Self-Attentive 3D Human Pose and Shape Estimation from Videos

Yun-Chun Chen\textsuperscript{a}, Marco Piccirilli\textsuperscript{b}, Robinson Piramuthu\textsuperscript{c}, Ming-Hsuan Yang\textsuperscript{d,∗∗}

\textsuperscript{a}Department of Computer Science, University of Toronto, ON, Canada
\textsuperscript{b}eBay Inc., San Jose, CA, USA
\textsuperscript{c}Amazon, Oakland, CA, USA
\textsuperscript{d}School of Engineering, University of California at Merced, CA, USA

\begin{abstract}
We consider the task of estimating 3D human pose and shape from videos. While existing frame-based approaches have made significant progress, these methods are independently applied to each image, thereby often leading to inconsistent predictions. In this work, we present a video-based learning algorithm for 3D human pose and shape estimation. The key insights of our method are two-fold. First, to address the inconsistent temporal prediction issue, we exploit temporal information in videos and propose a self-attention module that jointly considers short-range and long-range dependencies across frames, resulting in temporally coherent estimations. Second, we model human motion with a forecasting module that allows the transition between adjacent frames to be smooth. We evaluate our method on the 3DPW, MPI-INF-3DHP, and Human3.6M datasets. Extensive experimental results show that our algorithm performs favorably against the state-of-the-art methods.
© 2021 Elsevier Ltd. All rights reserved.
\end{abstract}

1. Introduction

3D human pose and shape estimation (Kanazawa et al., 2018; Kolotouros et al., 2019a; Bogo et al., 2016) is an active research topic in computer vision and computer graphics that finds numerous applications (Xu et al., 2019; Liu et al., 2019). The inherent under-constrained nature where multiple 3D meshes can explain the same 2D projection makes this problem very challenging. While frame-based methods (Kanazawa et al., 2018; Kolotouros et al., 2019a; Bogo et al., 2016) and video-based approaches (Kocabas et al., 2020; Lee et al., 2018b; Rayat Imtiaz Hossain and Little, 2018; Kanazawa et al., 2019; Zhang et al., 2019b) have been developed to recover human pose in the literature, numerous issues remain to be addressed. First, existing approaches employ recurrent neural networks (RNNs) to model temporal information for consistent predictions. However, it is difficult to train RNNs to capture long-range dependencies (Vaswani et al., 2017; Pascanu et al., 2013). On the other hand, one recent approach employing RNNs does not consistently render smooth predictions across frames (Kocabas et al., 2020). Second, as most real-world datasets do not contain ground-truth camera parameter annotations, existing methods typically reproject the predicted 3D joints onto the 2D space using the estimated camera parameters, followed by a loss enforced between the reprojected 2D joints and the corresponding ground-truth 2D joints. Nevertheless, such regularization terms are still insufficient to account for complex scenes. Third, existing methods (Kocabas et al., 2020; Kanazawa et al., 2019; Zhang et al., 2019b; Kanazawa et al., 2018) do not perform well for humans under heavy occlusion or out-of-view, as there is no
We demonstrate the effectiveness of the proposed SPS-Net on three standard benchmarks, including the 3DPW (von Marcard et al., 2018), MPI-INF-3DHP (Mehta et al., 2017a), and Human3.6M (Ionescu et al., 2013) datasets. Our main contributions can be summarized as follows:

- We present a video-based learning algorithm for 3D human pose and shape estimation.
- We propose a camera parameter consistency loss that provides additional supervisory signals for model training, resulting in more accurate camera parameter predictions.
- Our model learns to predict plausible estimations when occlusion or out-of-view occurs in a self-supervised fashion.
- Extensive evaluations on three challenging benchmarks demonstrate that our method achieves the state-of-the-art performance against existing approaches.

2. Related Work

3D human pose and shape estimation. Existing methods for 3D human pose and shape estimation can be broadly categorized as frame-based and video-based. Frame-based methods typically use an off-the-shelf keypoint detector (e.g., DeepCut (Pishchulin et al., 2016)) to fit the SMPL (Loper et al., 2015) body model (Bogo et al., 2016), leverage silhouettes and keypoints for model fitting (Lassner et al., 2017), or directly regress the parameters for the SMPL (Loper et al., 2015) body model from pixels using neural networks (Kolotouros et al., 2019a; Kanazawa et al., 2018; Kolotouros et al., 2019b). While these frame-based approaches are able to recover 3D poses from a single image, independently applying these algorithms to each video frame often leads to temporally inconsistent predictions. Video-based methods, on the other hand, usually adopt RNN-based models to generate temporally coherent predictions. These approaches either focus on estimating the human body of the current frame (Arnab et al., 2019; Sun et al., 2019; Kocabas et al., 2020) or predicting the past and future motions (Kanazawa et al., 2019; Zhang et al., 2019b).

Our algorithm differs from these video-based methods in three aspects. First, in contrast to adopting RNN-based models, we develop a self-attention module to aggregate temporal cues and a forecasting module to model human motion for predicting temporally coherent estimations. Second, we enforce a consistency loss on the prediction of camera parameters to regularize model learning. Third, we address the occlusion and out-of-view issues with a self-supervised learning scheme to generate plausible human pose and shape predictions.

Attention models. Attention models have been shown effective in neural machine translation (Vaswani et al., 2017) and image generation problems (Zhang et al., 2019a; Parmar et al., 2018). For machine translation, employing self-attention models (Vaswani et al., 2017) helps capture short-range and long-range correlations between tokens in the sentence for improving the translation quality. In image generation, the Image Transformer (Parmar et al., 2018) and SAGAN (Zhang et al., 2019a) show that leveraging self-attention mechanisms facilitates the models to generate realistic images. In 3D human pose and shape estimation, the VIBE (Kocabas et al., 2020) method adopts a self-attention scheme in the discriminator for feature aggregation, allowing the discriminator to better distinguish the motions of attended video frames between the real sequences and generated ones.

We adopt self-attention modules in both the SPS-Net and discriminator. Our method differs from the VIBE (Kocabas et al., 2020) in that our self-attention module aims to derive a representation for each frame that contains temporal information by jointly considering short-range and long-range dependencies across video frames, whereas the VIBE (Kocabas et al., 2020) method aims to derive a single representation for the entire pose sequence.

Future human pose predictions. Predicting future poses from videos has been studied by a few approaches in the literature. Existing algorithms estimate 2D poses from pixels (Denton and Birodkar, 2017; Finn et al., 2016), optical flow (Walker et al., 2016), or 2D poses (Walker et al., 2017), or predict 3D outputs based on 3D inputs (Butepage et al., 2017; Fragkiadaki et al., 2015; Jain et al., 2016; Li et al., 2018; Villegas et al., 2018). Other approaches learn 3D pose prediction from 2D inputs (Zhang et al., 2019b; Kanazawa et al., 2019).

Similar to the HMMP (Kanazawa et al., 2019) and PHD (Zhang et al., 2019b) methods, we leverage visual cues from human motion to predict temporally smooth predictions. Our method differs from them in that our self-attention module helps capture short-range and long-range dependencies across video frames in the input video, while the 1D convolution in the temporal encoder and autoregressive module of these methods does not have such ability.
Consistency constraints for visual learning. Exploiting consistency constraints to regularize model learning has been shown effective in numerous applications, including semantic matching (Zhou et al., 2015), optical flow estimation (Meister et al., 2018), depth prediction (Gordon et al., 2019), and image-to-image translation (Zhu et al., 2017; Lee et al., 2018a; Huang et al., 2018). Other methods exploit consistency constraints across multiple network outputs, including depth and optical flow estimation (Zou et al., 2018), joint semantic matching and object co-segmentation (Chen et al., 2020), ego-motion (Zhou et al., 2017), and domain adaptation (Chen et al., 2019b). In our work, we show that enforcing consistency constraints on the prediction of camera parameters for the overlapped video frames of two segments from the same video results in performance improvement.

