form when passed to the SMPL model but in 6D-vector form during the regression and loss computation.

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**Figure 5:** Occlusion sensitivity mesh. Meshes visualize the (a) SPIN and (b) PARE average joint errors.

**Figure 6:** Per joint occlusion sensitivity analysis of three different methods: SPIN [29], HMR-EFT [23] (trained with occlusion augmentation), and PARE. PARE is consistently more robust to occlusion.

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We evaluate both ResNet-50 [17] and HRNet-W32 [50] networks as the backbone. Since ResNet-50 is widely used in other SOTA methods [24, 27, 29], we choose it as the default backbone for most of the experiments unless stated otherwise. We extract the $7 \times 7 \times 2048$ feature volumes before global average pooling. For the 2D and 3D branches, we use three $2 \times$ upsampling followed by $3 \times 3$ convolutional layers applied with batch-norm and ReLU. The number of conv kernels is 256. For HRNet-W32, since it already provides volumetric features with a higher resolution, we only use two $3 \times 3$ convolutional layers applied with batch-norm and ReLU as the 2D and 3D branches.

To obtain part attention maps, we apply $J + 1 \times 1 \times 1$ convolutional kernels to 2D part features to reduce the channel dimension. After obtaining the $J \times C$ final feature $F''$, we use separate linear layers to predict each SMPL joint rotation $\theta_j$. We regress shape and camera parameters from the flattened $F''$ vector. We use a fixed image size of $224 \times 224$ for all experiments. The Adam optimizer with a learning rate of $5 \times 10^{-5}$ and batch size 64 is used to optimize our model. PARE is end-to-end trainable in a single stage, unlike recent multi-stage methods [10, 16, 38, 59].
Table 1: Evaluation on the 3DPW dataset. The units for mean joint and vertex errors are in mm. PARE models outperform temporal, multi-stage, and single-stage state-of-the-art methods.

| Method          | 3DPW | 3DPW-OCC | 3DOH |
|-----------------|------|----------|------|
|                 | MPJPE | PA-MPJPE | PVE  | MPJPE | PA-MPJPE | PVE  |
| HMR [24]        | 116.5 | 72.6     | -    | -     | -        | -    |
| Doersch et al. [12] | -    | 74.7     | -    | -     | -        | -    |
| Sun et al. [51]  | 93.5  | 56.5     | 113.4| -     | -        | -    |
| MEVA [35]        | 86.9  | 54.7     | -    | -     | -        | -    |
| Pose2Mesh [10]   | 89.2  | 58.9     | -    | -     | -        | -    |
| Zanfir et al. [59] | 90.0 | 57.1     | -    | -     | -        | -    |
| 2L-MeshNet [38]  | 93.2  | 58.6     | -    | -     | -        | -    |
| LearnedGD [49]   | -     | 56.4     | -    | -     | -        | -    |
| HMR-EFT [23]     | 130.0 | 76.7     | -    | -     | -        | -    |
| CMR [30]         | -     | 70.2     | -    | -     | -        | -    |
| SPIN [29]        | 96.9  | 59.2     | 135.1| -     | -        | -    |
| HMR-EFT [23]     | -     | 54.2     | -    | -     | -        | -    |
| PARE (R50)       | 82.9  | 52.3     | 99.7 | -     | -        | -    |
| PARE (HRNet-W32) | 82.0  | 50.9     | 97.9 | -     | -        | -    |
| PARE (HRNet-W32) w. 3DPW | 74.5 | 46.5     | 88.6 | -     | -        | -    |

Table 2: Evaluation on occlusion datasets 3DPW-OCC, 3DOH. Here all methods except SPIN are trained with the same datasets, i.e. COCO, Human3.6M and 3DOH.

