

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

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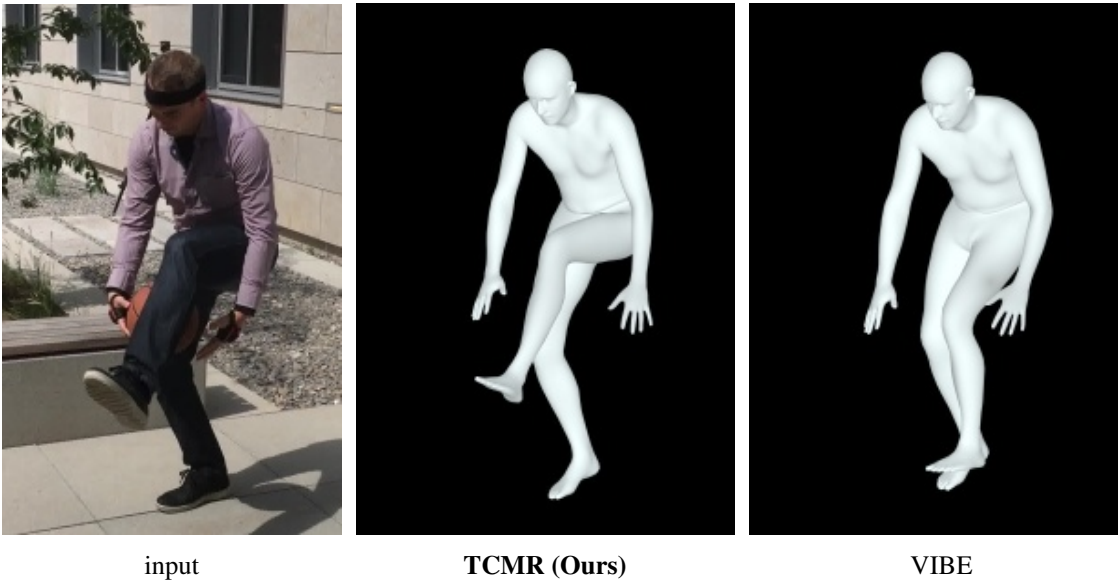


Figure 1: VIBE [14], the state-of-the-art video-based 3D human pose and shape estimation method, outputs very different 3D human poses per frame, although the frames have subtle differences. Our TCMR produces clearly more temporally consistent and smooth 3D human motion. *To watch the video, please refer to our arxiv paper.*

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 also 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, limited training data, and complexity of human articulations*.

Most of the previous methods [6, 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. Although single image-based methods predict a reasonable output from a static image, they tend to produce **temporally inconsistent** and **unsmooth 3D motion** when applied to a video per frame. The **temporal instability** is from **inconsistent 3D pose errors** for consecutive frames. For example, the errors could occur in different 3D directions, or the following frames' pose outputs could remain relatively the same, not reflecting the motion.

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 pretrained 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** aforementioned, 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 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 can **hinder** the system from learning useful temporal information. Given that the static feature is extracted by the **pretrained 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 can make the SMPL parameter regressor heavily depend on it and leverage the temporal feature **marginally**. This procedure can 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. This phenomenon is caused by the current static feature having the **most crucial information for 3D human pose and shape of a current frame**. Although the dominance will increase the per-frame accuracy of 3D pose and shape estimation, it can 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

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, although 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 PoseForecast, 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 PoseForecast are free from the current static feature; however, they contain essential temporal information of the past and future frames to **forecast** a current pose. The temporal features from PoseForecast are **integrated with the current temporal feature, which is extracted from all input frames, to predict current SMPL parameters**. The parameters estimated from the integrated temporal feature are the final output in inference time. By removing the strong dependency on the current static feature, **our SMPL parameter regressor can have 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. It also 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 compared to a baseline method.**
- TCMR 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 **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 uses **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 **self-improving system** that consists of an SMPL parameter regressor and an **iterative fitting framework** [2]. Georgakis *et al.* [8] incorporated **hierarchical kinematic prior** on a human body to a network.

Conversely, the model-free approach estimates the shape directly instead of regressing the model parameters. Varol *et al.* [31] proposed **BodyNet**, which estimates 3D human shape in the **3D volumetric space**. Kolotouros *et al.* [16] designed a **graph convolutional human mesh 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 localize mesh vertices in a **fully convolutional manner**. Choi *et al.* [6] proposed a graph convolutional network that **recovers 3D human pose and mesh from a 2D human pose**.