3. Proposed Algorithm

In this section, we first provide an overview of our approach. Next, we describe the details of the self-attention and forecasting modules, followed by formulating the proposed camera parameter consistency loss. We then motivate the self-supervised learning scheme for addressing the occlusion and out-of-view issues.

3.1. Algorithmic overview

Given an input video $V = \{I_i\}_{i=1}^N$ of length $N$ containing a single person, our goal is to learn a model that recovers the 3D human body of each frame. We present the Self-attentive Pose and Shape Network (SPS-Net), comprising four components: 1) feature encoder $E$, 2) self-attention module $A$, 3) forecasting module $F$, and 4) three parameter regressors $R_{\text{shape}}$, $R_{\text{pose}}$, and $R_{\text{camera}}$.

As shown in Figure 2, we first apply the encoder $E$ to each frame $I_i \in V$ to extract the feature $f_i = E(I_i) \in \mathbb{R}^d$, where $d$ denotes the number of channels of the feature $f_i$. Next, the self-attention module $A$ takes all the encoded features $\{f_i\}_{i=1}^N$ as input and outputs the corresponding latent representations $\{h_i\}_{i=1}^N$, where $h_i \in \mathbb{R}^d$ denotes the latent representation for $I_i$, containing temporal information of past and future frames. The forecasting module $F$ takes each encoded feature $f_i$ as input and forecasts the feature of the next time step $f'_{i+1} = F(f_i) \in \mathbb{R}^d$.

The latent representations $\{h_i\}_{i=1}^N$ and the predicted features $\{f'_{i+1}\}_{i=1}^N$ of the same time step (e.g., $h_i$ and $f'_i$) are passed to a feature fusion module to derive the fused representations $\{F_i\}_{i=1}^N$, where $F_i \in \mathbb{R}^d$ contains both global temporal and local motion information. The pose parameter regressor $R_{\text{pose}}$ takes each fused representation $F_i$ as input and renders the pose parameters $\theta_i$ for each frame $I_i$, where $\theta_i = R_{\text{pose}}(F_i) \in \mathbb{R}^{72}$. The shape parameter regressor $R_{\text{shape}}$, on the other hand, takes all the fused representations $\{F_i\}_{i=1}^N$ as input and regresses the shape parameters $\beta \in \mathbb{R}^{10}$ of the input video $V$.

3.2. 3D human body representation. Similar to the state-of-the-art methods (Kanazawa et al., 2018; Kolotouros et al., 2019a; Kocabas et al., 2020), we adopt the SMPL (Loper et al., 2015) body model to describe the human body using a 3D mesh representation. The SMPL (Loper et al., 2015) model is described by the pose $\theta \in \mathbb{R}^{72}$ and shape $\beta \in \mathbb{R}^{10}$ parameters. The pose parameters $\theta$ contain the global body rotation and the relative 3D rotation of 23 joints in axis-angle format. The shape parameters $\beta$ are parameterized by the first 10 linear coefficients of a PCA shape space. We use a gender-neutral shape model as in previous work (Kanazawa et al., 2018; Kolotouros et al., 2019a; Kocabas et al., 2020). The differentiable SMPL (Loper et al., 2015) body model takes the pose $\theta$ and shape $\beta$ parameters as input and outputs a triangular mesh $M(\theta, \beta) \in \mathbb{R}^{6890 \times 3}$ consisting of 6,890 mesh vertices by shaping a template body mesh based on forward kinematics. The 3D keypoints $X \in \mathbb{R}^{4 \times 3}$ of $k$ body joints can be obtained by applying a pre-trained linear regressor $W$ to the 3D mesh $M(\theta, \beta)$, and is defined as $X = WM(\theta, \beta)$.

Camera model. Similar to existing approaches (Kanazawa et al., 2018; Kolotouros et al., 2019a; Kocabas et al., 2020), we use a weak-perspective camera model in this work. By estimat-
Fig. 3: Overview of the self-attention module A. Our self-attention module A is composed of an attention network Q and an attention network K. Given a sequence of input features, the self-attention module first predicts the attention vector \( q_i \) and the attention vector \( k_i \) for each frame. Next, we compute the inner product between each attention vector \( q_i \) and all attention vectors \( \{k_j\}_{j=1}^N \), followed by normalizing the weights using a softmax function. The input features are first fused using the associated weights and then summed with the skipped input features to derive the final latent representations as output.

3.2. Self-attention module

Given a sequence of features \( \{f_i\}_{i=1}^N \) encoded by the encoder \( E \), our goal is to leverage temporal cues in the input video to provide more information that helps regularize the estimation of human pose and shape. Existing methods exploit temporal information by resorting to an RNN-based model, e.g., GRU (Kocabas et al., 2020) or LSTM (Lee et al., 2018b; Rayat Imtiaz Hosain and Little, 2018). However, training RNN-based models is difficult to capture long-range dependencies (Vaswani et al., 2017; Pascanu et al., 2013).

Motivated by the attention models (Vaswani et al., 2017; Zhang et al., 2019a; Parmar et al., 2018) which have been shown effective to jointly capture short-range and long-range dependencies while being more parallelizable to train (Vaswani et al., 2017), we develop a self-attention module to learn latent representations \( h \) that jointly observe past and future video frames for producing temporally consistent pose and shape predictions. In this work, we aim to exploit the idea that the occluded frames can benefit from the information of the non-occluded frames, while the non-occluded frames do not have to depend on the information from the occluded frames (i.e., anti-symmetric attention of humans that can be occluded and un-occluded between frames in either direction). To achieve this, we have an attention network \( Q \) and an attention network \( K \) in our self-attention module \( A \).

As shown in Figure 3, for each feature \( f_i \), we first apply the attention network \( Q \) and the attention network \( K \) to encode an attention vector \( q_i = Q(f_i) \in \mathbb{R}^d \) and an attention vector \( k_i = K(f_i) \in \mathbb{R}^d \), respectively. To consider the dependency between two input frames \( I_i \) and \( I_j \), we compute the inner product between the attention vector \( q_i \) of frame \( I_i \) and the attention vector \( k_j \) of frame \( I_j \), i.e., \( w^i_j = q_i \cdot k_j \in \mathbb{R} \). To derive the latent representation \( h_i \) for frame \( I_i \), we first apply a softmax layer to all the weights \( \{w^i_j\}_{j=1}^N \) computed between the attention vector \( q_i \) of frame \( I_i \) and all attention vectors \( \{k_j\}_{j=1}^N \) for normalization to derive the attention weights. The attention weights \( \{a^i_j\}_{j=1}^N \) are computed by

\[
a^i_j = \frac{\exp(w^i_j)}{\sum_{m=1}^N \exp(w^i_m)}. \tag{1}
\]

We then apply a weighted sum layer to sum over all input features \( \{f_i\}_{i=1}^N \) with the associated attention weights \( \{a^i_j\}_{j=1}^N \). In addition, we add a residual connection (He et al., 2016) to pass the input feature \( f_i \) to the output of the self-attention module. Specifically, the latent representation \( h_i \) is described by

\[
h_i = f_i + \sum_{j=1}^N a^i_j \cdot f_j. \tag{2}
\]

3.3. Forecasting module

In addition to considering global temporal information as in the self-attention module \( A \), we exploit visual cues from human motion to encourage our model to generate temporally smooth predictions. Motivated by methods that focus on tackling human motion prediction (Kanazawa et al., 2019; Zhang et al., 2019b), we develop a forecasting module \( F \) that takes each encoded feature \( f_i \) as input and forecasts the feature of the next time step \( f_{i+1} \). As the feature of the next time step is available (given by the encoder), we train the forecasting module \( F \) in a self-supervised fashion with a feature regression loss:

\[
\mathcal{L}_{\text{feature}} = \sum_{i=1}^{N-1} ||f_{i+1} - f_{i+1}'||_2. \tag{3}
\]

We note that since the feature of the next time step of \( f_N \) is not available, we do not compute the feature regression loss on
The feature regression loss $\mathcal{L}_{\text{feature}}$ allows the forecasting module $F$ to forecast the feature of the next time step for each input feature by exploiting visual cues from human motion that provide more temporal context for generating temporally smooth predictions.

