Beyond Static Features for Temporally Consistent 3D Human Pose and Shape from a Video

Hongsuk Choi¹  Gyeongkik Moon¹  Ju Yong Chang²  Kyoung Mu Lee¹

¹ECE & ASRI, Seoul National University, Korea  ²ECE, Kwangwoon University, Korea

{redarknight, mks0601, kyoungmu}@snu.ac.kr, juyong.chang@gmail.com

Abstract

Despite the recent success of single image-based 3D human pose and shape estimation methods, recovering temporally consistent and smooth 3D human motion from a video is still challenging. Several video-based methods have been proposed; however, they fail to resolve the single image-based methods’ temporal inconsistency issue due to a strong dependency on a static feature of the current frame. In this regard, we present a temporally consistent mesh recovery system (TCMR). It effectively focuses on the past and future frames’ temporal information without being dominated by the current static feature. Our TCMR significantly outperforms previous video-based methods in temporal consistency with better per-frame 3D pose and shape accuracy. We will release the codes.

1. Introduction

Various methods have been proposed to analyze humans from images, ranging from estimating a simplistic 2D skeleton to recovering 3D human pose and shape. Despite the recent improvements, estimating 3D human pose and shape from images is still a challenging task, especially in the monocular case due to depth ambiguity, the limited training data, and the complexity of the human articulations.

Most of the previous methods [7, 11, 15, 16, 22, 26] attempt to recover 3D human pose and shape from a single image. They are generally based on parametric 3D human mesh models, such as SMPL [18], and directly regress the model parameters from the input image. While the single image-based methods achieve high accuracy on a static image, they tend to output temporally inconsistent and un-

Figure 1: VIBE [14], the state-of-the-art video-based 3D human pose and shape estimation method, outputs very different 3D human poses per frame, although the frames have subtle differences. Our TCMR produces clearly more temporally consistent and smooth 3D human motion. This is a video figure that is best viewed by Adobe Reader.
smooth 3D motion when applied to a video per frame. The temporal instability is from inconsistent 3D pose errors from consecutive frames. For example, a 3D pose output from the following frame may have a significantly higher error than the before output, or could fail in a different direction.

Several methods [12, 14, 19] have been proposed to extend the single image-based methods to the video case effectively. They feed a sequence of images to the pre-trained single image-based 3D human pose and shape estimation networks [11, 15] to obtain a sequence of static features. All input frames’ static features are passed to a temporal encoder, which encodes a temporal feature for each input frame. Then, a body parameter regressor outputs SMPL parameters for each frame from the temporal feature of the corresponding time step.

Although the above works quantitatively improved the per-frame 3D pose accuracy and motion smoothness, their qualitative results still suffer from the temporal inconsistency, as shown in Figure 1. We argue that the failure comes from a strong dependency on the static feature of the current frame. For terminological convenience, we use a word current to indicate the time step of a target frame where SMPL parameters are to be estimated. The first reason for the strong dependency is a residual connection between the current frame’s static and temporal features. While the residual connection has been widely verified to facilitate a learning process, naively applying it to the temporal encoding could hinder the system from learning useful temporal information. Since the static feature is extracted by the pre-trained network [11, 15], it contains a strong cue for the SMPL parameters of the current frame. Thus, the residual connection’s identity mapping of the static feature could make the SMPL parameter regressor heavily depend on it and leverage the temporal feature marginally. This could constrain the temporal encoder from encoding more meaningful temporal features. The second reason is the temporal encoding that takes static features from all frames, which include a current static feature. The current static feature has the largest potential to affect the current temporal feature, from which SMPL parameters are predicted. It is because the current static feature has the most crucial information for 3D human pose and shape of a current frame. While the dominance would increase the per-frame accuracy of 3D pose and shape estimation, it could prevent the temporal encoder from fully exploiting the past and future frames’ temporal information. Taken together, the existing video-based methods have a strong preference for the current static feature, and suffer from the temporal inconsistency issue as the single image-based methods do.

In this work, we propose a temporally consistent mesh recovery system (TCMR). It is designed to resolve the strong dependency on the current static feature for temporally consistent and smooth 3D human motion output from a video. First, while we follow the previous video-based works [12, 14, 19] to encode a temporal feature of the current frame, we remove the residual connection between the static and temporal features. Moreover, we introduce Pose-Forecast, which consists of two temporal encoders, to forecast a current pose from the past and future frames without the current frame. The temporal features from Pose-Forecast are free from the current static feature; however, contain essential temporal information of the past and future frames, respectively, to forecast a current pose. They are integrated with the current temporal feature, which is extracted from all the input frames, to predict current SMPL parameters. The parameters estimated from the integrated temporal feature is used as the final output in inference time. By removing the strong dependency on the current static feature, our SMPL parameter regressor can have a more chance to focus on the past and future frames without being dominated by the current frame.

