PCLs: Geometry-aware Neural Reconstruction of 3D Pose with Perspective Crop Layers

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Abstract

Local processing is an essential feature of CNNs and other neural network architectures—it is one of the reasons why they work so well on images where relevant information is, to a large extent, local. However, perspective effects stemming from the projection in a conventional camera vary for different global positions in the image. We introduce Perspective Crop Layers (PCLs)—a form of perspective crop of the region of interest based on the camera geometry—and show that accounting for the perspective consistently improves the accuracy of state-of-the-art 3D pose reconstruction methods. PCLs are modular neural network layers, which, when inserted into existing CNN and MLP architectures, deterministically remove the location-dependent perspective effects while leaving end-to-end training and the number of parameters of the underlying neural network unchanged. We demonstrate that PCL leads to improved 3D human pose reconstruction accuracy for CNN architectures that use cropping operations, such as spatial transformer networks (STN), and, somewhat surprisingly, MLPs used for 2D-to-3D keypoint lifting. Our conclusion is that it is important to utilize camera calibration information when available, for classical and deep-learning-based computer vision alike. PCL offers an easy way to improve the accuracy of existing 3D reconstruction networks by making them geometry-aware.

1. Introduction

Convolutional neural networks (CNNs) have proven highly effective for image-based prediction tasks because of their translation invariance and the locality of the computation they perform. For 3D pose estimation, this allows them to focus on image locations that carry information about the pose while discarding other ones [43, 30, 6, 27, 32, 39, 44, 42, 20, 51, 17, 47].

Convolutions in the image plane, however, ignore the perspective effects caused by projecting a 3D scene in 2D. For example, as shown in Figure 1, a person captured by static camera in a fixed pose and moving in a constant di-
We demonstrate the benefits of our PCLs for 3D human pose estimation of both rigid objects and articulated people. PCLs yield a consistent boost in performance, of $2 - 10\%$ on average and up to $25\%$ at the image boundary where perspective effects are strongest. Notably, the improvements attributable to our PCLs are consistent across the baseline we seek to improve, which validates our claim that even the most-advance deep networks do not learn these perspective effects on the existing datasets. This includes a PCL variant that undoes the perspective effect on 2D keypoints, thus allowing us to showcase the benefits of our approach on state-of-the-art 3D pose estimation methods that lift 2D keypoint detections to 3D poses [22, 33]. We will make our code publicly available.

2. Related Work

In this section, we discuss existing ways of handling image distortions and review the existing attention window mechanisms upon which PCLs are built.

Handling perspective effects. Many works sidestep perspective effects by training and testing on synthetic renderings [1, 7, 49, 48] or real images [10, 49] where the object of interest is centered manually. However, these methods are not applicable to natural images where the object can be at an arbitrary location. If the object location is known in advance, perspective distortion can be undone in a preprocessing stage. For instance, [24] propose to rotate locally inferred 3D poses back to the camera frame. This strategy has later been adopted by [14], but neither of these works undistorts the input images or input 2D pose. [38, 37] apply an image correction, however, only approximating the homography with an affine transformation. In other words, the above-mentioned approaches neither model the perspective correction geometrically accurately nor formulate it as a differentiable layer. However, differentiability is an important prerequisite for end-to-end training on natural images, particularly for unsupervised approaches, that deal with unknown object locations.

Radial undistortion. Fisheye cameras and others with a large field of view yield large deformations when mapped to a rectangular pixel grid. They are better represented with spherical images, thereby avoiding location-dependent deformation entirely. This, however, gives rise to challenges when one wants to process the resulting non-rectangular pixel grids with convolutions. [3] compute convolutions on spherical harmonics, but such frequency-domain networks do not yet reach the accuracy of regular CNNs. A common workaround is to unfold the spherical images along the azimuth and longitude dimensions, which leads to lesser artifacts than perspective projection to a planar image. Nevertheless, extreme stretching at the sphere poles remains. This deformation has been handled by learning filters that have the same response as processing local planar patches [40] or by using Deformable Convolutional Networks [5]. However, any convolution is location invariant and misses the geometric position that caused the deformation. To coun-
Attention windows. Processing RoIs instead of the entire input image leads to computationally more efficient and more accurate models. Most prominent and related to our approach are Spatial Transformer Networks (STN) [13] that learn invariance to translation, scale, rotation and more generic warping by spatially transforming the feature maps with an affine or free-form deformation. Multiple STNs have also been stacked [18] to model more complex transformations. STNs proceed in two steps: First, a grid of sample points is defined in the original image, either by direct regression or by predicting the parameters of a restricted family of transformations, such as a $3 \times 3$ matrix for affine transformations. Second, the pixel value at each grid point is mapped to the target by bilinear interpolation of the neighboring image pixels. This yields differentiability and enables end-to-end training as an ordinary layer within deep network architectures. It also applies to 3D transformations [48]. In this work, we generate a sampling grid that undoes perspective effects in the RoI and use the STN to maintain differentiability with respect to the RoI position and scale.