### 3.4. 3D human pose and shape estimation

To jointly consider the latent representations $\{h_i\}_{i=1}^N$ that contain global temporal information and the predicted features $\{f'_i\}_{i=1}^N$ that contain local motion information for predicting the parameters for 3D human pose and shape estimation, we have a feature fusion module that fuses $\{h_i\}_{i=1}^N$ and $\{f'_i\}_{i=1}^N$ at the same time step to derive the fused representations $\{f_i\}_{i=1}^N$. We note that since our encoder $E$ is pre-trained on single-image pose and shape estimation task and fixed during training as in prior work (Kanazawa et al., 2018; Kocabas et al., 2020), the feature $f_i$ encoded by the encoder $E$ is static and does not contain motion information. Therefore, we use the predicted feature $f'_i$ from the forecasting module $F$ that contains motion information for feature fusion.

As shown in Figure 4, our feature fusion module is composed of a fully connected (FC) layer, followed by a softmax layer. Given a latent representation $h_i$ and a predicted feature $f'_i$, we first apply the FC layer to each input feature to predict a weight. The predicted weights are then normalized using a softmax layer. The two input features are then fused by $F_i = a_h_i h_i + a_f_i f'_i \in \mathbb{R}^d$. We note that since $f'_i$ is not available, we define $F_i = h_i$.

Next, we pass all the fused features $\{f_i\}_{i=1}^N$ to the shape $R_{\text{shape}}$, pose $R_{\text{pose}}$, and camera $R_{\text{camera}}$ parameter regressors to predict the corresponding parameters, respectively. Similar to one prior work (Kanazawa et al., 2018), we adopt an iterative error feedback scheme to regress the parameters. To train the proposed SPS-Net, we impose a SMPL parameter regression loss $\mathcal{L}_{\text{SMPL}}$ on the estimated pose $\{\theta_i\}_{i=1}^N$ and shape $\beta$ parameters, a 3D joint loss $\mathcal{L}_{\text{joint}}^{\text{3D}}$ on the predicted 3D joints $\{\hat{X}_i\}_{i=1}^N$, and a 2D joint loss $\mathcal{L}_{\text{joint}}^{\text{2D}}$ on the reprojected 2D joints $\{\hat{x}_i\}_{i=1}^N$ (Kanazawa et al., 2018; Kocabas et al., 2020). Specifically, the SMPL parameter regression loss $\mathcal{L}_{\text{SMPL}}$, the 3D joint loss $\mathcal{L}_{\text{joint}}^{\text{3D}}$, and the 2D joint loss $\mathcal{L}_{\text{joint}}^{\text{2D}}$ are defined as

\[
\mathcal{L}_{\text{SMPL}} = \|\beta - \tilde{\beta}\|_2 + \sum_{i=1}^N \|\theta_i - \tilde{\theta}_i\|_2, \\
\mathcal{L}_{\text{joint}}^{\text{3D}} = \sum_{i=1}^N \|X_i - \hat{X}_i\|_2, \\
\mathcal{L}_{\text{joint}}^{\text{2D}} = \sum_{i=1}^N \|x_i - \hat{x}_i\|_2.
\]

#### Mask loss.

Since the ground-truth pose $\{\theta_i\}_{i=1}^N$, shape $\beta$, and 3D joint $\{X_i\}_{i=1}^N$ annotations are usually not available, using the 2D joint loss $\mathcal{L}_{\text{joint}}^{\text{2D}}$ alone is insufficient to train the SPS-Net as there are numerous 3D meshes that can explain the same 2D projection. To address this issue, we exploit the idea that the reprojection of the 3D mesh using the estimated camera parameters should be consistent with the segmentation mask obtained by directly segmenting the human from the input video frame. We leverage an off-the-shelf instance segmentation model (Bolya et al., 2019) to compile a pseudo ground-truth segmentation mask $m^\text{pseudo}$ for each input video frame $I_i$. Then, we use the pseudo ground-truth segmentation mask to supervise the reprojection of the 3D mesh with a mask loss:

\[
\mathcal{L}_{\text{mask}} = -\sum_{i=1}^N m^\text{pseudo}_i \log(m^\text{proj}_i),
\]

where $m^\text{proj}_i$ denotes the reprojection of the 3D mesh using the estimated camera parameters.

#### Camera parameter consistency loss.

Since there are no ground-truth camera parameter annotations for most datasets, existing methods (Kocabas et al., 2020; Kanazawa et al., 2018; Kolotouros et al., 2019a) regularize the estimation of camera parameters via reprojecting the detected 3D keypoints onto 2D space and enforcing a 2D joint loss $\mathcal{L}_{\text{joint}}^{\text{2D}}$ between the reprojected 2D joints and the corresponding ground-truth 2D joints. This weaker form of supervision, however, is still under-constrained. To address the absence of ground-truth camera parameter annotations, we exploit the idea that the overlapped video frames in different sequence segments from the same video should have the same camera parameter predictions. Given two input sequence segments $S_1 = \{f^1_i\}_{i=1}^k$ and $S_2 = \{f^2_i\}_{i=1}^k$ from the same video $V$, the overlapped frames are $\{I_i\}_{i=n+1}^{n+k}$. We enforce the camera parameter predictions of the overlapped frames $\{I_i\}_{i=n+1}^{n+k}$ to be the same in these two input sequence segments $S_1$ and $S_2$. To achieve this, we propose a camera parameter consistency loss $\mathcal{L}_{\text{camera}}$ which is defined as

\[
\mathcal{L}_{\text{camera}} = \sum_{i=n+1}^k \|R_{\text{camera}}(F^1_i) - R_{\text{camera}}(F^2_i)\|_2, \tag{6}
\]

where $F^1_i \in \mathbb{R}^d$ and $F^2_i \in \mathbb{R}^d$ are the fused feature of frame $f^1_i$ and frame $f^2_i$, respectively. Incorporating such consistency loss during training not only regularizes the prediction of camera parameters but also provides more supervisory signals to facilitate model training.

#### Adversarial loss.

In addition to the aforementioned loss functions, we also adopt an adversarial learning scheme that aims to encourage our method to recover a sequence of 3D

---

1We note that while other existing instance segmentation models can also be used for compiling segmentation masks, we leave the discussion of adopting different instance segmentation models as future work.
meshes with realistic motions (Kocabas et al., 2020). Similar to the VIBE (Kocabas et al., 2020) method, we adopt the AMASS (Mahmood et al., 2019) dataset and employ a discriminator $D$ that takes as input a sequence of pose parameters with the associated shape parameters $\Theta = [\theta_1, ..., \theta_N, \beta]$ estimated by the SPS-Net (treated as a fake example) and a sequence of those $\Theta = [\theta_1, ..., \theta_N, \beta]$ sampled from the AMASS (Mahmood et al., 2019) dataset (treated as a real example), and aims to distinguish whether the input sequences are realistic or not.