Despite moderate performance 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. Dörsch *et al.* [7] trained their network on a sequence of **optical flow** and 2D poses to make their network **generalize well** to unseen videos. Sun *et al.* [30] 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 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)** [5], and feeds it to an SMPL parameter regressor. A **motion discriminator** is introduced to encourage the regressor to produce plausible 3D human motion. MEVA [19] addresses the problem in a **coarse-to-fine manner**. Their system initially estimates the coarse 3D human motion using a **variational motion estimator (VME)**, and predicts the **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, 7, 12, 14, 19, 21, 27, 28, 30], most of them showed their results only qualitatively, and did not report numerical evaluation on temporal consistency. After the 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. The HMMR outputs smoother 3D human motion but provides low per-frame 3D pose accuracy. Conversely, the VIBE [14] shows high per-frame 3D pose accuracy; however, the output is temporally inconsistent in quantitative metrics and qualitative results compared with HMMR.

In this regard, MEVA [19] attempts to establish the balance between the per-frame 3D pose accuracy and the temporal smoothness. Although it provides 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, which is used to **refine initial 3D pose and shape by MRR**, is encoded from static features of all frames, which include the current frame. **This procedure can 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 contrary, our TCMR is **deliberately designed to reduce the strong dependency on the static feature**. The residual connection is removed, and **PoseForecast forecasts additional temporal features from past and future frames without a current frame**. Our approach **alleviates the dependency** and provides temporally consistent and accurate 3D human motions in both qualitative and quantitative manners.

Forecasting 3D human poses from images. Recently, [4, 12, 33, 34] proposed to predict a person’s future 3D human poses from RGB input. Chao *et al.* [4] 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. The 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.* [34] proposed a **neural autoregressive framework** that takes past video frames as input to predict future 3D motion. Yuan *et al.* [33] adopted **deep reinforcement learning** to forecast future 3D human poses from egocentric videos. Although 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.

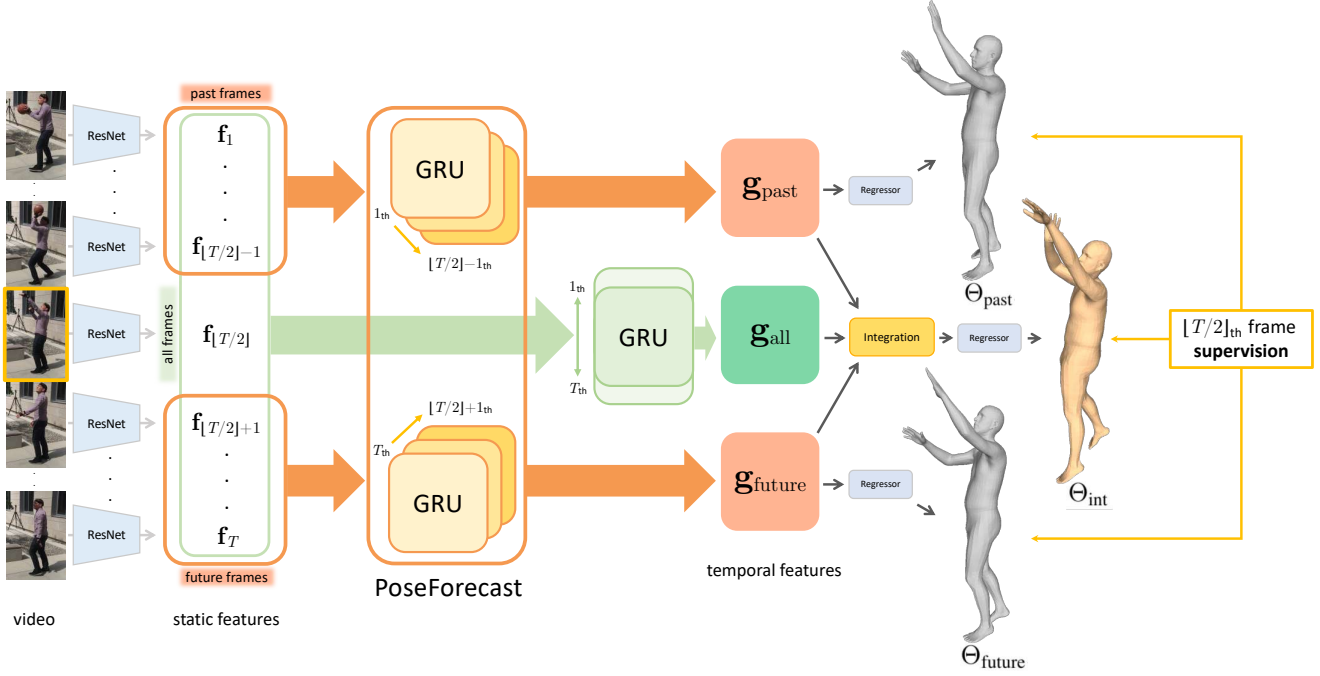


Figure 2: The overall pipeline of TCMR. The gold-colored output Θ_{int} is used in inference time, which is regressed from the integrated temporal feature.