3. Perspective Crop Layer

We start our derivation by formulating local processing and existing cropping solutions mathematically as an affine transformation between a real and virtual camera of fixed orientation. Subsequently, we derive the perspective transformation underlying PCL, which corresponds to a rotation of the virtual camera frame, and finally introduce the implementation of PCL via two neural network layers that sandwich the backbone prediction network.

3.1. Motivation and Rectangular Crops

Each point $\hat{q}$ of a rescaled rectangular or trapezoidal image patch can be expressed in terms of the original image coordinates $q$. This affine transformation can be written in projective coordinates as

$$\hat{q} = Cq, \quad \text{with} \quad C = \begin{bmatrix} s_x & c_x & a_x \\ c_y & s_y & a_y \\ 0 & 0 & 1 \end{bmatrix},$$

(1)

where $a = [a_x, a_y]$ defines a 2D translation, $s = [s_x, s_y]$ are scalings in two different directions, and $c = [c_x, c_y]$ are skew parameters. Therefore, as shown in Fig. 2, a cropped image can be thought of as being taken by a virtual camera with intrinsic parameters $K_{\text{virt}} = CK$, where $K$ is the true $3 \times 3$ matrix of intrinsic parameters. As the translation $a$ is usually chosen so that the patch contains an object of interest, the optical center of the virtual camera depends on the target location, which means that objects projected far from the image center are deformed differently from those near it, as shown in Fig. 1. To remedy this, our goal is to design a crop operation such that the optical center of the virtual camera is always at the center of the patch, which makes perspective distortion independent from image location.

The centering of 2D human pose commonly done in the state-of-the-art 2D-to-3D lifting approaches is a form of rectangular cropping, too. A pose is root-centered by multiplication with an affine matrix $C$, in which $a$ is the pelvis/root position, $s = 1$ and $c = 0$. The subsequent root-centered processing with an MLP has the same downsides as cropping in STNs and convolution in CNNs in that information about the image location is removed while being affected by position-dependent perspective effects.

3.2. Defining a Virtual Camera

We introduce a virtual camera with the same optical center as the real one but whose optical axis points at the center of the target patch $p = [p_x, p_y]$ and whose focal length is chosen to zoom onto the region of interest with factor $s = [s_x, s_y]$, as shown in Fig. 2. Below, we derive the virtual extrinsic parameters, in the form of rotation matrix...
\( \mathbf{R}_{\text{virt} \rightarrow \text{real}} \), and virtual intrinsic parameter matrix, \( \mathbf{K}^{\text{virt}} \), such that these constraints are fulfilled.

**Cropping as a change of camera perspective.** We aim to find camera parameters such that mapping a pixel from the original image to the cropped patch can be done by multiplying an image coordinate in homogeneous coordinates, \((u, v, 1)^\top\), by the matrix

\[
\Gamma(u, v, s, \mathbf{K}) = \mathbf{K}^{\text{virt}} \mathbf{R}_{\text{virt} \rightarrow \text{real}}^{-1} \mathbf{K}^{-1}.
\]

(2)

This transformation undoes the original projection using \( \mathbf{K}^{-1} \), rotates the resulting point to the virtual camera with \( \mathbf{R}_{\text{virt} \rightarrow \text{real}}^{-1} \) and projects it using \( \mathbf{K}^{\text{virt}} \). As for the typical rectangular cropping defined in Eq. 1, mapping from the image to the patch remains a warp and does not depend on the generally unknown scene geometry. By contrast to rectangular cropping, this warp is non-linear.