As shown in Figure 5, our discriminator $D$ is composed of a self-attention module $A_D$ and a classifier $C_D$. We first concatenate the estimated shape parameters $\hat{\beta}$ with each of the estimated pose parameters $[\hat{\theta}_1]_i^{N}$ to form the joint representations $[J_i]_i^{N}$, where $\hat{J}_i = [\hat{\beta}, \hat{\theta}_i] \in \mathbb{R}^{82}$. We then pass all joint representations $[J_i]_i^{N}$ to the self-attention module $A_D$ to derive the latent representations $[\hat{H}_i]_i^{N}$, where $\hat{H}_i \in \mathbb{R}^{82}$ is the latent representation of $\hat{J}_i$. To derive the motion representation $M$ of $\Theta$, we average all the latent representations $[\hat{H}_i]_i^{N}$, i.e., $M = \frac{1}{N} \sum_{i=1}^{N} \hat{H}_i \in \mathbb{R}^{82}$. The motion representation $M \in \mathbb{R}^{82}$ of $\Theta$ can be derived similarly. The classifier $C_D$ takes the motion representations $M$ and $\hat{M}$ as input and distinguishes whether the input motion representations are realistic or not. Specifically, we have an adversarial loss $L_{adv}$ which is defined as

$$L_{adv} = \mathbb{E}_{\Theta \sim p_{\Theta}}[|D(\Theta) - 1|_2] + \mathbb{E}_{\Theta \sim p_{\Theta}}[|D(\hat{\Theta})|_2].$$

(7)

Leveraging the unpaired data from the AMASS (Mahmood et al., 2019) dataset serves as a weak supervision to encourage the SPS-Net to recover a sequence of 3D meshes with realistic motions.

We note that our discriminator $D$ is different from that of the VIBE (Kocabas et al., 2020) method in two aspects. First, our discriminator has a self-attention module, while the discriminator of the VIBE (Kocabas et al., 2020) method has two GRU layers. Second, we use self-attention to derive a representation for each frame that contains temporal information by jointly considering short-range and long-range dependencies across video frames, whereas the VIBE (Kocabas et al., 2020) method leverages self-attention to derive a single representation for the entire pose sequence.

Self-supervised occlusion handling. While the aforementioned loss functions regularize the learning of the SPS-Net, the 2D and 3D joint losses and the mask loss are only enforced on the visible keypoints and regions of the human body. That is, there is no explicit constraint imposed on the invisible keypoints and regions. We develop a self-supervised learning scheme to allow our model to produce plausible predictions in order to account for the occlusion and out-of-view scenarios. For each input frame $I_i$, we first synthesize the occluded version $I'_i$ by randomly masking out some regions. We then leverage the predictions of the original frames to supervise those of the synthesized occluded or partially visible frames and develop a self-supervised parameter regression loss $L_{param}$ to exploit this property with

$$L_{param} = ||\hat{\beta} - \beta'||_2 + \sum_{i=1}^{N} ||\hat{\theta}_i - \theta'_i||_2$$

$$+ \sum_{i=1}^{N} ||R_{camera}(F_i) - R_{camera}(F'_i)||_2.$$  

(8)

4. Experimental Results

In this section, we first describe the implementation details. Next, we describe the datasets for model training and testing, followed by the evaluation metrics. We then present the quantitative and visual comparisons to existing methods as well as the ablation study.

4.1. Implementation details

We implement our model using PyTorch (Paszke et al., 2019). Same as prior work (Kanazawa et al., 2018; Kocabas et al., 2020), we adopt the ResNet-50 (He et al., 2016) pre-trained on single-image pose and shape estimation task (Kanazawa et al., 2018; Kolotouros et al., 2019a) to serve as our encoder $E$. Our encoder $E$ is fixed and outputs a 2,048-dimensional feature for each frame, i.e., $f_i \in \mathbb{R}^{2048}$. We set the length of the input sequence to 32 with a batch size of 16. Both the attention network $Q$ and the attention network $K$ in the self-attention module $A$ consist of 2 fully connected layers, each of which has a hidden size of 2,048, followed by a LeakyReLU layer. As for the forecasting module $F$, unlike prior methods (Zhang et al., 2019b; Kanazawa et al., 2019) that use 1D convolution layers, our forecasting module $F$ is composed of 2 fully connected layers, each of which has a hidden size of 2,048, followed by a LeakyReLU layer. Both the attention network $Q$ and the attention network $K$ in the self-attention module $A$ also consist of 2 fully connected layers, each of which has a hidden size of 82, followed by a LeakyReLU layer. The classifier $C_D$ in the discriminator $D$ is composed of a fully connected layer, followed by a sigmoid function. The input and output dimensions of the classifier $C_D$ are 82 and 1, respectively. Similar to the HMR (Kanazawa et al., 2018), the SMPL (Loper et al., 2015) parameter regressor $[R_{pose}, R_{shape}]$ is composed of 2 fully connected layers with a hidden size of 1,024. The shape $R_{shape}$, pose $R_{pose}$, and camera $R_{camera}$ parameter regressors are initialized from the pre-trained weights of the HMR (Kanazawa et al., 2018) approach. The weights of the self-attention module $A$, the forecasting module $F$, the feature
fusión module, and the discriminator $D$ are randomly initialized. We use the ADAM (Kingma and Ba, 2014) optimizer for training. The learning rates for the SPS-Net and the discriminator $D$ are set to $5 \times 10^{-5}$ and $1 \times 10^{-4}$, respectively. Following the VIBE (Kocabas et al., 2020) method, we set the hyperparameters for the loss functions as follows: $\lambda_{\text{adv}}=0.06$, $\lambda_{\text{part}}=60$, $\lambda_{\text{3D}}=300$, $\lambda_{\text{2D}}=300$, and $\lambda_{\text{adv}}=2$. For the other hyperparameters, we set $\lambda_{\text{feature}}=1$, $\lambda_{\text{mask}}=300$, $\lambda_{\text{camera}}=0.1$, $\lambda_{\text{param}}^{\text{intra}}=0.06$, $\lambda_{\text{param}}^{\text{inter}}=60$, and $\lambda_{\text{param}}=0.1$. We train our model on a single NVIDIA V100 GPU with 32GB memory for 120 epochs. For each epoch, there are 500 iterations.

Camera parameter consistency loss $L_{\text{camera}}$. To compute the camera parameter consistency loss $L_{\text{camera}}$, in each iteration we sample two consecutive sequence segments by shifting the starting index for data sampling by 1. Assuming that the starting index for data sampling is $n$, we first sample a sequence segment $S_1 = [I_{i}]_{i=n+1}^{n+31}$. Then we shift the starting index for data sampling by 1 and sample another sequence segment $S_2 = [I_{i}]_{i=n+32}^{n+62}$. Given these two sequence segments $S_1$ and $S_2$, the overlapped video frames are $[I_{i}]_{i=n+31}^{n+32}$. We enforce the camera parameter predictions of the overlapped video frames $[I_{i}]_{i=n+1}^{n+31}$ to be the same in these two sequence segments with a camera parameter consistency loss.

Self-supervised occlusion handling. Since the ground-truth 2D joint annotations are available, for each training image, we randomly sample 3 to 5 keypoints. For each keypoint, we randomly sample a width offset between 25 and 50 pixels and a height offset between 25 and 50 pixels to determine the region to be masked out for synthesizing the occluded training data. The shape, pose, and camera parameter predictions of the occluded training data are supervised by those of the original training data. We note that for frames with ground-truth pose parameter annotations, the self-supervised parameter regression loss $L_{\text{param}}$ can be computed against the ground truth. However, in our training set, only the MPI-INF-3DHP (Mehta et al., 2017a) and Human3.6M (Ionescu et al., 2013) datasets contain ground-truth pose parameter annotations. For ease of implementation, we choose to compute the loss against the predictions of the original frames. The formulation of the self-supervised parameter regression loss $L_{\text{param}}$ is applicable to all training data, with or without ground truth.

Multi-person tracking. To recover human body from videos that contain multiple person instances, we first leverage a multi-person tracker to detect and track each person instance. We then apply our SPS-Net to each person tracking result to estimate the 3D human pose and shape. The multi-person tracker is composed of an object detector and an object tracker. We adopt the YOLOv4 (Bochkovskiy et al., 2020) as the object detector and the SORT (Bewley et al., 2016) as the object tracker. The multi-person tracker first applies the YOLOv4 (Bochkovskiy et al., 2020) detector to each video frame to detect each person instance. Then the person detection results are passed to the SORT (Bewley et al., 2016) method to associate the detected person instances in the current frame to the existing ones. Specifically, the SORT (Bewley et al., 2016) first predicts the bounding box in the current frame for each existing person. Then, we compute the intersection over union (IoU) between the detected bounding boxes and the predicted bounding boxes. By using the Hungarian algorithm with a minimum IoU threshold, we can assign each detected person instance to an existing one or consider the detected person instance a new one.