Despite its simplicity, we observed that our newly designed temporal architecture is highly effective on obtaining the temporally consistent and smooth 3D human motion. Also, it improves the accuracy of the 3D pose and shape per frame by utilizing better temporal information. We show that the proposed TCMR outperforms the previous video-based methods [12, 14, 19] on various 3D video benchmarks, especially in temporal consistency.

Our contributions can be summarized as follows.

• We present a temporally consistent mesh recovery system (TCMR), which produces temporally consistent and smooth 3D human motion from a video. It effectively leverages temporal information from the past and future frames without being dominated by the static feature of the current frame.

• Despite its simplicity, TCMR not only improves the temporal consistency of 3D human motion, but also increases per-frame 3D pose and shape accuracy.

• The proposed system outperforms previous video-based methods in temporal consistency by a large margin, while achieving better per-frame 3D pose and shape accuracy.

2. Related works

Single image-based 3D human pose and shape estimation. Most of the current single image-based 3D human pose and shape estimation methods are based on the model-based approach, which predicts parameters of a predefined 3D human mesh model, SMPL [18]. Kanazawa et al. [11] proposed an end-to-end trainable human mesh recovery (HMR) system that uses the adversarial loss to make their output 3D human mesh anatomically plausible.
Pavlakos et al. [26] used 2D joint heatmaps and silhouette as cues for predicting accurate SMPL parameters. Omran et al. [23] proposed a similar system, which exploits human part segmentation as a cue for regressing SMPL parameters. Pavlakos et al. [25] proposed a system that uses multi-view color consistency to supervise a network using multi-view geometry. Kolotouros et al. [15] introduced a disentangling framework, which separates 3D human pose and mesh from the 3D volumetric space. Kolotouros et al. [16] designed a graph convolutional human motion regression system. Their graph convolutional network takes a template human mesh in a rest pose as input and predicts mesh vertex coordinates using image features from ResNet [9]. Moon and Lee [22] introduced a lixel-based 1D heatmap to locate mesh vertices in a fully convolutional manner. Choi et al. [7] proposed a graph convolutional network that recovers 3D human pose and mesh from a 2D human pose. Despite high accuracy on a static image, the single image-based works suffer from temporal inconsistency (e.g., sudden change of poses), when applied to a video.

Video-based 3D human pose and shape estimation. HMMR [12] extracts static features and encodes them to a temporal feature using a 1D fully convolutional temporal encoder. It learns temporal context representation to reduce the 3D prediction’s temporal inconsistency by predicting 3D poses in the nearby past and future frames. Doversch et al. [8] trained their network on a sequence of optical flow and 2D poses to make their network generalize well to unseen videos. Sun et al. [32] proposed a skeleton-disentangling framework, which separates 3D human pose and shape estimation into multi-level spatial and temporal subproblems. They enforced the network to order shuffled frames to encourage better temporal feature learning. VIBE [14] encodes static features from the input frames into a temporal feature by using a bi-directional gated recurrent unit (GRU) [6], and feeds it to a body parameter regressor. A motion discriminator is introduced to encourage the regressor to produce plausible 3D human motion. MEVA [19] tackled the problem in a coarse-to-fine manner. Their system first estimates overall coarse 3D human motion using a variational motion estimator (VME), and predicts residual motion with a motion residual regressor (MRR).

Temporally consistent 3D human motion from a video. Although there have been many methods for video-based 3D human motion estimation [3, 8, 12, 14, 19, 21, 27, 28, 32], most of them showed their results only qualitatively, and did not report numerical evaluation on the temporal consistency. After HMMR [12] introduced the 3D pose acceleration error for the temporal consistency and smoothness of human motion, the following works [14, 19] have reported the error metric. HMMR and VIBE [14] lowered the acceleration error compared with the single image-based methods. However, they revealed a trade-off between per-frame accuracy and temporal consistency. HMMR outputs smoother 3D human motion, but provides low per-frame 3D pose accuracy. VIBE [14] shows high per-frame 3D pose accuracy, but the output is temporally inconsistent both in quantitative metrics and qualitative results compared to HMMR.

In this regard, MEVA [19] tried to establish the balance between the per-frame 3D pose accuracy and the temporal smoothness. While it did provide better results in both metrics, the qualitative results still expose unsmooth 3D motion. The reason is that the system strongly depends on the current static feature to estimate the current 3D pose and shape. First, MEVA uses a residual connection between the current frames’ static and temporal features. In addition, the current temporal feature, used to refine initial 3D pose and shape by MRR, is encoded from static features of all frames, which include the current frame. This could make the temporal feature dominated by the current static feature. As a result, the refinement is significantly driven by the current static feature, and the 3D errors from consecutive frames appear inconsistent. On the other hand, our TCMR is deliberately designed to reduce the strong dependency on the static feature. The residual connection is removed, and it forecasts additional temporal features from past and future frames without a current frame. Our approach successfully alleviates the dependency and provides temporally consistent and accurate 3D human motions in both qualitative and quantitative ways.