**Extrinsic Parameters.** Let \( \mathbf{R}_{\text{virt} \rightarrow \text{real}} \) be the \( 3 \times 3 \) rotation matrix that defines the virtual camera orientation. It can be written as \( \mathbf{R}_x \mathbf{R}_z \mathbf{R}_y \), where \( \mathbf{R}_x, \mathbf{R}_z \), and \( \mathbf{R}_y \) are the Euler rotation matrices that rotate counter-clockwise around the \( x, y, \) and \( z \) axes of the original camera coordinate system, as depicted by Fig. 2. Two degrees of freedom of \( \mathbf{R}_{\text{virt} \rightarrow \text{real}} \), \( \mathbf{R}_x \) and \( \mathbf{R}_y \), are determined by pinning the center of the virtual camera to the backprojected point \( \mathbf{p} = \mathbf{K}^{-1}(u, v, 1)^\top \) in the real camera. Formally, we compute

\[
\mathbf{R}_{\text{virt} \rightarrow \text{real}} = \begin{bmatrix}
\frac{1}{\sqrt{1+p_z^2}} & \frac{-p_x p_y}{\sqrt{1+p_z^2} (1+p_y^2)} & \frac{p_y}{\sqrt{1+p_z^2} (1+p_y^2)} \\
0 & \frac{1}{\sqrt{1+p_z^2}} & \frac{-p_x p_y}{\sqrt{1+p_z^2} (1+p_y^2)} \\
\frac{-p_x p_z}{\sqrt{1+p_z^2} (1+p_y^2)} & \frac{p_y}{\sqrt{1+p_z^2} (1+p_y^2)} & \frac{1}{\sqrt{1+p_z^2} (1+p_y^2)}
\end{bmatrix},
\]

(3)

The details are provided in the appendix.

The yaw angle around the optical axis is unconstrained. We set it to zero (pointing upwards) in our experiments. Instead, \( \mathbf{R}_x \) could be controlled, to normalize subject orientation to pose human subjects upright in the virtual view.

**Intrinsic Parameters.** Let

\[
\mathbf{K}^{\text{virt}} = \begin{bmatrix}
f_x^{\text{virt}} & 0 & t_x^{\text{virt}} \\
0 & f_y^{\text{virt}} & t_y^{\text{virt}} \\
0 & 0 & 1
\end{bmatrix}
\]

(4)

be the \( 3 \times 3 \) matrix of intrinsic parameters of the virtual camera. Putting the optical center in the middle of the patch means that \( f_x^{\text{virt}} = f_y^{\text{virt}} = 0.5 \). The virtual focal lengths are \( f^{\text{virt}} = [f_x^{\text{virt}}, f_y^{\text{virt}}] = h^{\text{virt}} \), where \( h^{\text{virt}} \) is a function of the original focal length in the horizontal and vertical direction stored in \( \mathbf{K} \), and \( s \) determines the crop scale in relation to the full image. Together with \( \mathbf{p} \), it defines the area of interest and is the input to PCL.

There is no universal way for choosing \( h^{\text{virt}} \), the virtual camera’s focal length, without scaling to the smaller crop size. We propose the following three alternatives and evaluate their influence empirically in Section 4:

A. Setting \( h^{\text{virt}} \) to \( f \), the original focal length.

B. Setting \( h^{\text{virt}} \) to \( f \| \mathbf{p} \| \), so that the virtual image plane intersects with the real one at \( \mathbf{p} \).

C. Setting \( h_x^{\text{virt}} = f_x \| \mathbf{p} \| \sqrt{p_z^2 + 1} \) and \( h_y^{\text{virt}} = f_y \| \mathbf{p} \| \sqrt{p_z^2 + 1} \) to preserve pixel scales.

Although the nature of such a perspective transformation cannot maintain scale in all parts of the image, the last choice of parameters guarantees that scale between the original and virtual image is preserved along the vertical and horizontal axis, while scaling non-linearly in the diagonal direction. Fig. 1 visualizes this behavior, and Fig. 3 illustrates the crop width after with each of the three choices.

### 3.3. Differentiable Network Layer

PCLs are designed to facilitate perspective correction within existing deep neural network architectures. We propose the two forms that are depicted in Fig. 5. Two layers are involved, the projection to the virtual camera and the transformation of the reconstruction to the original camera.
3D Pose change. Because networks equipped with a PCL layer operate in a virtual camera, the 3D pose prediction living in these coordinates is transformed back from virtual to original camera coordinates in the PCL_inv layer by applying $R_{\text{virt} \rightarrow \text{real}}$.

PCL for lifting 2D keypoints to 3D with MLPs. For networks taking 2D keypoints as input, such as the locations of the human body parts detected in the image plane, Eq. 2 can be applied directly on every 2D coordinate and becomes a simple pre-processing that normalizes the 2D pose for perspective effects. The target center location $p$ can be chosen as the mean of all joints, or a root joint. We use the pelvis location as crop target for human pose estimation.