4.2. Experimental settings

We describe the datasets and the evaluation metrics below.

4.2.1. Datasets

Similar to the state-of-the-art human pose and shape estimation methods (Kanazawa et al., 2018, 2019; Kolotouros et al., 2019a; Kocabas et al., 2020), we adopt a number of datasets that contain either 2D or 3D ground-truth annotations for training. Specifically, we use the PennAction (Zhang et al., 2013), InstaVariety (Kanazawa et al., 2019), PoseTrack (Andriluka et al., 2018), MPI-INF-3DHP (Mehta et al., 2017a), and Human3.6M (Ionescu et al., 2013) datasets for training. Same as the VIBE (Kocabas et al., 2020) method, we use the Kinetics-400 (Kay et al., 2017) dataset to complement the missing parts of the InstaVariety (Kanazawa et al., 2019) dataset. We evaluate our method on the 3DPW (von Marcard et al., 2018), MPI-INF-3DHP (Mehta et al., 2017a), and Human3.6M (Ionescu et al., 2013) datasets. The details of each dataset are described below.

3DPW (von Marcard et al., 2018). The 3DPW dataset is an in-the-wild 3D dataset, containing 60 videos of several in-the-wild and indoor activities. The training, validation, and test sets are composed of 24, 12, and 24 video sequences, respectively. We evaluate our method on the 3DPW test set.

MPI-INF-3DHP (Mehta et al., 2017a). The MPI-INF-3DHP dataset consists of multi-view videos captured in indoor environments. The training set contains 8 subjects, each of which has 16 videos. Following existing approaches (Kolotouros et al., 2019a; Kocabas et al., 2020), we use the training set for model training and evaluate our SPS-Net on the test set.

Human3.6M (Ionescu et al., 2013). The Human3.6M dataset is composed of 15 sequences of several people performing different actions. This dataset is collected in an indoor and controlled environment. The training set contains 1.5 million images, each of which has 3D ground-truth annotations. Same as the VIBE (Kocabas et al., 2020) method, we train our model on 5 subjects (i.e., S1, S5, S6, S7, and S8) and evaluate our method on the remaining 2 subjects (i.e., S9 and S11).

PennAction (Zhang et al., 2013). The PennAction dataset is composed of 2,326 videos of 15 actions. Each video is annotated with 2D keypoints. We use this dataset for training.

InstaVariety (Kanazawa et al., 2019). The InstaVariety dataset is composed of videos of 24-hour long collected from Instagram. Each video is annotated with 2D joints obtained by using the OpenPose (Cao et al., 2019) and Detect and Track (Girdhar et al., 2018) methods. We adopt this dataset for training.

PoseTrack (Andriluka et al., 2018). The PoseTrack dataset consists of 1,337 videos. The training set is composed of 792 videos. The validation set contains 170 videos. The test set comprises 375 videos. Each video is annotated with 15 keypoints. We use the training set for model training.
We present the experimental results with comparisons to existing methods. (Left) Results on the 3DPW (von Marcard et al., 2018) dataset. (Middle) Results on the MPI-INF-3DHP (Mehta et al., 2017a) dataset. (Right) Results on the Human3.6M (Ionescu et al., 2013) dataset. The **bold** and *italic* numbers indicate the top two results, respectively. The “-” indicates the result is not available.

**Table 1: Experimental results of 3D human pose and shape estimation.** We present the experimental results with comparisons to existing methods. (Left) Results on the 3DPW (von Marcard et al., 2018) dataset. (Middle) Results on the MPI-INF-3DHP (Mehta et al., 2017a) dataset. (Right) Results on the Human3.6M (Ionescu et al., 2013) dataset.

| Method                  | Number of parameters | 3DPW (von Marcard et al., 2018) | MPI-INF-3DHP (Mehta et al., 2017a) | Human3.6M (Ionescu et al., 2013) |
|-------------------------|----------------------|----------------------------------|------------------------------------|-----------------------------------|
|                         | PA-MPJPE ↓           | MPJPE ↓                          | Acceleration Error ↓               | PA-MPJPE ↓           | MPJPE ↓ | PCK ↓ | PA-MPJPE ↓ | MPJPE ↓ | PCK ↓ |
| Yang et al. (Yang et al., 2018) | -                    | -                                | 90.3                               | -                    | -       | -     | -          | -       | -     |
| Chen et al. (Chen et al., 2019a) | -                    | -                                | -                                  | -                    | -       | -     | -          | -       | -     |
| Mehta et al. (Mehta et al., 2017b) | 9.83M                | -                                | -                                  | -                    | -       | -     | -          | -       | -     |
| EpipolarPose (Kocabas et al., 2019) | 34.28M               | -                                | -                                  | -                    | -       | -     | -          | -       | -     |
| TCN (Cheng et al., 2020) | 10.03M               | -                                | -                                  | -                    | -       | -     | -          | -       | -     |
| RepNet (Wandt and Rosenhahn, 2019) | 46.31M               | 70.2                             | -                                  | -                    | -       | -     | -          | -       | -     |
| CMR (Kolotouros et al., 2019b) | -                    | -                                | -                                  | -                    | -       | -     | -          | -       | -     |
| STRAPS (Sengupta et al., 2020) | 12.48M               | 66.8                             | -                                  | -                    | -       | -     | -          | -       | -     |
| NBF (Duman et al., 2018) | 66.1M                | 90.7                             | -                                  | -                    | -       | -     | -          | -       | -     |
| EnPose (Choutas et al., 2020) | 47.22M               | 60.7                             | 93.4                               | -                    | -       | -     | -          | -       | -     |
| HUND (Zanfir et al., 2020) | 26.99M               | 56.5                             | 82.7                               | -                    | 97.8    | 82.5  | -          | -       | -     |
| SPIN (Kolotouros et al., 2019a) | 26.99M               | 59.2                             | 96.9                               | 116.4                | 29.8    | 67.5  | 105.2      | 76.4    | -     |
| Temporal 3D Kinetics (Arnab et al., 2019) | -                    | 72.2                             | -                                  | -                    | -       | -     | -          | -       | -     |
| Motion to the Rescue (Doersch and Zisserman, 2019) | -                    | 74.7                             | -                                  | -                    | -       | -     | -          | -       | -     |
| DSD-SATN (Sun et al., 2019) | 69.5                 | -                                | -                                  | -                    | -       | -     | -          | -       | -     |
| HMR (Kanazawa et al., 2018) | 29.76M               | 72.6                             | 116.5                               | 139.3                | 15.2    | 63.4  | 97.7       | 89.0    | 41.5  |
| SPIN (Kocabas et al., 2020) | 48.30M               | 56.5                             | 93.5                               | 113.4                | 27.1    | 63.4  | 97.7       | 89.0    | 41.5  |
| Others | 51.43M               | 59.2                             | 85.8                               | 106.5                | 22.1    | 60.7  | 94.3       | 90.1    | 38.7  |

**Fig. 6: Visual comparisons.** We present two visual comparisons with the SPIN (Kolotouros et al., 2019a) and VIBE (Kocabas et al., 2020) methods. Our method is capable of estimating shapes that cover human bodies well and predicting more accurate poses for limbs in particular.

### 4.2.2. Evaluation metrics

We use the procrustes aligned mean per joint position error (PA-MPJPE), mean joint position error (MPJPE), percentage of correct keypoints (PCK) (Mehta et al., 2017a), per vertex error (PVE), and mean acceleration error of every joint in millimeters per second (mm/s) (Kanazawa et al., 2019) for performance evaluation.