| Method          | 3DPW | 3DPW-OCC | 3DOH |
|-----------------|------|----------|------|
|                 | MPJPE | PA-MPJPE | PVE  | MPJPE | PA-MPJPE | PVE  |
| Zhang et al. [61] | -    | 72.2     | -    | -     | -        | 58.5 |
| SPIN [29]        | 95.6  | 60.8     | 121.6| 104.3 | 68.3     |      |
| HMR-EFT [23]     | 94.4  | 60.9     | 111.3| 75.2  | 53.1     |      |
| PARE (R50)       | 90.5  | 56.6     | 107.9| 63.3  | 44.3     |      |

5. Experiments

Training. We train PARE on COCO [32], MPII [2], LSP-EF [22], MPI-INF-3DHP [37], and Human3.6M [20] datasets. More details about these datasets are provided in Sup. Mat. Pseudo-ground-truth SMPL annotations for the-wild datasets are provided by EFT [23]. The part segmentation labels are obtained through rendering segmented SMPL meshes, as visualized in Fig. 4. We use 24 parts corresponding to 24 SMPL joints. See Sup. Mat. for samples of part segmentation labels. We used the PyTorch implementation [28] of Neural Mesh Renderer [26] to render the parts. For samples without a part segmentation label, we do not supervise the 2D branch.

For the ablation experiments, we train PARE and our baselines on COCO for 175K steps and evaluate on 3DPW and 3DPW-OC datasets. We then incorporate all the training data to compare PARE to previous SOTA methods. This pretrained strategy accelerates convergence and reduces the overall training time. It takes about 72 hours to train PARE until convergence on an Nvidia RTX2080Ti GPU.

To increase robustness to occlusion, we use common occlusion augmentation techniques; i.e. synthetic occlusion (SynthOcc) [45] and random crop (RandCrop) [23, 44]. All PARE and baseline HMR-EFT models are trained with SynthOcc augmentation unless stated otherwise, e.g. Table 4.

Evaluation. The 3DPW [54] test split, 3DPW-OC [54, 61], and 3DOH [61] datasets are used for evaluation. We report Procrustes-aligned mean per joint position error (PA-MPJPE) and mean per joint position error (MPJPE) in mm. For 3DPW we also report per vertex error (PVE) in mm.

Comparison to the state-of-the-art. Table 1 compares PARE with previous single-RGB-image HPS estimation methods. We report PARE results with two different backbones: ResNet-50 and HRNet-W32. PARE improves the PA-MPJPE performance by 10% compared to HMR-EFT [23], one of the best-performing recent methods.

Table 2 demonstrates the performance of PARE on occlusion-specific datasets. Here Zhang et al. [61], HMR-EFT [23], and PARE are trained with COCO, Human3.6M, and 3DOH for a fair comparison. We report the SPIN results for reference. HMR-EFT is the fair alternative to SPIN, since SPIN uses HMR as the architecture. PARE consistently improves the performance on these occlusion datasets. Although HMR-EFT is trained with exactly the same augmentation and data as PARE, it performs worse.

We also quantify our occlusion sensitivity analysis. Figure 5 shows the average joint error of SPIN and PARE methods on the 3DPW test split. SPIN is quite sensitive to upper body occlusions, especially around the head and back. PARE is more robust to occlusions and yields lower error overall. See Sup. Mat. for the per-joint version of Fig. 5. Figure 6 shows the per-joint breakdown of the mean 3D error from the occlusion sensitivity analysis for three different methods, SPIN, HMR-EFT, and PARE. Here, we retrain HMR-EFT using SynthOcc for a fair comparison. Again, PARE improves the occlusion robustness of all joints.

Qualitative comparison. We qualitatively compare SPIN, HMR-EFT, and PARE in Fig. 8. Even though occlusion augmentation improves robustness to occlusion as seen in the HMR-EFT results, it is not sufficient on its own. PARE, with its attention mechanism, performs well even in challenging occlusion scenarios. More qualitative samples, including failure cases, are provided in Sup. Mat.