PCL for CNNs. Applying PCL to CNNs requires a two-stage CNN architecture. First, one or more RoIs $(p_s)_{i=1}^N$ are predicted from the input image $I \in \mathbb{R}^{W \times H \times F}$ using a detection network. Subsequently, the input is cropped to focus the attention of the subsequent reconstruction network. PCL replaces the cropping by implementing Eq. 2 and Eq. 3. The pixels are warped using bilinear interpolation, as in the conventional STNs [13] we introduced in the related work section. Because the transformation $\Gamma$, the definition of $R_{\text{virt} \rightarrow \text{real}}$, and the virtual camera matrix $K_{\text{virt}}$ rely on simple algebraic operations, the entire process becomes differentiable. To improve efficiency and numerical stability, we parametrize $R_{\text{virt} \rightarrow \text{real}}$ in terms of length measures (Eq. 3) instead of angles and computationally-expensive trigonometric functions in the general definition of Euler angles. The derivation and relation of both are detailed in the appendix.

PCL_inv: back-transformation to the real camera. The derived perspective crop has the regular grid structure of a normal image or feature map. Any neural image processing steps can be performed on it as is. However, the derived quantities will live in the coordinates of the virtual camera. As for classical attention windows, if the spatial context is important, the processed crop needs to be translated back to the original camera coordinates. For 3D quantities, such as 3D human pose, this amounts to applying $R_{\text{virt} \rightarrow \text{real}}$ on the reconstruction, as shown in Fig. 4. This PCL_inv layer is the same for MLPs and CNNs.

4. Experiments

We evaluate the improvements brought about by PCL on the task of 3D human pose estimation from either images or 2D keypoints, and show that they hold for neural networks of diverse complexity. The benefits of PCL for the 2D to 3D lifting task on Human 3.6 Million dataset [12] and MPI-INF-3DHP dataset [25] are shown qualitatively in both Fig. 6 and in additional experiments in the supplemental video.

Baselines. We integrate PCL into the three neural network architectures for 3D pose estimation discussed below, and compare the resulting networks with the original ones.

MLP+RC: As a first baseline, we use the four-layer MLP from [21] with root centering. To ensure a fair comparison, we scale the 2D input of the baseline by the crop scales $s$ that are used in PCL.

T-CNN: Our second baseline consists of the temporal convolution 2D to 3D lifting approach of Pavllo et al. [33], which operates on pose sequences. To date, it is the most accurate method in its class.

CNN+STN: ResNet [9] is the most widely used backbone for predicting 3D pose from images. As baseline, we use an STN that takes a $265 \times 265$ image as input and outputs a $128 \times 128$ patch. We do almost all tests with ground-truth crop locations determined by bounding box annota-
Datasets. **H3.6M**: We evaluate the effectiveness of PCL on the popular Human 3.6 Million dataset [12] that features eleven subjects performing 14 different actions and provides ground-truth 3D poses and camera calibration. We use the established train/validation/test split, 17-joint skeleton, and the pre-processing of [29]. We set the rectangular and PCL crop location to the pelvis 2D joint and compute the crop scale as the width and height of a tightly-fitting bounding box. We also experiment with using the GT depth for scale estimation. We compare variants using 2D detections from [41, 46] and ground truth as input for 2D to 3D lifting. When we compare to [33], we use their preprocessing and train/validation/test split since consecutive frames are required.

**MPI-INF-3DHP**: We also evaluate our approach on the MPI-INF-3DHP dataset [25], which, compared to H3.6M, contains more extreme poses, outdoor environments, and is shot with wide field-of-view cameras, leading to stronger perspective effects. The cameras are calibrated, and all frames are labeled with 3D pose. We use the color augmentation from [29] and the official test set and training subjects 1-8 for training, while withholding the first sequence of subject 4 and the last sequence of subject 8 for validation. We set the rectangular and PCL crop location to the pelvis joint for 2D to 3D lifting and at the mean of the 2D poses for the image-based variants. The crop scale is computed as the width and height of a tightly fitting bounding box.

**ToyCube**: We introduce a synthetic dataset containing images of a rendered cube of edge length 0.5 m. We use this toy example to ablate individual factors of variation, such as the effect of illumination and pose distribution.

Training setup. The 3D pose is trained on an L2 loss using Adam [16] with a learning rate of 0.001 for the 2D to 3D lifting models and 0.0005 for the image to 3D networks. The temporal convolution networks are trained using Adam [16] with an initial learning of 0.001 and a learning rate decay factor of 0.95 applied after each epoch. We train 2D to 3D lifting methods for 200 epochs and batch size 64 and the temporal convolution networks for 80 epochs and batch size 1024 with up to 243 frames in each batch element. Lastly, image to 3D networks using a ResNet-50 backbone are trained for 40 and 150 epochs on H3.6M and MPI-INF-3DHP respectively. The ResNet-18 backbone trained on H3.6M is trained for 60 epochs.