### 4.3. Performance evaluation and comparisons

We compare the performance of our SPS-Net with existing frame-based methods (Yang et al., 2018; Chen et al., 2019a; Kocabas et al., 2019; Mehta et al., 2017b; Cheng et al., 2020; Wandt and Rosenhahn, 2019; Kolotouros et al., 2019b; Sengupta et al., 2020; Omran et al., 2018; Choutas et al., 2020; Zanfir et al., 2020; Kanazawa et al., 2018; Kolotouros et al., 2019a) and video-based approaches (Kanazawa et al., 2019; Arnab et al., 2019; Doersch and Zisserman, 2019; Sun et al., 2019; Kocabas et al., 2020). Table 1 presents the quantitative results on the 3DPW (von Marcard et al., 2018), MPI-INF-3DHP (Mehta et al., 2017a), and Human3.6M (Ionescu et al., 2013) datasets.

Experimental results on all three datasets show that our method performs favorably against existing frame-based and video-based approaches on the PA-MPJPE, MPJPE, PVE, and PCK evaluation metrics. However, the acceleration error of our method is inferior to that of the HMMR (Kanazawa et al., 2019) approach. The reason for the inferior performance is that the goal of the HMMR (Kanazawa et al., 2019) method lies in predicting past and future motions given a single image. While we have a forecasting module $F$ that predicts the feature of the current frame given a single image. While we have a forecasting module $F$ that predicts the feature of the current frame given a single image. While we have a forecasting module $F$ that predicts the feature of the current frame given a single image. While we have a forecasting module $F$ that predicts the feature of the current frame given a single image. While we have a forecasting module $F$ that predicts the feature of the current frame given a single image.
In addition to quantitative comparisons, we present 1) visual comparisons with the VIBE (Kocabas et al., 2020) and SPIN (Kolotouros et al., 2019a) methods, 2) visual results of occlusion handling, and 3) visual results of different viewpoints.

Visual comparisons with the VIBE and SPIN methods. Figure 6 shows two visual comparisons with the VIBE (Kocabas et al., 2020) and SPIN (Kolotouros et al., 2019a). We observe that our model recovers bodies that well cover humans and estimates more accurate poses for limbs in particular.

Visual results of occlusion handling. Figure 7 presents example visual results of occlusion handling on the CrowdPose dataset (Li et al., 2019). We observe that our model is able to recover plausible human bodies for the occluded person instances.

Visual results of different viewpoints. We visualize human bodies recovered by our SPS-Net from different viewpoints in Figure 8. Our results show that our method estimates accurate rotation parameters.

4.4. Ablation study

Loss functions. To analyze the effectiveness of each loss function, we conduct an ablation study by removing one loss function at a time. Specifically, we analyze how much performance gain each loss function contributes. Table 2 shows the results on the 3DPW (von Marcard et al., 2018) test set.

Without the camera parameter consistency loss $L_{\text{camera}}$, there is no explicit constraint imposed on the prediction of camera parameters, leading to performance drops of 1.7 in PA-MPJPE and 3.5 in PVE. When removing the mask loss $L_{\text{mask}}$, our model does not have any constraints to regularize the 3D mesh. Performance drops of 5.9 in PA-MPJPE and 7.0 in PVE occur. Without the self-supervised parameter regression loss $L_{\text{param}}$, our model does not learn to produce plausible predictions when the occlusion or out-of-view issues occur, resulting in performance drops of 5.4 in PA-MPJPE and 4.6 in PVE. When removing the adversarial loss $L_{\text{adv}}$, our model does not learn to render 3D meshes that have realistic motions. Performance drops on all three evaluation metrics occur, which also concur with the findings in the HMR (Kanazawa et al., 2018) and VIBE (Kocabas et al., 2020).

Figure 9 presents two visual comparisons with the variant methods of our SPS-Net (i.e., Ours w/o $L_{\text{camera}}$ and Ours w/o $L_{\text{mask}}$). Our visual results show that both the camera parameter consistency loss $L_{\text{camera}}$ and the mask loss $L_{\text{mask}}$ allow our model to predict more accurate pose and shape estimates.

The ablation study on loss functions shows that all four losses are crucial to the SPS-Net.

Self-attention and forecasting modules. We conduct an ablation study to analyze the contribution of the self-attention module $A$ and the forecasting module $F$ in the SPS-Net. Specific-
Fig. 8: Qualitative results of 3D human pose and shape estimation. We visualize the 3D human body from different viewpoints recovered by our SPS-Net on the 3DPW (von Marcard et al., 2018) test set.

Table 3: Ablation study on the self-attention and forecasting modules. We report the experimental results on the 3DPW (von Marcard et al., 2018) test set. The bold and underlined numbers indicate the top two results, respectively.

| Method                        | Number of parameters | PA-MPJPE ↓ | MPJPE ↓ | PVE ↓ | Acceleration Error ↓ |
|-------------------------------|----------------------|------------|---------|-------|-----------------------|
| Ours                          | 51.43M               | 50.4       | 85.8    | 100.6 | 22.1                  |
| Ours w/o Forecasting $F$      | 47.23M               | 54.2       | 91.9    | 104.3 | 23.3                  |
| Ours w/o Self-Attention $A$   | 34.64M               | 57.6       | 96.6    | 104.7 | 22.9                  |

Self-attention module vs. GRU. To analyze the effectiveness of employing different temporal modules, we conduct an ablation study by swapping the self-attention module $A$ in the SPS-Net with a two-layer GRU module as in the VIBE (Kocabas et al., 2020) model, i.e., comparing the performance between the “Ours (Self-Attention)” method and the “Ours (GRU)” approach. Table 4 presents the results on the 3DPW (von Marcard et al., 2018) test set. We observe that employing the self-attention module results in performance improvement over adopting the GRU on all three evaluation metrics.

Input sequence length. We conduct an ablation study to analyze the effect of the input sequence length. Table 5 presents

Table 4: Ablation study on different temporal modules. We report the experimental results on the 3DPW (von Marcard et al., 2018) test set. The bold and underlined numbers indicate the top two results, respectively.

| Method                     | Number of parameters | PA-MPJPE ↓ | MPJPE ↓ | PVE ↓ |
|----------------------------|----------------------|------------|---------|-------|
| Ours (Self-Attention)      | 51.43M               | 50.4       | 85.8    | 100.6 |
| Ours (GRU)                 | 50.88M               | 52.8       | 87.7    | 103.2 |

Table 5: Ablation study of the input sequence length. We present the experimental results on the 3DPW (von Marcard et al., 2018) test set. The bold and underlined numbers indicate the top two results, respectively.

| Input sequence length | PA-MPJPE ↓ | MPJPE ↓ | PVE ↓ |
|-----------------------|------------|---------|-------|
| 8 16 32 48            | 55.3 53.1 50.4 | 92.4 87.6 85.8 | 110.8 105.5 100.6 |

Table 5: Ablation study of the input sequence length. We present the experimental results on the 3DPW (von Marcard et al., 2018) test set. The bold and underlined numbers indicate the top two results, respectively.

Finally, we show the contribution of each component by disabling (removing) one at a time. Table 3 shows the results on the 3DPW (von Marcard et al., 2018) test set. Without either the forecasting module $F$ or the self-attention module $A$, the degraded method suffers from significant performance loss in all metrics. When both modules are jointly utilized, our model achieves the best results, demonstrating the complementary importance of these two components.

Figure 12 shows visual comparisons with the variants of our SPS-Net (i.e., Ours w/o Self-Attention $A$ and Ours w/o Forecasting $F$) on the CrowdPose dataset (Li et al., 2019). Our visual results show that without either the self-attention module $A$ or the forecasting module $F$, the degraded model cannot recover accurate poses.
Fig. 9: Visual comparisons with our variant methods. (Left) Visual comparisons with the Ours w/o \( L_{\text{camera}} \) method. (Right) Visual comparisons with the Ours w/o \( L_{\text{mask}} \) approach.