Does part attention help? Table 3 summarizes our ablation experiments that explore the concept of part attention. First, we compare our results with Neural Body Fitting [39] trained with identical settings to ours. NBF [39] can be seen as a straightforward combination of part segmentation and human body regression. Table 3 shows that NBF’s two-stage approach is outperformed even by the HMR-EFT baseline. Subsequently, we compare different types of supervision for the 2D part branch P and sampling methods to obtain final features $F'$. "Unsup" means $P$ is not supervised. Inspired by Holopose [16], we first supervise the 2D branch with keypoints and pool the 3D features via bilin-
Figure 7: PARE attention visualization. Attention maps predicted by the 2D part branch for different joints in image (a). For occluded joints like row 2 right hand, PARE learns to attend to larger, more distant, regions to glean information.

Table 3: Exploring part attention. The "F Supervision" column shows the type of supervision for the 2D part branch $F$. "F Sampling" shows the type of feature sampling method for $F$. All methods are trained on COCO-EFT with a ResNet-50 backbone.

Table 4: Ablation of different occlusion augmentation strategies. We demonstrate the effect of synthetic occlusion (SynthOcc) and random crop (RandCrop) augmentation on the final performance. All methods are trained on COCO-EFT with ResNet-50 as the backbone.

Table 5: Ablation of backbone architectures. All methods are trained on COCO-EFT.
Figure 8: Qualitative results on COCO (rows 1-4) and 3DPW (rows 5-6) datasets. From left to right: Input image, (a) SPIN [29] results, (b) HMR-EFT [23] results, (c) PARE results.

Effect of CNN backbones. As shown in Table 5, HRNet-W32, which produces effective high-resolution representations, performs better than ResNet-50. PARE provides consistent improvements over HMR-EFT with both backbones.

6. Conclusion
We present a novel Part Attention Regressor, PARE, which regresses 3D human pose and shape by exploiting information about the visibility of individual body parts, and thus gaining robustness to occlusion. PARE is based on the insights gleaned from our occlusion sensitivity analysis. In particular, we observe dependencies between body parts and argue that the network should rely on visible parts to improve predictions for occluded parts and, hence, the overall performance of 3D pose estimation. Our novel body-part-driven attention mechanism captures such dependencies, using soft attention guided by regressed body part segmentation masks. The network learns to use part segmentations as visibility cues to reason about occluded joints and aggregating features from the attended regions. This improves robustness to occlusions of different types: scene, self, and frame occlusion. Detailed ablation studies show how each choice contributes to our state-of-the-art performance on benchmark datasets.
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Supplementary Material

The Supplementary Material consists of this document and a video. They include acknowledgement, disclosure, additional information and visualizations of our method and results.

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**Disclosure:** [https://files.is.tue.mpg.de/black/CoI/ICCV2021.txt](https://files.is.tue.mpg.de/black/CoI/ICCV2021.txt)

**A. Methods**

**Implementation Details.** In all our experiments, we use the weights pretrained on MPII [2] for a 2D pose estimation task to initialize both ResNet-50 and HRNet-W32, because we observe slower convergence with ImageNet pretrained weights. For Table 3-5 in the main paper, we train PARE and our baselines on COCO for 175K steps and evaluate on 3DPW and 3DPW-OCC datasets. We then include all the training data for the SOTA experiment in Table 1 of the main paper. For Table 2, we use the training data of [61] to align the experiment settings.

**Loss.** We use different weight coefficients $\lambda$ for each term in the loss function. They are $\lambda_{3D} = 300$, $\lambda_{2D} = 300$, $\lambda_{SMPL} = 60$, $\lambda_{P} = 60$.

**Body Part Segmentation labels.** Since we have SMPL annotations for most of the samples in our datasets, we do not need additional body part segmentation annotations. We directly use the SMPL annotations to obtain supervision. In Fig 9, we visualize this body part labels. For each joint in the SMPL kinematic tree, we have a corresponding body part label.