Metrics. To quantitatively evaluate 3D pose accuracy, we use the Mean Per Joint Position Error (MPJPE), computed as the average Euclidean distance of the predicted 3D joints to the ground-truth ones, where both poses are centered at the pelvis. All MPJPE results are reported in millimeters. We also report the percentage of correct keypoints (PCK), encoding the proportion of joints whose distance to the ground truth is less than a threshold, using thresholds of 50 and 100 millimeters.

4.1. PCL for 2D to 3D Keypoint Lifting

The results for the 2D to 3D lifting task on H3.6M and MPI-INF-3DHP are provided in Table 1. For H3.6M, MLP+PCL achieves an MPJPE of 67.0 mm vs. 69.8 mm MPJPE of the MLP+RC baseline [21] when using 2D detections from [41, 46] as input, a 4% improvement. Even larger improvements are achieved when using the GT 2D pose as input and when using the 3D root joint position for
Table 1: Shown are the reported MPJPE in millimeters as well as the PCK for 2D to 3D keypoint lifting tests performed on H3.6M. The reported mean and standard deviation is computed over three runs with varying random seed. For MPJPE, lower values are better and for PCK, higher values are better. We can see from the table that our method significantly outperforms the baselines that do not use PCL. We bold the best performing models in each category.

| Input Model | H3.6M | MPI-Inf-3DHP |
|-------------|-------|---------------|
|             | MPJPE | PCK \( \downarrow \) @ 50mm | PCK \( \downarrow \) @ 100mm | MPJPE | PCK \( \downarrow \) @ 50mm | PCK \( \downarrow \) @ 100mm |
| 2D GT + 3D Root GT MLP + RC ([21]) | 43.4 ± 0.2 | 66.8 ± 0.3 | 91.4 ± 0.2 | 60.4 ± 0.4 | 46.4 ± 0.5 | 77.0 ± 0.3 |
| 2D GT + 3D Root GT MLP + PCL (Ours) | 40.1 ± 0.5 | 72.8 ± 0.5 | 93.3 ± 0.2 | 45.6 ± 0.5 | 70.1 ± 0.5 | 89.7 ± 0.3 |
| 2D GT MLP + RC ([21]) | 48.4 ± 0.4 | 62.9 ± 0.5 | 90.3 ± 0.2 | 74.1 ± 0.2 | 43.0 ± 0.3 | 74.7 ± 0.7 |
| 2D GT MLP + PCL (Ours) | 43.8 ± 0.1 | 68.3 ± 0.1 | 92.2 ± 0.0 | 50.1 ± 0.2 | 65.5 ± 0.2 | 87.8 ± 0.1 |
| 2D Detection MLP + RC ([21]) | 69.7 ± 0.2 | 46.3 ± 0.5 | 80.5 ± 0.1 | - | - | - |
| 2D Detection MLP + PCL (Ours) | 67.0 ± 0.1 | 48.7 ± 0.2 | 82.1 ± 0.0 | - | - | - |
| Image CNN (ResNet50) + STN | 96.5 ± 3.2 | 64.6 | - | 117.7 | 33.6 | 60.1 |
| Image CNN (ResNet50) + PCL (Ours) | 94.1 ± 3.4 | 65.8 | 109.5 | 40.3 | 66.2 |
| Image CNN (ResNet18) + STN | 95.9 ± 3.5 | 65.6 | - | - | - |
| Image CNN (ResNet18) + PCL (Ours) | 93.9 ± 3.7 | 66.6 | - | - | - |

Table 2: Temporal CNN tests, computed as the MPJPE over two runs with varying seed on H3.6M. While the baseline performs the best using the original camera, it is unable to generalize to new camera settings. The PCL equipped version strikes the best compromise.

| Model | Original \( f \) | New \( f \) |
|-------|-----------------|-------------|
| T-CNN | 47.5 ± 0.0 | 72.7 ± 0.5 |
| T-CNN + RC | 51.5 ± 0.1 | 51.5 ± 0.1 |
| T-CNN + PCL (known \( f \)) | 48.8 ± 0.3 | 48.9 ± 0.2 |

Figure 7: Improvement of reconstruction error, binned with respect to the image position. Left: MLP+RC suffers from perspective effects away from the center, while MLP+PCL effectively compensates these leading to improvements of up to 25%. Right: The consistent difference of MLP+RC and MLP+PCL is also reflected over a 2D tiling, showing the average MPJPE error difference of cells with 10 or more frames on the validation set.

scale estimation. Notably, our method with a scale computed from the 2D pose still outperforms the STN baseline using 3D ground truth for scale prediction.