Fig. 10: Sensitivity analysis of hyperparameters. We report the PA-MPJPE results of our method on the 3DPW (von Marcard et al., 2018) dataset. Experimental results show that the performance of our SPS-Net is stable when the hyperparameters are set within a suitable range.

Table 6: Run time analysis. We report the GPU platform, the model training time in hours, and the inference time for processing an image in seconds. The "-" indicates the result is not available.

| Method                     | Platform | Training | Inference |
|----------------------------|----------|----------|-----------|
| Yang et al. (Yang et al., 2018) | Titan X  | -        | 1.1       |
| Mehta et al. (Mehta et al., 2017b) | Titan X  | -        | 3.3       |
| RepNet (Wandt and Rosenhahn, 2019) | Titan X  | -        | 10        |
| CMR (Kolotouros et al., 2019b) | RTX 2080Ti  | -        | 3.3       |
| STRAPS (Sengupta et al., 2020) | RTX 2080Ti  | 120      | 0.25      |
| NBF (Omran et al., 2018) | V100  | 18       |           |
| ExPose (Choutas et al., 2020) | Quadro P5000  | -        | 0.16      |
| HUND (Zanfir et al., 2020) | P100  | 72       | 0.055     |
| HMR (Kanazawa et al., 2018) | Titan 1080Ti  | 120      | 0.04      |
| SPIN (Kolotouros et al., 2019a) | -        | -        | 3         |
| Temporal 3D Kinetics (Arnab et al., 2019) | RTX 2080Ti  | -        | 2         |
| VIBE (Kocabas et al., 2020) | V100  | 12       | 0.07      |
| Ours                       | V100  | 12       | 0.09      |

the results on the 3DPW (von Marcard et al., 2018) dataset. Our results show that the performance on all three metrics improves as the input sequence length increases. When the input sequence length increases from 32 (the default setting in our experiments) to 48, our results can be further improved. However, due to GPU memory constraints, we are not able to experiment with longer input sequence lengths.

**Sensitivity analysis.** To analyze the sensitivity of the SPS-Net with respect to the hyperparameters, we perform a sensitivity analysis on the hyperparameters \( \lambda_{\text{mask}} \) and \( \lambda_{\text{camera}} \). We report the PA-MPJPE results on the 3DPW (von Marcard et al., 2018) test set. Figure 10 presents the experimental results.

We observe that when the hyperparameter is set to 0 (i.e., the corresponding loss function is removed), our SPS-Net suffers from performance drops. When the hyperparameters are set within a suitable range (i.e., around 300 for \( \lambda_{\text{mask}} \) and around 0.1 for \( \lambda_{\text{camera}} \)), the performance of our SPS-Net is improved, demonstrating the effectiveness of the corresponding loss function. When the hyperparameters are set to large values (e.g., \( 1 \times 10^4 \) for \( \lambda_{\text{mask}} \) and \( 1 \times 10^3 \) for \( \lambda_{\text{camera}} \)), our model training will be dominated by optimizing the corresponding loss, leading to performance drops.

The sensitivity analysis of hyperparameters shows that when each hyperparameter is set within a suitable range, the performance of our method is improved and remains stable.

### 4.5. Run-time analysis

We report the model training time in hours, the inference time for processing an image in seconds, and the GPU platform used by each method in Table 6. First, the training time of our method is shorter than that of the HMR (Kanazawa et al., 2018), STRAPS (Sengupta et al., 2020), and HUND (Zanfir et al., 2020). Second, the inference time of our method is comparable to that of the VIBE method (Kocabas et al., 2020), and shorter than that of the ExPose (Choutas et al., 2020) and STRAPS (Sengupta et al., 2020) approaches. Third, our method performs favorably against existing frame-based and video-based approaches on all three datasets as shown in Table 1.

### 4.6. Failure modes

We present the failure cases of our method in Figure 11. As our SPS-Net assumes that the input video frames contain a single person, if missing detection happens, our method will not be able to perform human pose and shape estimation.

### 5. Conclusions

We propose the SPS-Net for estimating 3D human pose and shape from videos. The main contributions of this work lie
in the design of the self-attention module that captures short-range and long-range dependencies across video frames and the forecasting module that allows our model to exploit visual cues from human motion for producing temporally coherent predictions. To address the absence of ground-truth camera parameter annotations, we propose a camera parameter consistency loss that not only regularizes the learning of camera parameter prediction but also provides additional supervisory signals to facilitate model training. We develop a self-supervised learning scheme that explicitly models the occlusion and out-of-view scenarios by masking out some regions in the video frames. By leveraging the predictions of the original video frames to supervise those of the synthesized occluded or partially visible data, our model learns to predict plausible estimations. Extensive experimental results on three challenging datasets show that our SPS-Net performs favorably against the state-of-the-art 3D human pose and shape estimation methods.

References

Andriluka, M., Iqbal, U., Insafutdinov, E., Pishchulin, L., Milan, A., Gall, J., Schiele, B., 2019. Posetrack: A benchmark for human pose estimation and tracking, in: CVPR.

Arnab, A., Doersch, C., Zisserman, A. 2019. Exploiting temporal context for 3d human pose estimation in the wild, in: CVPR.

Bewley, A., Ge, Z., Ott, L., Ramos, F., Upcroft, B., 2016. Simple online and realtime tracking, in: ICIIP.

Bochkovskiy, A., Wang, C.Y., Liao, H.Y.M., 2020. Yolov4: Optimal speed and accuracy of object detection, arXiv.

Bogo, F., Kanazawa, A., Lassner, C., Gehler, P., Romero, J., Black, M.J., 2016. Keep it smpl: Automatic estimation of 3d human pose and shape from a single image, in: ECCV.

Bolya, D., Zhou, C., Xiao, F., Lee, Y.J., 2019. Yolact: real-time instance segmentation, in: ICCV.

Butepage, J., Black, M.J., Kräger, D., Kjellström, H., 2017. Deep representation learning for human motion prediction and classification, in: CVPR.

Cao, Z., Martinez, G.H., Simon, T., Wei, S.E., Sheikh, Y.A., 2019. Openpose: Realtime multi-person 2d pose estimation using part affinity fields. TPAMI.

Chen, C.H., Tyagi, A., Agrawal, A., Drover, D., Stojanov, S., Rehg, J.M., 2019a. Unsupervised 3d pose estimation with geometric self-supervision, in: CVPR.

Chen, Y.C., Lin, Y.Y., Yang, M.H., Huang, J.B., 2019b. Crdoco: Pixel-level domain transfer with cross-domain consistency, in: CVPR.

Chen, Y.C., Lin, Y.Y., Yang, M.H., Huang, J.B., 2020. Show, match and segment: Joint weakly supervised learning of semantic matching and object co-segmentation. TPAMI.

Cheng, Y., Yang, B., Wang, B., Tan, R.T., 2020. 3d human pose estimation using spatio-temporal networks with explicit occlusion training, in: AAAI.

Choutas, V., Pavlakos, G., Bolkart, T. 2020. Monocular expressive body regression through body-driven attention, in: ECCV.

Denton, E., Birodkar, V., 2017. Unsupervised learning of disentangled representations from video, in: NeurIPS.

Doersch, C., Zisserman, A., 2019. Sim2real transfer learning for 3d human pose estimation: motion to the rescue, in: NeurIPS.

Finn, C., Goodfellow, I., Levine, S., 2016. Unsupervised learning for physical interaction through video prediction, in: NeurIPS.

Frangiadaki, K., Levine, S., Felsen, P., Malik, J., 2015. Recurrent network models for human dynamics, in: ICCV.

Girdhar, R., Gkioxari, G., Torresani, L., Paluri, M., Tran, D., 2018. Detect-and-track: Efficient pose estimation in videos, in: CVPR.

Gordon, A., Li, H., Jonschkowski, R., Angelova, A., 2019. Depth from videos in the wild: Unsupervised monocular depth learning from unknown cameras, in: ICCV.

He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep residual learning for image recognition, in: CVPR.