Forecasting 3D human poses from images. Recently, [5, 12, 35, 36] proposed to predict a person’s future 3D human poses from RGB input. Chao et al. [5] leveraged a recurrent neural network (RNN) to forecast a sequence of 2D poses from a static image, and estimate 3D poses from the predicted 2D poses. HMMR [12] predicts the current, future, and past 3D poses from a current input image using a hallucinator. It hallucinates the past and future 3D poses from a current frame, and is self-supervised by the output of the 1D fully convolutional temporal encoder. Zhang et al. [36] proposed a neural autoregressive framework that takes past video frames as input to predict future 3D motion. Yuan et al. [35] adopted deep reinforcement learning to forecast future 3D human poses from egocentric videos. While the objective of the above methods is to forecast future 3D poses, our system aims to learn useful temporal features free from a current static feature by the forecasting.

3. TCMR

Figure 2 shows the overall pipeline of our TCMR. We provide descriptions of each part in the system below.
3.1. Temporal encoding from all frames

Given a sequence of $T$ RGB frames $I_1, \ldots, I_T$, ResNet [9], pre-trained by Kolotouros et al. [15], extracts a static image feature per frame. Then, a global average pooling is applied on the ResNet outputs, which become $f_1, \ldots, f_T$, where $f_\bullet \in \mathbb{R}^{2048}$. The network weights of the ResNet are shared for all frames.

From the extracted static features of all input frames, we compute the current frame’s temporal feature using a bi-directional GRU, which consists of two uni-directional GRUs. We denote the bi-directional GRU as $G_{\text{all}}$. The current frame is defined as a $\lfloor T/2 \rfloor$th frame among $T$ input frames. The two uni-directional GRUs extract temporal features from the input static features in the opposite time directions. The initial inputs of the two GRUs are $f_1$ and $f_T$, respectively, and the initial hidden states of them are initialized as zero tensors. Then, they recurrently updates their hidden states by aggregating the static features from the next frames $f_2, \ldots, f_{\lfloor T/2 \rfloor}$ and $f_{T-1}, \ldots, f_{\lfloor T/2 \rfloor}$, respectively. The concatenated hidden states of the GRUs at the current frame become the current temporal feature from all input frames $g_{\text{all}} \in \mathbb{R}^{2048}$. Unlike VIBE [14], we do not add residual connection between $f_{\lfloor T/2 \rfloor}$ and $g_{\text{all}}$ not to let the current temporal feature be dominated by $f_{\lfloor T/2 \rfloor}$.

3.2. Temporal encoding by PoseForecast

PoseForecast forecasts additional temporal features for the current target pose from the past and future frames by employing two additional GRUs, denoted as $G_{\text{past}}$ and $G_{\text{future}}$, respectively. The past and future frames are defined as $1, \ldots, \lfloor T/2 \rfloor - 1$th frames and $\lfloor T/2 \rfloor + 1, \ldots, T$th frames, respectively. The initial input of the $G_{\text{past}}$ is $f_1$, and the initial hidden state is initialized as a zero tensor. Then, it recurrently updates its hidden state by aggregating the static features from the next frames $f_2, \ldots, f_{\lfloor T/2 \rfloor} - 1$. The final hidden state of the $G_{\text{past}}$ becomes the temporal feature from the past frames $g_{\text{past}} \in \mathbb{R}^{1024}$. Likewise, $G_{\text{future}}$ takes $f_T$ as an initial input with a zero-initialized hidden state, and recurrently updates its hidden state by aggregating the static features from the next frames $f_{T-1}, \ldots, f_{\lfloor T/2 \rfloor} + 1$. The final hidden state of the $G_{\text{future}}$ becomes the temporal feature from the future frames $g_{\text{future}} \in \mathbb{R}^{1024}$.

3.3. Temporal feature integration

We integrate the extracted temporal features from all frames $g_{\text{all}}$, from the past frames $g_{\text{past}}$, and from the fu-
uture frames $g_{\text{feature}}$ for the final 3D mesh estimation, as illustrated in Figure 3. For the integration, we pass each temporal feature to ReLU activation function and a fully connected layer to change the size of the channel dimension to 2048. The outputs of the fully connected layer are denoted as $g'_{\text{all}}$, $g'_{\text{past}}$, and $g'_{\text{future}}$. Then, the output features are resized to 256 by a shared fully connected layer and concatenated. The concatenated feature is passed to several fully connected layers, followed by the softmax activation function, which produces attention values $\alpha = (\alpha_{\text{all}}, \alpha_{\text{past}}, \alpha_{\text{future}}) \in \mathbb{R}^3$. The attention values represent how much the system should give a weight for the feature integration. The final integrated temporal feature is obtained by $g'_{\text{int}} = \alpha_{\text{all}}g'_{\text{all}} + \alpha_{\text{past}}g'_{\text{past}} + \alpha_{\text{future}}g'_{\text{future}}$.