**Occlusion augmentation.** In Fig. 10, we demonstrate the results of synthetic occlusion and random crop augmentations on two sample images.

**Runtime** PARE is only 1 ms/image slower than HMR, with runtime of 14.8ms on a GTX2080Ti.

**B. Experiments**

**B.1. Training Datasets**

Our training datasets closely follow previous work, namely EFT [23], SPIN [29], and HMR [24]. Here we provide the details for completeness.

**MPI-INF-3DHP** [37] is a multi-view indoor 3D human pose estimation dataset. 3D annotations are captured via a commercial markerless mocap software, therefore it is less accurate than some of the 3D datasets e.g. Human3.6M [20]. We use all of the training subjects S1 to S8 which makes 90K images in total.

**Human3.6M** [20] is an indoor, multi-view 3D human pose estimation dataset. Following previous methods, for training, we use 5 subjects (S1, S5, S6, S7, S8) which means 292K images.

**In-the-wild 2D datasets** COCO [32], MPII [2] and LSPET [22] are in-the-wild 2D keypoint datasets. MPII has 14K, COCO has 75K, LSPET has 7K instances labeled with 2D keypoints. In addition to 2D keypoint annotations, we utilize the pseudo SMPL annotations provided by the EFT [23] method.

**Training Dataset Ratios.** To obtain the final best performing model, we follow EFT [23] and SPIN [29] which use fixed data sampling ratios for each batch. After training 100% with COCO-EFT for 175K steps, we incorporate 50% Human3.6M, 30% In-the-wild (i.e. [COCO, MPII, LSPET ]-EFT), and 20% MPI-INF-3DHP datasets into training. We also observe that using [50% Human3.6M, 30% COCO-EFT, 20% MPI-INF-3DHP ] or [20% Human3.6M, 30% COCO-EFT, 50% MPI-INF-3DHP ] gives equivalent performance on the 3DPW dataset.

**Figure 9:** Body part segmentation labels used for the 2D part branch. For each joint in the SMPL kinematic tree, we have a body part label. Correspondences between joints (right) and body part labels (left) are shown in this figure.
Figure 10: Training samples after synthetic occlusion and random crop augmentations are applied.

| Method                  | 3DPW       |
|-------------------------|------------|
|                         | MPIJPE ↓  | PA-MPIJPE ↓ |
| HMMR [24]               | 116.5      | 72.6        |
| Doersch et al. [12]     | -          | 74.7        |
| Sun et al. [51]         | -          | 69.5        |
| VIBE [27]               | 93.5       | 56.5        |
| MEVA [35]               | 86.9       | 54.7        |

Table 6: Evaluation on the 3DPW dataset. The numbers are average joint errors in mm. PARE models outperform video-based models which leverage temporal information.

| Method                  | PCK ↑     |
|-------------------------|-----------|
| SPIN [29]               | 81.5      |
| HMR-EFT                 | 83.4      |
| PARE                    | **85.1**  |

Table 7: Evaluation of 2D keypoint project accuracy on 3DPW dataset.

Failure Cases. In Fig. 11, we show a few examples where PARE fails to reconstruct reasonable human body poses. The scenarios range from (a-b) too many people in the crop, (b-d) rarely-seen extreme poses, (e-f) children whose body shapes cannot be fully explained by the SMPL model, and (g-h) extreme occlusion.

Comparing to state-of-the-art Temporal Models. In Table 6, we compare PARE to recent state-of-the-art video based models. To do so, we run a SOTA multi-object tracker and then run PARE independently on each frame of the tracklets, with no temporal smoothing. Even the SOTA video methods have access to extra temporal information, PARE outperforms them. We show some qualitative results of VIBE and PARE on some challenging images in Fig 14. Please see the supplemental video for a better visualization of the video results (starts at 05:21).

2D keypoint projection accuracy We evaluate the 2D keypoint accuracy of our method by projecting the 3D keypoints to the image space using the estimated camera parameters on 3DPW test set. Percentage of correct keypoints (PCK) is used as the evaluation metric. The results are reported in Table 7.