Huang, X., Liu, M.Y., Belongie, S., Kautz, J., 2018. Multimodal unsupervised image-to-image translation, in: ECCV.

Ionescu, C., Papava, D., Olaru, V., Sminchisescu, C., 2013. Human3.6m: Large scale datasets and predictive methods for 3d human sensing in natural environments. TPAMI.

Jain, A., Zamir, A.R., Savarese, S., Saxena, A., 2016. Structural-rnn: Deep learning on spatio-temporal graphs, in: CVPR.

Kanazawa, A., Black, M.J., Jacobs, D.W., Malik, J., 2018. End-to-end to predict human shape and pose, in: CVPR.

Kanazawa, A., Zhang, J.Y., Felsen, P., Malik, J., 2019. Learning 3d human dynamics from video, in: CVPR.

Kay, W., Carreira, J., Simonyan, K., Zhang, B., Hillier, C., Vijayanarasimhan, S., Viola, F., Green, T., Back, T., Nates, P., Suleyman, M., Zisserman, A., 2017. The kinetics human action video dataset. arXiv.

Kingma, D.P., Ba, J., 2014. Adam: A method for stochastic optimization, in: ICLR.

Kocabas, M., Athanasiou, N., Black, M.J., 2020. Vibe: Video inference for human body pose and shape estimation, in: CVPR.

Kocabas, M., Karagöz, S., Akbas, E., 2019. Self-supervised learning of 3d human pose using multi-view geometry, in: CVPR.

Kolotouros, N., Pavlakos, G., Black, M.J., Daniilidis, K., 2019a. Learning to reconstruct 3d human pose and shape via model-fitting in the loop, in: ICCV.

Kolotouros, N., Pavlakos, G., Daniilidis, K., 2019b. Convolutional mesh regression for single-image human shape reconstruction, in: CVPR.

Lassner, C., Romero, J., Kiefel, M., Bogo, F., Black, M.J., Geiler, P.V., 2017. Unite the people: Closing the loop between 3d and 2d human representations, in: CVPR.

Lee, H.H., Tseng, H.Y., Huang, J.B., Singh, M., Yang, M.H., 2018a. Diverse image-to-image translation via disentangled representations, in: ECCV.

Lee, K., Lee, I., Lee, S., 2018b. Propagating lstm: 3d pose estimation based on joint interdependency, in: ECCV.

Li, J., Wang, C., Zhu, H., Mao, Y., Fang, H.S., Lu, C., 2019. Crowdpose: Efficient crowded scenes pose estimation and a new benchmark, in: CVPR.

Li, Z., Zhou, Y., Xiao, S., He, C., Huang, Z., Li, H., 2018. Auto-conditioned recurrent networks for extended complex human motion synthesis, in: ICLR.

Liu, L., Xu, W., Zollhoefer, M., Kim, H., Bernard, F., Habermann, M., Wang, W., Theobalt, C., 2019. Neural rendering and reenactment of human actor videos. ACM TOG.

Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., Black, M.J., 2015. Smpl: A skinned multi-person linear model. ACM TOG.

Mahmood, N., Ghorbani, N., Troje, N.F., Pons-Moll, G., Black, M.J., 2019. Amass: Archive of motion capture as surface shapes, in: ICCV.

von Marcard, T., Henschel, R., Black, M.J., Rosenhahn, B., Pons-Moll, G., 2018. Recovering accurate 3d human pose in the wild using imu and a moving camera, in: ECCV.

Mehta, D., Rhodin, H., Casas, D., Fua, P., Sotnychenko, O., Xu, W., Theobalt, C., 2017a. Monocular 3d human pose estimation in the wild using improved cnn supervision, in: 3DV.

Mehta, D., Sridhar, S., Sotnychenko, O., Rhodin, H., Shafiei, M., Seidel, H.P., Xu, W., Casas, D., Theobalt, C., 2017b. Vnect: Real-time 3d human pose estimation with a single rgb camera. ACM TOG.

Meister, S., Hur, J., Roth, S., 2018. Unflow: Unsupervised learning of optical flow with a bidirectional census loss, in: AAAI.

Momra, M., Lassner, C., Pons-Moll, G., Gehler, P., Schiele, B., 2018. Neural body fitting: Unifying deep learning and model based human pose and shape estimation, in: 3DV.

Parmar, K., Vaswani, A., Uszkoreit, J., Kaiser, Ł., Shazeer, N., Ku, A., Tran, D., 2018. Image transformer, in: ICML.

Pascual, R., Mikolov, T., Bengio, Y., 2013. On the difficulty of training recurrent neural networks, in: ICMIL.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Köpf, A., Yang, E., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., 2019. PyTorch: PyTorch: An imperative style, high-performance deep learning library, in: NeurIPS.
Bai, J., Chintala, S., 2019. Pytorch: An imperative style, high-performance deep learning library, in: NeurIPS.

Pishchulin, L., Insafutdinov, E., Tang, S., Andres, B., Andriluka, M., Gehler, P.V., Schiele, B., 2016. Deepcut: Joint subset partition and labeling for multi person pose estimation, in: CVPR.

Sun, Y., Ye, Y., Liu, W., Gao, W., Fu, Y., Mei, T., 2019. Human mesh recovery from monocular images via a skeleton-disentangled representation, in: ICCV.

Sengupta, A., Budvytis, I., Cipolla, R., 2020. Synthetic training for accurate 3d human pose and shape estimation in the wild. arXiv.

Rayat Imtiaz Hossain, M., Little, J.J., 2018. Exploiting temporal information for 3d human pose estimation, in: ECCV.

Walker, J., Doersch, C., Gupta, A., Hebert, M., 2017. Neural kinematic networks for unsupervised motion retargetting, in: CVPR.

Walker, J., Marino, K., Gupta, A., Hebert, M., 2017. The pose knows: Video forecasting by generating pose futures, in: ICCV.

Wandt, B., Rosenhahn, B., 2019. Repnet: Weakly supervised training of an adversarial reprojection network for 3d human pose estimation, in: CVPR.

Xu, W., Chatterjee, A., Zollhoefer, M., Rhodin, H., Fua, P., Seidel, H.P., Theobalt, C., 2019. Mo 2 cap 2: Real-time mobile 3d motion capture with a cap-mounted fisheye camera. TVCG.

Yang, W., Ouyang, W., Wang, X., Ren, J., Li, H., Wang, X., 2018. 3d human pose estimation in the wild by adversarial learning, in: CVPR.

Zanfir, A., Bazavan, E.G., Zanfir, M., Freeman, W.T., Sukthankar, R., Sminchisescu, C., 2020. Neural descent for visual 3d human pose and shape. arXiv.

Zhang, H., Goodfellow, I., Metaxas, D., Odena, A., 2019a. Self-attention generative adversarial networks, in: ICML.

Zhang, J.Y., Felsen, P., Kanazawa, A., Malik, J., 2019b. Predicting 3d human dynamics from video, in: ICCV.

Zhang, W., Zhu, M., Derpanis, K.G., 2013. From actemes to action: A strongly-supervised representation for detailed action understanding, in: ICCV.

Zhou, T., Brown, M., Snavely, N., Lowe, D.G., 2017. Unsupervised learning of depth and ego-motion from video, in: CVPR.

Zhou, T., Jae Lee, Y., Yu, S.X., Efros, A.A., 2015. Flowweb: Joint image set alignment by weaving consistent, pixel-wise correspondences, in: CVPR.

Zhu, J.Y., Park, T., Isola, P., Efros, A.A., 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks, in: ICCV.

Zou, Y., Luo, Z., Huang, J.B., 2018. Df-net: Unsupervised joint learning of depth and flow using cross-task consistency, in: ICCV.
Fig. 12: Visual comparisons with our variant methods. We present visual comparisons with the Ours w/o Self-Attention A and Ours w/o Forecasting F methods on the CrowdPose dataset (Li et al., 2019).