In the training stage, we pass $g'_{\text{past}}$, $g'_{\text{future}}$, and $g'_{\text{int}}$ to the SMPL parameter regressor, which outputs $\Theta_{\text{past}}$, $\Theta_{\text{future}}$, and $\Theta_{\text{int}}$ from each input temporal feature, respectively. The regressor is shared for all outputs. $\Theta_{\bullet}$ denotes a union of SMPL parameter set $\{\Theta_{\bullet}, \beta_{\bullet}\}$ and weak-perspective camera parameter set $\{s_{\bullet}, l_{\bullet}\}$. $\theta$, $\beta$, $s$, and $t$ represent SMPL pose parameter, identity parameter, scale, and translation, respectively. In the testing stage, we only pass $g'_{\text{int}}$ to the SMPL parameter regressor and use $\Theta_{\text{int}}$ for the final 3D human mesh.

3.4. Loss functions

For the training, we supervise all three outputs $\Theta_{\text{past}}$, $\Theta_{\text{future}}$, and $\Theta_{\text{int}}$ with current frame groundtruth. $L2$ loss between predicted and groundtruth SMPL parameters and 2D/3D joint coordinates are used, following VIBE [14]. The 3D joint coordinates are obtained by forwarding the SMPL parameters to the SMPL layer, and the 2D joint coordinates are obtained by projecting the 3D joint coordinates using the predicted camera parameters.

4. Implementation details

Following VIBE [14], we set the length of the input sequence $T$ and the input video frame rate to 16 and 25-30 frames per second, respectively, and initialize the backbone and regressor with the pre-trained SPIN [15]. The weights are updated by the Adam optimizer [13] with a mini-batch size of 32. The human body region is cropped using a groundtruth box in both of training and testing stages following previous works [11, 14–16]. The cropped image is resized to 224×224. Inspired by Sarandi et al. [31], we occlude the cropped image with various objects for data augmentation. Following [12, 14], we precompute the static features from the cropped images by ResNet [9] to save training time and memory. All the 3D rotations of $\theta$ are initially predicted in the 6D rotational representation of Zhou et al. [38], and converted to the 3D axis-angle rotations. The initial learning rate is set to $5^{-5}$ and reduced by a factor of 10, when the 3D pose accuracy does not improve after every 5 epochs. We train the network for 30 epochs with one NVIDIA RTX 2080Ti GPU. PyTorch [24] is used for code implementation.

5. Experiment

5.1. Evaluation metrics and datasets.

Evaluation metrics. We report per-frame and temporal evaluation metrics. For the per-frame evaluation, we use mean per joint position error (MPJPE), Procrustes-aligned mean per joint position error (PA-MPJPE), and mean per vertex position error (MPVPE). The position errors are measured in millimeter (mm) between the estimated and groundtruth 3D coordinates after aligning the root joint. In particular, we use PA-MPJPE as the main evaluation metric for per-frame accuracy. For the temporal evaluation, we use the acceleration error proposed in HMMR [12]. The acceleration error computes an average of the difference between the predicted and groundtruth acceleration of each joint in $(mm/s^2)$.

Datasets. We use 3DPW [34], Human3.6M [10], MPI-INF-3DHP [20], InstaVariety [12], Penn Action [37], and PoseTrack [1] for training, following VIBE [14]. 3DPW, Human3.6M, MPI-INF-3DHP are also used for evaluation. Details of the datasets can be found in the supplementary material.

5.2. Ablation study

In this study, we show how each component of our temporal architecture reduces the dependency of the model on a current static feature, and make it focus on temporal features from the past and future. We take the same baseline used in VIBE [14]. The baseline has a single bi-directional GRU that encodes temporal features from all input frames and a residual connection between the static and temporal features as VIBE. But it does not employ the motion
Effectiveness of removing the residual connection. To analyze the effect of the residual connection between the static and temporal features, we compare the models with and without it. As shown in Table 1, removing the residual connection decreases the acceleration error significantly, which indicates temporal consistency and smoothness of 3D human motion become fair better. This verifies that the identity mapping of the current static feature inside the residual connection hinders a model from learning meaningful temporal features. Moreover, the increased temporal consistency of 3D motion improves per-frame 3D pose accuracy. Figure 4 illustrates how the enhanced temporal consistency contributes to better per-frame 3D pose estimation. The sudden change of poses, due to the occasional inaccurate 3D pose estimation, is disappeared. The above comparisons clearly validate the effectiveness of removing the residual connection in terms of both per-frame and temporal metrics.