3. TCMR

Figure 2 shows the overall pipeline of our TCMR. We provide descriptions of each part in the system as follows.

3.1. Temporal encoding from all frames

Given a sequence of T RGB frames $\mathbf{I}_1, \dots, \mathbf{I}_T$, ResNet [9], pretrained 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 $\mathbf{f}_1, \dots, \mathbf{f}_T$, where $\mathbf{f}_\bullet \in \mathbb{R}^{2048}$. 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 \mathcal{G}_{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 \mathbf{f}_1 and \mathbf{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 $\mathbf{f}_2, \dots, \mathbf{f}_{\lfloor T/2 \rfloor}$ and $\mathbf{f}_{T-1}, \dots, \mathbf{f}_{\lfloor T/2 \rfloor+1}$, respectively.** The concatenated hidden states of the GRUs at the current frame become the current temporal feature from all input frames $\mathbf{g}_{\text{all}} \in \mathbb{R}^{2048}$. Unlike VIBE [14], we do not add residual connection between $\mathbf{f}_{\lfloor T/2 \rfloor}$ and \mathbf{g}_{all} , such that the current temporal feature will not be dominated by $\mathbf{f}_{\lfloor T/2 \rfloor}$.

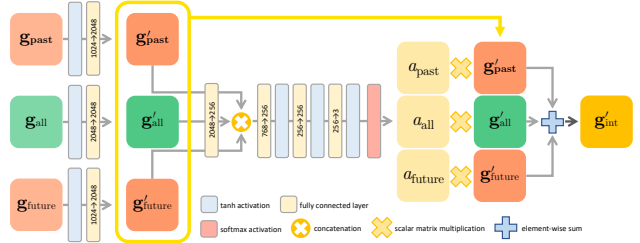


Figure 3: Temporal feature integration to estimate 3D human mesh for the current frame.

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 $\mathcal{G}_{\text{past}}$ and $\mathcal{G}_{\text{future}}$, respectively. The past and future frames are defined as $1, \dots, (\lfloor T/2 \rfloor - 1)$ th frames and $(\lfloor T/2 \rfloor + 1), \dots, T$ th frames, respectively. **The initial input of the $\mathcal{G}_{\text{past}}$ is \mathbf{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 $\mathbf{f}_2, \dots, \mathbf{f}_{\lfloor T/2 \rfloor - 1}$. The final hidden state of the $\mathcal{G}_{\text{past}}$ becomes the temporal feature from the past frames $\mathbf{g}_{\text{past}} \in \mathbb{R}^{1024}$. Similarly, $\mathcal{G}_{\text{future}}$ takes \mathbf{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 $\mathbf{f}_{T-1}, \dots, \mathbf{f}_{\lfloor T/2 \rfloor + 1}$. The final hidden state of the $\mathcal{G}_{\text{future}}$ becomes the temporal feature from the future frames $\mathbf{g}_{\text{future}} \in \mathbb{R}^{1024}$.

3.3. Temporal feature integration

We integrate the extracted temporal features from all frames \mathbf{g}_{all} , from the past frames \mathbf{g}_{past} , and from the future frames $\mathbf{g}_{\text{future}}$ 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 \mathbf{g}'_{all} , $\mathbf{g}'_{\text{past}}$, and $\mathbf{g}'_{\text{future}}$. 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 $\mathbf{a} = (a_{\text{all}}, a_{\text{past}}, a_{\text{future}}) \in \mathbb{R}^3$. The attention values represent how much the system should give a weight for the feature integration. The final integrated temporal feature is obtained by $\mathbf{g}'_{\text{int}} = a_{\text{all}}\mathbf{g}'_{\text{all}} + a_{\text{past}}\mathbf{g}'_{\text{past}} + a_{\text{future}}\mathbf{g}'_{\text{future}}$.