We obtain even larger improvements with PCL on the MPI-INF-3DHP dataset, with 2.4 cm in MPJPE and 22 PCK points. This dramatic improvement is no surprise since the larger field of view (smaller focal length \( f \)) of the MPI-INF-3DHP cameras leads to stronger perspective effects and, therefore, a larger difference between the corrected and uncorrected views. These experiments also show that PCL is not specific to any particular focal length.

In Figure 7, we analyze the position dependent effect of our method on H3.6M. As shown by the plot, the baseline MPJPE increases with the distance from the subject to the image center, hinting at the negative effect of perspective distortion. PCLs undo this effect, leading to a more stable MPJPE and outperforming the baseline by a growing margin as the distance increases. PCL even decreases with the distance to the center, which is surprising. We believe this is because the most complex poses in H3.6M, such as sitting and lying on the ground, are performed in the image center while walking dominates for the off-center ones.

4.2. PCL for Temporal CNNs

As shown in Table 2 incorporating PCL into the temporal convolutional network of [33] does not improve results on their original implementation. Our following analysis shows that this is due to [33] already learning position-dependent effects by operating on unnormalized 2D pose. This, however, overfits to the camera used at training time. By contrast, PCL generalizes perfectly when the camera changes at test time so long as its properties are known approximately.

To analyze the effect, we artificially change the focal length of the test sequences by multiplying all 2D testing poses by a factor of 2/3. This simulates a camera with a slightly smaller focal length and larger field of view. T-CNN generalizes poorly, as it seemingly overfits to the global position and scale of the training set, while PCL can adapt perfectly to the new capture setup without loss in performance.

To facilitate a fair comparison, we created a second baseline, T-CNN+RC. It centers and scales the input pose sequence by subtracting the root joint of the central frame and...
4.3. PCL for CNN Architectures

As shown in the last four rows of Table 1, when using images as input to a ResNet regressing 3D pose on H3.6M, the baselines achieve an MPJPE of 96.5 mm, while our model with PCL yields 94.1 mm, a 2.5% reduction. The improvement is lower compared to 2D to 3D lifting, likely because the overall higher error for image to 3D pose prediction compared to 2D to 3D lifting is dominated by other error factors.

On the MPI-INF-3DHP dataset, the improvement of PCL is more pronounced, improving by 8 mm and 6 PCK points, which further validates the previous findings that perspective effects are stronger on MPI-INF-3DHP, therefore leading to a clear improvement despite higher total errors.

4.4. Robustness to Errors in Focal Length

Although PCL requires knowledge of the camera’s focal length, it is often known or can be estimated approximately from image features [45, 11]. To evaluate the robustness of PCL to erroneous estimates, we experiment with an artificial disturbance to the true focal length at test time. The 2D input poses to the MLP+PCL network are deformed as if they would stem from a camera with different zoom. As shown in Fig. 8, PCL is relatively robust when the estimated focal length ranges between 0.7 and 1.5 times the true one.

4.5. Ablation Study on Synthetic Data

For the synthetic cube dataset, we can stage the same cube at different locations in the image. Fig. 9 demonstrates that PCL compensates perspective effects pixel-perfect, except for depth-dependent and illumination effects. On this dataset, the baseline attains an MPJPE of 13 mm and our PCL variant improves to 8.2 mm. The improvement for end-to-end training is equivalent, with an 4.4 mm improvement from 11.2 to 6.8 mm. While this test is simplistic, the synthetic nature allows us to analyze the generalization capabilities of PCL by training on a version of the cube dataset where the cube is always centered in the training images and tested on the original version with general position, with the ground truth 2D crop location provided. PCL shows good generalization, outperforming the baseline by 36.1% on the unseen test set. We also investigated the effect of illumination by switching from point lights to ambient illumination, which had negligible effect on the reconstruction quality.

5. Limitations

The gained improvements come at the cost of requiring an estimate of the focal length \( f \). Yet, the robustness towards errors in \( f \) shows that improvements can still be obtained with a rough guess. It is worth to note that PCL compensates for location-dependent perspective effects. Those effects that originate from varying distance of the object to the camera, e.g., selfie vs. third person picture, can not be resolved with image warps but would require knowledge of the 3D geometry. Data-driven approaches have been proposed to compensate these [35, 50].
Figure 10: **Improvement of reconstruction error**, binned with respect to the image position. Left: MLP+RC suffers from perspective effects away from the center, while MLP+PCL effectively compensates these leading to improvements of approximately 50%. Right: The consistent difference of MLP+RC and MLP+PCL is also reflected over a 2D tiling, showing the average MPJPE error difference of cells with 10 or more frames on the validation set.