Table 1: Comparison between different temporal architectures. All networks estimate only on the middle frame of the input sequence.

| remove residual | PoseForecast | PA-MPJPE\(\downarrow\) | Accel\(\downarrow\) |
|-----------------|--------------|------------------------|-----------------|
| \(\checkmark\) | \(\checkmark\) | 55.6 | 29.2 |
| \(\checkmark\) | \(\times\) | 55.0 | 24.9 |
| \(\times\) | \(\times\) | 54.2 | 8.7 |
| \(\times\) | (Ours) | 53.9 | 7.7 |

Table 2: Comparison between PoseForecast that takes a current frame and that does not take a current frame.

| PoseForecast input | PA-MPJPE\(\downarrow\) | Accel\(\downarrow\) |
|--------------------|------------------------|-----------------|
| w. current frame   | 53.8 | 10.3 |
| wo. current frame  (Ours) | 53.9 | 7.7 |

Table 3: Comparison between different supervision on estimated SMPL parameters from the PoseForecast.

| PoseForecast supervision target | PA-MPJPE\(\downarrow\) | Accel\(\downarrow\) |
|---------------------------------|------------------------|-----------------|
| none                            | 55.1 | 8.3 |
| GT of past and future frames    | 54.1 | 8.5 |
| GT of current frame  (Ours)     | 53.9 | 7.7 |

discriminator. We use 3DPW [34], MPI-INF-3DHP [20], InstaVariety [12], and Penn Action [37] for training, and 3DPW for evaluation.

Effectiveness of removing the residual connection. To analyze the effect of the residual connection between the static and temporal features, we compare the models with and without it. As shown in Table 1, removing the residual connection decreases the acceleration error significantly, which indicates temporal consistency and smoothness of 3D human motion become fair better. This verifies that the identity mapping of the current static feature inside the residual connection hinders a model from learning meaningful temporal features. Moreover, the increased temporal consistency of 3D motion improves per-frame 3D pose accuracy. Figure 4 illustrates how the enhanced temporal consistency contributes to better per-frame 3D pose estimation. The sudden change of poses, due to the occasional inaccurate 3D pose estimation, is disappeared. The above comparisons clearly validate the effectiveness of removing the residual connection in terms of both per-frame and temporal metrics.

Effectiveness of PoseForecast. We compare the models with and without PoseForecast to verify the effectiveness of forecasting current temporal features only from the past and future frames. Referring to the results in Table 1, PoseForecast consistently improves both per-frame and temporal metrics regardless of the residual connection. In particular, the acceleration error consistently decreases by over 11%. This proves that the temporal encoding that takes all frames with the current frame may be suboptimal, and forecasting the current temporal features from past and future frames is beneficial to produce temporally consistent 3D human motion.

To further validate the forecasting, we compare our PoseForecast with its variations. First, we show the effectiveness of taking only past and future frames without a current frame in Table 2. As the table shows, additionally taking current frames increases the acceleration error by 33%. This indicates that maintaining the temporal features free from the current static feature is important for temporally consistent and smooth 3D human motion. Second, we validate the effectiveness of supervising the predicted SMPL parameters from PoseForecast (i.e., \(\Theta_{\text{past}}\) and \(\Theta_{\text{future}}\)) with groundtruth of the current frame in Table 3. As shown in the table, supervising the predicted parameters with the current groundtruth provides better per-frame 3D pose accuracy and temporal consistency than the other supervisions. When we supervise the predicted parameters with groundtruth of \([T/2] - 1\)th and \([T/2] + 1\)th frames (the second row), the acceleration error increases by 10%. The performance degrades, because the temporal features of PoseForecast are encoded from the input including the static features of the target frames (i.e., \([T/2] - 1\)th and \([T/2] + 1\)th frames). As verified in Table 2, including the target static feature hinders PoseForecast from learning useful temporal information for temporally consistent and smooth 3D human motion. The encoded temporal feature is likely to be dominated by the target static feature, and marginally leverage temporal information from other times steps. When there is no supervision (the first row), both 3D pose accuracy and temporal consistency decrease compared to ours. This proves that designing our PoseForecast to forecast the current SMPL parameters by supervising it with the current target (the third row) facilitates the network to learn more useful temporal features.

In summary, the above comparisons show that forecasting the current temporal features from past and future frames is effective for temporally consistent 3D human motion by reducing the strong dependency on the current static feature.