C. More on visualizing attention of networks

Two new visualizations are proposed in this work: (1) an occlusion sensitivity map/mesh and (2) a part attention map. We provide more examples and discussions for both visualizations. Please see the video for an animation of the sensitivity analysis, which more clearly illustrates the approach.
Occlusion Sensitivity. There are many visualization techniques [36, 46, 60, 62] available to inspect what CNNs learn. We are, however, more interested in studying how perturbations in the input image affect the output rather than visualizing the internal filters learned by CNNs. We therefore follow the framework of [60] and replace the classification score with an error measure for body poses, as described in the main paper. We choose MPJPE as the error measure without Procrustes Alignment, because PA-MPJPE leads to artificially low error by aligning global orientations, which are a major source of error.

This analysis is not limited to a particular network architecture so we also apply it on PARE and visualize the error maps together with those from SPIN [29] in Fig. 15. Warmer colors correspond to higher MPJPEs w.r.t. ground truth when those pixels are occluded, suggesting that methods rely on the regions to estimate body poses. One clearly sees that PARE is more robust to localized part occlusion. Please see the video for animation (starts at 00:53).

Additionally, we also map the per-pixel error to the overlaying 3D vertex, and aggregate over the whole 3DPW dataset [54]. In this way, we visualize the per-joint error on the SMPL template mesh, which we term the occlusion sensitivity mesh. Fig. 16 shows the occlusion sensitivity mesh for four different joints and averaged over all joints from both SPIN and PARE. We again observe that SPIN is very sensitive to localized part occlusion. For example, occlusions of right arm or face regions result in high error for right wrist. On the other hand, occlusion sensitivity meshes of PARE have more consistent cold colors over the body, again confirming that it is more robust to partial occlusion.

Part Attention. We also visualize the estimated part attention $P$ before softmax in Fig. 17 for four sample images from 3DPW [54]. When body parts are visible, the shapes of warm regions resemble part segmentation labels, which means the network focuses on body part regions (e.g. Left/Right Knee and Ankle in the third row). For naturally occluded body parts, the attended regions get wider, covering other parts and the scene. This suggests that PARE implicitly learns to reason about the visibility of body parts and leverages available information to solve the task. In particular, Fig. 12 illustrates the progression of attention maps during training for two occluded parts Left/Right Ankles. We see that deactivating the part supervision helps attention maps to focus on more meaningful and explainable regions.

In addition to part attention maps, we also visualize the results as segmentation maps in Fig. 18. We visualize the results of two different models; (a) a model trained with
full part segmentation supervision, (b) a model trained with part segmentation initially and unsupervised for the final stages. Note that part segmentation IoU decreases significantly when we do not use part segmentation, however we see an increase in body reconstruction accuracy especially in the case of occlusion.

Figure 12: Attention map progression during training. Training uses body-part supervision only until step 125K (a-b). Note that the final attention maps for occluded parts (at 200K (c-d)) focus on visible parents.
Figure 13: **Qualitative comparison.** Here, we compare PARE with recent state-of-the-art methods i.e. SPIN [29], HMR-EFT [23], and Zhang et al. [61].
Figure 14: Comparison of VIBE [27] with our method, PARE. Note that VIBE is a video-based method, while PARE is run on each video frame independently.
Figure 15: Occlusion Sensitivity Maps of SPIN [29] and PARE
Figure 16: Occlusion sensitivity meshes per joint.
Figure 17: Part attention maps.
Figure 18: Part segmentation results in two different scenarios: (a) full part segmentation supervision is applied during training, (b) part segmentation supervision is applied at the initial stages and training is continued without part supervision. At the top of each result, we denote the part segmentation IoU, MPJPE and PA-MPJPE. Notice how part segmentation IoU decreases, but per-joint accuracy improves.