6. Conclusion

We have presented a drop-in replacement for rectangular cropping and root centering that removes location-dependent perspective effects. It is fully differentiable, lends itself to end-to-end training, is efficient to compute, does not impose additional network parameters, and the empirical evaluation demonstrates significant improvements for 3D pose estimation. Notably, the strong influence of perspective effects on the reconstruction accuracy is widely overlooked in the 3D pose reconstruction literature and these improvements are observed irrespective of the network architecture. PCL is therefore an important contribution to pushing state-of-the-art 3D reconstruction methods further.

Appendix

A. MPI-INF-3DHP Additions

In this section, we repeat the detailed error distribution analysis done on the H3.6M dataset for the MPI-INF-3DHP dataset. Figure 10 depicts significant improvements from using PCL. The error by PCL is stable or even improving with the distance to the center, while the MLP+RC model degrades due to perspective effects. PCL even gains an improvement at the image center. This is unexpected on the first glance but can be explained with the MPI-INF-3DHP dataset using different cameras for training and testing. The MLP+RC model seemingly overfits to the perspectives seen during training while the automatic correction of PCL leads to better generalization.

In Figure 11, we can see the distribution of hip joints in the testing dataset for H3.6M and MPI-INF-3DHP. While H3.6M has most of the images around the center of the frame, MPI-INF-3DHP contains poses that are widely spread out across the image. This along with the fact that MPI-INF-3DHP uses a wider field-of-view camera explains the significant improvement we see from introducing PCL on MPI-INF-3DHP.

B. Cube Experiment Details

The Cube Dataset contains images of a single coloured cube with edge length 0.5m at random locations and orientations within the frame. To further demonstrate the effect that ignoring perspective effects has on 3D pose estimation we introduce a variation of this dataset in which the cube has a random orientation but is always placed at the center of the frame. We refer to this variation as the Centered Cube Dataset. We now train models on the Centered Cube Dataset with a central crop and analyze their generalization capabilities to crops from the general dataset with the position of the cube given. Table 3 compares the performance of PCL and STN models on these two datasets, supporting the results reported in the main document in text form.

C. Implementation details

We normalize the 2D input poses and 3D output poses with their mean and standard deviation. On the input side, the mean and standard deviation are computed after the PCL layer and in the case of rectangular cropping (RC) after the
crop and scaling operation. On the output side, the mean and standard deviation for PCL and the baselines are computed in the pelvis-centered coordinates. We found it more effective to multiply the output by the computed standard deviation and adding the mean instead of doing the inverse operation on the label. This ensures that the network output has mean zero and unit standard deviation, which fares well with network layer initialization, while the loss operates on the scales of the original output space.

D. Derivations of the PCL Virtual Camera

Rotation Derivation. The rotation that maps from the virtual to the real camera, \( \mathbf{R}_{\text{virt-real}} \), stems from the definition of rotation matrices. We use the right-handed rule, i.e., counter-clockwise rotation for positive angles and a right-handed coordinate system with the y-axis pointing downwards, x-axis rightwards, and positive z pointing in camera direction. The definition of \( \mathbf{R}_{\text{virt-real}} = \mathbf{R}_y \mathbf{R}_x \) reads thereby

\[
\mathbf{R}_y \mathbf{R}_x = \begin{bmatrix}
\cos(\phi) & 0 & \sin(\phi) \\
0 & 1 & 0 \\
-\sin(\phi) & 0 & \cos(\phi)
\end{bmatrix}
\begin{bmatrix}
1 & 0 & 0 \\
0 & \cos(\theta) & -\sin(\theta) \\
0 & \sin(\theta) & \cos(\theta)
\end{bmatrix}
\]

\[
= \begin{bmatrix}
\cos(\phi) & \sin(\phi) & \cos(\phi) \\
0 & \cos(\theta) & -\sin(\theta) \\
-\sin(\phi) & \sin(\phi) & \cos(\phi)
\end{bmatrix}, \tag{5}
\]

where \( \phi \) and \( \theta \) are, respectively, the vertical and horizontal rotations depicted in Figure 2 of the main document. The equation given in the main document follows from the following trigonometric relations,

\[
\sin(\phi) = \frac{p_x}{\sqrt{1 + p_x^2}}, \quad \cos(\phi) = \frac{1}{\sqrt{1 + p_x^2}},
\]

\[
\sin(\theta) = \frac{-p_y}{\sqrt{1 + p_x^2 + p_y^2}}, \quad \cos(\theta) = \frac{\sqrt{1 + p_x^2 + p_y^2}}{\sqrt{1 + p_x^2 + p_y^2}}. \tag{6}
\]

where \( p \) is the point on the original image plane to which the virtual camera is rotated.