5.3. Comparison with state-of-the-art methods

Comparison with video-based methods. We compare our TCMR with previous state-of-the-art video-based methods [12,14,19] that report the acceleration error in Table 4. Following Luo et al. [19], all methods except HMMR [12] are trained on the train set including 3DPW [34], but do not leverage Human3.6M [10] SMPL parameters obtained from Mosh [17] for supervision. The numbers of VIBE [14] are from MEVA [19]. As the table shows, our proposed system outperforms the previous video-based methods on all
Table 4: Evaluation of state-of-the-art methods on 3DPW, MPI-INF-3DHP, and Human3.6M. All methods except HMR [12] do not use Human3.6M SMPL parameters from Mosh [17], but use 3DPW train set for training following MEVA [19].

| method       | 3DPW  | 3DPW  | 3DPW  | 3DPW  | 3DPW  | 3DPW  | 3DPW  | 3DPW  | 3DPW  | 3DPW  | 3DPW  |
|--------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|              | MPJPE | MPJPE | MPVPE | Accel | MPJPE | MPJPE | MPJPE | Accel | MPJPE | MPJPE | Accel |
| HMMR [12]    | 72.6  | 116.5 | 139.3 | 15.2  | -     | -     | -     | -     | -     | -     | -     |
| VIBE [14]    | 57.6  | 91.9  | -     | 25.4  | 68.9  | 103.9 | 27.3  | 53.3  | 78.0  | 27.3  | 36.9  |
| MEVA [19]    | 54.7  | 86.9  | -     | 11.6  | 65.4  | 96.4  | 11.1  | 53.2  | 76.0  | 15.3  | 30.2  |
| TCMR (Ours)  | 52.7  | 86.5  | 102.9 | 7.1   | 63.5  | 97.3  | 8.5   | 52.0  | 73.6  | 3.9   | 36.9  |
| number of input frames | 20 | 16 | 90 | 16 |

Figure 5: Comparison between the acceleration errors of the proposed TCMR, MEVA [19], and VIBE [14]. Our TCMR shows clearly lower acceleration errors along the time step than previous methods, which indicates temporally consistent 3D motion output. The previous methods reveal extreme acceleration error spikes compared to our TCMR.

Table 5: Comparison between ours and previous methods applied with average filtering on 3DPW.

| method       | PA-MPJPE | MPJPE | MPVPE | Accel |
|--------------|----------|-------|-------|-------|
| VIBE [14]    | 57.6     | 91.9  | 25.4  |       |
| + Avg. filter| 57.8     | 91.6  | 13.5  |       |
| MEVA [19]    | 54.7     | 86.9  | 11.6  |       |
| + Avg. filter| 55.5     | 87.7  | 8.2   |       |
| TCMR (Ours)  | 52.7     | 86.5  | 7.1   | 6.5   |

Table 5: Comparison between ours and previous methods applied with average filtering on 3DPW. benchmarks both in per-frame 3D pose accuracy and temporal consistency. These results prove that our system effectively leverages temporal information of the past and future by resolving the system’s strong dependency on a current static feature. While MEVA [19] also improved both per-frame and temporal metrics, the model consumes nearly 6 times more input frames during training and testing, and provides worse results than ours. Figure 5 describes the clear advantage of our TCMR on the temporal consistency among video-based methods. The previous methods expose numerous spikes, which represent unstable and unsmooth 3D motion estimation. Our TCMR provides relatively low acceleration errors along the time step, which indicates temporally consistent 3D motion output. The figure’s acceleration errors are measured on a sequence of the 3DPW validation set that has diverse motion.

To further confirm the effectiveness of the proposed system on temporal consistency, we compare our TCMR to VIBE [14] and MEVA [19] with an average filter applied as post-processing in Table 5. The average filtering is done by spherical linear interpolation in quaternions of estimated SMPL [18] pose parameters. The numbers of other methods
Table 6: Evaluation of state-of-the-art methods on 3DPW, MPI-INF-3DHP, and Human3.6M. All methods do not use 3DPW [34] on training. ‘single image’ or ‘video’ denotes whether the input of a method is a single image or a video.

| method        | 3DPW   | PA-MPJPE ↓ | MPJPE ↓ | MPVPE ↓ | Accel ↓ | MPI-INF-3DHP | PA-MPJPE ↓ | MPJPE ↓ | Accel ↓ | Human3.6M | PA-MPJPE ↓ | MPJPE ↓ | Accel ↓ |
|---------------|--------|------------|---------|---------|---------|-------------|------------|---------|---------|-----------|------------|---------|---------|
|               | 3DPW   | 3DPW       | 3DPW    | 3DPW    | 3DPW    | 3DPW        | 3DPW       | 3DPW    | 3DPW    | 3DPW      | 3DPW       | 3DPW   | 3DPW   |
| HMR [11]      | 76.7   | 130.0      | -       | 37.4    | -       | 89.8        | 124.2      | -       | -       | 56.8      | 88.0        | -       | -       |
| GraphCMR [16] | 70.2   | -          | -       | -       | -       | 67.5        | 105.2      | -       | -       | 41.1      | -          | 18.3    | -       |
| SPIN [15]     | 59.2   | 96.9       | 116.4   | 29.8    | -       | 67.5        | 105.2      | -       | -       | 41.1      | 55.7        | 13.4    | -       |
| I2L-MeshNet [22] | 57.7   | 93.2       | 110.1   | 30.9    | -       | 46.3        | 64.9       | 23.9    | -       | 46.3      | 64.9        | 23.9    | -       |
| Pose2Mesh [7] | 58.3   | 88.9       | 106.3   | 22.6    | -       | 56.9        | -          | -       | -       | 56.9      | -          | -       | -       |
| Doersch et al. [8] | 72.6   | 116.5      | 139.3   | 15.2    | -       | 42.4        | 59.1       | -       | -       | 42.4      | 59.1        | -       | -       |
| Sun et al. [32] | 74.7   | -          | -       | -       | -       | -           | -          | -       | -       | -         | -          | -       | -       |
| VIBE [14]     | 56.5   | 93.5       | 113.4   | 27.1    | -       | 63.4        | 97.7       | 29.0    | -       | 41.5      | 65.9        | 18.3    | -       |
| TCMR (Ours)   | 55.8   | 95.0       | 111.5   | 7.0     | -       | 41.1        | 62.3       | 5.3     | -       | 41.1      | 62.3        | 5.3     | -       |

Figure 6: Qualitative results of our TCMR on 3DPW [34]. Our method produces temporally consistent and smooth 3D motion. Per-frame 3D pose accuracy is also well preserved on a sequence with fast motion and difficult poses. This is a video figure that is best viewed by Adobe Reader.

Comparison with single image-based and video-based methods. We compare our system with previous 3D pose and shape estimation methods including single image-based methods in Table 6. None of the methods are trained on 3DPW [34]. For evaluation on Human3.6M [10], we use the frontal view images following [12, 15], while all views are tested in Table 4 and 5. In addition, to confirm the acceleration error of VIBE [14] on MPI-INF-3DHP [20] and Human3.6M, we re-evaluate the model using the pre-trained weights provided in the official code repository.

As shown in the table, our method outperforms all the previous methods on 3DPW, a challenging in-the-wild benchmark, and MPI-INF-3DHP in both per-frame 3D pose accuracy (PA-MPJPE) and temporal consistency. Especially the temporal consistency is largely improved compared to single image-based methods. While VIBE decreases the acceleration error of SPIN [15] by 9% and is defeated by Pose2Mesh [7] in the temporal consistency, our system provides over 3 times better performance than both SPIN and Pose2Mesh in 3DPW. Also, VIBE gives a higher acceleration error than I2L-MeshNet [22] but our TCMR outperforms it by a wide margin in Human3.6M.

Figure 6 shows Qualitative results on the 3DPW [34]. More results on diverse video input are provided in the online video 1.

6. Conclusion

We present TCMR, a novel and powerful system that estimates a 3D human mesh from a RGB video. Previous video-based methods suffer from the temporal inconsistency issue because of the strong dependency on the static feature of the current frame. We resolve this issue by removing the residual connection between the static and temporal features, and employing PoseForecast that forecasts the current temporal feature from the past and future frames. Compared to the previous video-based methods, the proposed TCMR provides highly temporally consistent 3D motion and a more accurate 3D pose per frame.

1https://www.youtube.com/watch?v=W8nIIbS3QDII
Supplementary Material for
Beyond Static Features for Temporally Consistent 3D Human Pose and Shape from a Video

In this supplementary material, we present more experimental results and details about the datasets that could not be included in the main manuscript due to the lack of space.

7. More qualitative results

We provide more qualitative results in the online video 2, which consists of three parts. The first part shows the qualitative results of our TCMR on in-the-wild videos that have fast and diverse motions from 3DPW [34]. We also provide the outputs rendered from the opposite view. The second part compares the proposed TCMR with VIBE [14] and MEVA [19]. The results are rendered on a plain background with a fixed camera to clearly compare the temporal consistency and smoothness of 3D human motion following MEVA [19]. The fixed camera has the fixed weak-perspective camera parameters s and t, which are set to one and zero, respectively. The last part provides the results of TCMR on Internet videos. The bounding boxes of people in the videos are tracked by a multi-person tracker that uses YOLOv3 [29]. With the cropped images from the bounding boxes, our TCMR processes 41 frames per second (fps) for the video 3 with 5 people. A single NVIDIA RTX 2080Ti GPU is used for the test.