Virtual Focal Length Selection The focal length of the virtual camera defines the zoom level of the PCL crop. It controls the crop size in the original images. Therefore, it needs to be set individually for every crop target, depending on its desired size and position in the image. In the following, we explain the derivation of the three options we propose. Figure 12 shows example crops of each method and their tightness of fit.

A. By setting \( h_{\text{virt}} \) to \( f \), the camera is only rotated, without any change in zoom. A crop is obtained by scaling with factor \( s \), that means, \( f = \frac{h}{s} \). Figure 12, second row, shows that this simple choice leads to inconsistent crop sizes. The object appears smaller the further away it is.

B. By multiplying the virtual length with \( \| \mathbf{p} \| \), the distance of the crop target position on the image plane to the camera center, this distance-related effect is compensated. However, as the third row in Figure 12 shows, this match is not perfect as it does not account for the foreshortening effect when projecting from the original image plane onto the virtual one.

C. Our final choice models foreshortening with

\[
h_{\text{virt}}^x = f_x \| \mathbf{p} \| \sqrt{p_x^2 + 1} \quad \text{and} \quad h_{\text{virt}}^y = f_y \frac{\| \mathbf{p} \|}{\sqrt{p_y^2 + 1}}.
\]

It is derived as follows.

Derivation of Option C. Let \( \mathbf{p} = (x, y, z)^T \) be the target crop position on the image plane, a 3D position. By construction, \( \mathbf{p} \) will be at the image center. Therefore, projecting the infinitesimal motion offset \( \mathbf{p} + (\delta x, \delta y, 0)^T \) and comparing the ratio of the offset in the original and projection yields the desired scale estimate. Formally, we write

\[
(u, v, 1)^T = \mathbf{P} \left( \mathbf{p} + (\delta x, \delta y, 0)^T \right), \tag{7}
\]
where $P$ projects points in the original coordinate system to the virtual one, as defined in the main document. For the sake of simpler equations we do computations in camera coordinates with the origin at the image center and the focal length $f = 1$. In this case, $P = R_{\text{virt} \rightarrow \text{real}}^{-1}$. Using the definition of $R_{\text{virt} \rightarrow \text{real}}$ above, the identity $R_{\text{virt} \rightarrow \text{real}}^{-1} \equiv R_{\text{virt} \rightarrow \text{real}}^{T}$, and computing the partial derivatives with respect to $\delta x$ and $\delta y$ at $\delta x = \delta y = 0$ we obtain

$$\frac{\partial (u, v, 1)^T}{\partial u} \bigg|_{\delta u=0} = \frac{1}{\sqrt{(1 + x^2)\|p\|}} \quad (8)$$

and

$$\frac{\partial (u, v, 1)^T}{\partial v} \bigg|_{\delta v=0} = \frac{\sqrt{(1 + x^2)\|p\|^{2}}}{\|p\|} \quad (9)$$

These equations compute the horizontal and vertical pixel scale ratio between the original and virtual image at $p$. To maintain the scale, the focal length must be set to the inverse of this scaling factor, which is Option C for $f_{\text{virt}}$ that also incorporates the original focal length and the desired crop scale.

Note that the equation for $h^*_{\text{virt}}$ and $h^*_y$ are not equivalent with $x$ and $y$ exchanged because the $x$ and $y$ axes in the virtual camera do not, in general position, project to perpendicular lines in the original view. Figure 1 of the main paper provides examples of this perspective effect. In our definition, the up-direction is kept fixed and the horizontal axis is rotated, therefore, behaving differently in the slant compensation. An equivalent formulation could be derived with the horizontal axis fixed and the vertical axis rotated.

**Maintaining the original aspect ratio** To enable computations with a different focal length in the $x$ and $y$ directions, which models the case of non-square pixels, the above notation was performed individually for the horizontal and vertical directions. This, however, can lead to stretched crops if different scales are predicted for $s$ in horizontal and vertical directions. To maintain the original aspect ratio, we set the focal length to the minimum of the axis-specific lengths. This leads to a crop that is the same or larger than the original one with mismatching aspect ratio, thereby strictly containing the object of interest.

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