8. Datasets

3DPW. 3DPW [34] is captured from in-the-wild and contains 3D human pose and shape annotations. It consists of 60 videos and 51K video frames in total, which are captured with a phone at 30 fps. IMU sensors are leveraged to acquire the groundtruth 3D human pose and shape. We follow the official split protocol to train and test our model, where train, validation, test sets consist of 24, 12, 24 videos, respectively. In addition, we report MPVPE on 3DPW because it only has groundtruth 3D shape among the datasets we used. We use 14 joints defined by Human3.6M [10] for evaluating PA-MPJPE and MPJPE following the previous works [11, 12, 14, 15].

Human3.6M. Human3.6M [10] is a large-scale indoor 3D human pose benchmark, which consists of 15 action categories and 3.6M video frames. Following [14], our TCMR is trained on 5 subjects (S1, S5, S6, S7, S8) and tested on 2 subjects (S9, S11). We subsampled the dataset to 25 fps (originally 50 fps) for training and evaluation on the acceleration error. 14 joints defined by Human3.6M are used for computing PA-MPJPE and MPJPE.

MPI-INF-3DHP. MPI-INF-3DHP [20] is a 3D benchmark mostly captured from indoor environment. The train set has 8 subjects, 16 videos per subject, and 1.3M video frames captured at 25 fps in total. It exploits a marker-less motion capture system and provides 3D human pose annotations.

The test set contains 6 subjects performing 7 actions in both the indoor and outdoor environment. The positional errors (i.e., PA-MPJPE and MPJPE) of TCMR are measured on the valid frames, which are composed of every 10th frame approximately, using 17 joints defined by MPI-INF-3DHP. The acceleration error is computed using all frames.

InstaVariety. InstaVariety is a 2D human dataset curated by HMMR [12], whose videos are collected from Instagram using 84 motion-related hashtags. There are 28K videos with an average length of 6 seconds, and OpenPose [4] is leveraged to acquire pseudo-groundtruth 2D pose annotations.

Penn Action. Penn Action [37] contains 2.3K video sequences of 15 different sports actions. It has a total of 77K video frames annotations for 2D human poses, bounding boxes, and action categories.

PoseTrack. PoseTrack [1] is a 2D benchmark for multi-person pose estimation and tracking in videos. It contains 1.3K video sequences and 46K annotated video frames in total. The videos are captured at different fps, which varies around 25 fps. We use 792 videos from the official train set, which has 2D pose annotations for 30 frames in the center of the videos.

9. Effect of pre-trained ResNet

Due to lack of video data, our TCMR and previous video-based methods [12, 14, 19] employ ResNet [9] pre-trained by the single image-based 3D human pose and shape estimation methods [11, 15] to extract static features from input frames. The pre-trained ResNet is trained on large-scale in-the-wild 2D human pose datasets and provides reliable static features. However, it is also one reason for the strong dependency of the system on the current static feature. The current static feature extracted by the pre-trained ResNet already contains strong cue on the current 3D human pose and shape, leading the system to leverage temporal information marginally.

In this regard, an alternative to our TCMR, one could
Table 7: Comparison between different models using ResNet with different initialization to extract static features. All models use the same SMPL parameter regressor pre-trained by SPIN [15].

| ResNet initialization                                      | remove residual | PoseForecast | PA-MPJPE ↓ | Accl ↓ |
|------------------------------------------------------------|-----------------|--------------|------------|--------|
| ResNet with random initialization                          | √               | ×            | 126.5      | 24.3   |
| ResNet pre-trained on ImageNet [30]                        | √               | ×            | 103.7      | 65.5   |
| ResNet from SPIN [15]                                      | ×               | ×            | 55.6       | 29.2   |
| **ResNet from SPIN [15] (TCMR. Ours.)**                    | ✓               | ✓            | **53.9**   | **7.7** |

train models from scratch without using the ResNet pre-trained by [11, 15] to extract static features to reduce the strong dependency. Table 7 compares our TCMR, the baseline (the third row), and the models that do no use the ResNet pre-trained by SPIN [15]. As the table shows, the models that do no use the ResNet pre-trained by SPIN [15] reveal very high per-frame 3D pose errors. This indicates that training the models with only video data in the current literature is not sufficient for accurate 3D human pose estimation. The interesting part is that the model using ResNet with random initialization provides the highest 3D pose error but the lowest acceleration error among the models without our TCMR. While the high pose error attributes to the lack of train data, the low acceleration error implies that the strong cue of the current static feature adversely affects the temporal consistency of 3D human motion.

In summary, with the insufficient video data in the current literature, the proposed TCMR significantly improves the temporal consistency of 3D human motion by reducing the strong dependency on the current static feature. It also preserves the per-frame 3D pose accuracy by leveraging the ResNet pre-trained on large-scale in-the-wild 2D human pose datasets to extract useful static features.

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