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

3.4. Loss functions

For the training, we supervise all three outputs Θ_{past} , Θ_{future} , and Θ_{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 to 16 and the input video frame rate to 25-30 frames per second and initialize the backbone and regressor with the pretrained 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.* [29], we occlude the cropped image with various objects for data augmentation. The occlusion augmentation reduces both pose and acceleration errors approximately by 1mm. Following [12, 14], we precompute the static features from the cropped images by ResNet [9] to save training time and memory. All the

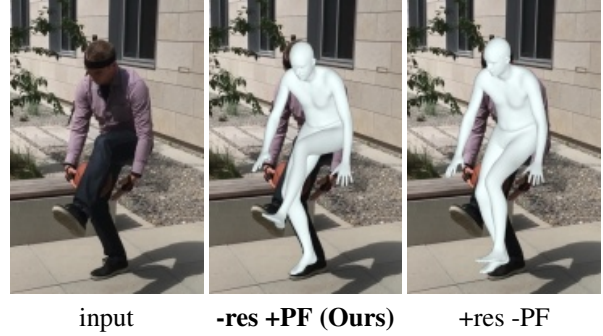


Figure 4: Qualitative comparison between our TCMR (middle) and the baseline (right). TCMR learns more useful temporal features, and provides a more accurate 3D pose and temporally consistent 3D motion. res denotes the residual connection and PF is the abbreviation for PoseForecast. To watch the video, please refer to our arxiv paper.

3D rotations of θ are initially predicted in the 6D rotational representation of Zhou *et al.* [36], 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 the per-frame and temporal evaluation metrics. For the per-frame evaluation, we use mean per joint position error (MPJPE), Procrustes-aligned MPJPE (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. Particularly, we use PA-MPJPE as the main metric for per-frame accuracy, since it excludes the effect of outputs' scale ambiguity on errors. 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 [32], Human3.6M [10], MPI-INF-3DHP [20], InstaVariety [12], Penn Action [35], and PoseTrack [1] for training, following VIBE [14]. 3DPW is the only in-the-wild dataset that contains accurate groundtruth SMPL parameters. 3DPW, Human3.6M, MPI-INF-3DHP are also used for evaluation. More details are 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

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

remove residual	PoseForecast	PA-MPJPE↓	Accel↓
✗	✗	55.6	29.2
✗	✓	55.0	24.9
✓	✗	54.2	8.7
✓ (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↓	Accel↓
w. current frame	53.8	10.3
wo. current frame (Ours)	53.9	7.7

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. It also predicts each 3D pose and shape for all input frames in a single feed-forward, but does not use the motion discriminator. We use 3DPW [32], MPI-INF-3DHP [20], InstaVariety [12], and Penn Action [35] for training, and 3DPW for evaluation.

Effectiveness of residual connection removal. 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 a considerable improvement in temporal consistency and smoothness of 3D human motion. This finding 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 the 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, caused by the inaccurate 3D pose estimation on specific frames, 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. On the basis of the results in Table 1, PoseForecast consistently improves per-frame and temporal metrics regardless of the residual connection. Particularly, the acceleration error consistently decreases by over 11%

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

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

. Thus, the temporal encoding that takes all frames with the current frame may be suboptimal, and forecasting the current temporal features from the past and future frames is beneficial for temporally consistent 3D human motion.

To further validate the forecasting, we compare our PoseForecast with its variations. First, we show the effectiveness of taking 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%. Thus, 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.*, Θ_{past} and Θ_{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 the groundtruth of $\lfloor T/2 \rfloor - 1$ th and $\lfloor T/2 \rfloor + 1$ 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.*, $\lfloor T/2 \rfloor - 1$ th and $\lfloor T/2 \rfloor + 1$ 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 frames. When no supervision is observed (the first row), both 3D pose accuracy and temporal consistency decrease compared with ours. Hence, 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.

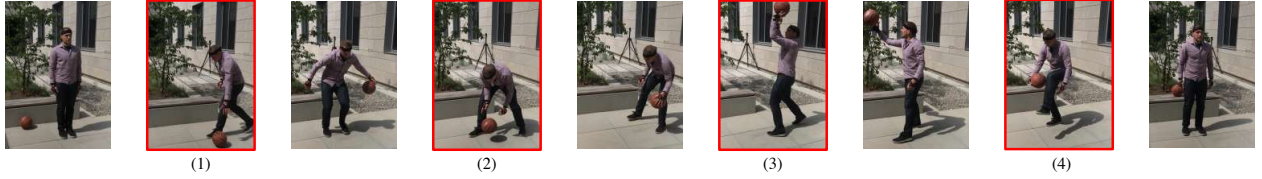
In summary, the above comparisons show that forecasting current temporal features from past and future frames is effective for temporally consistent 3D human motion by reducing the strong dependency on a current static feature.

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

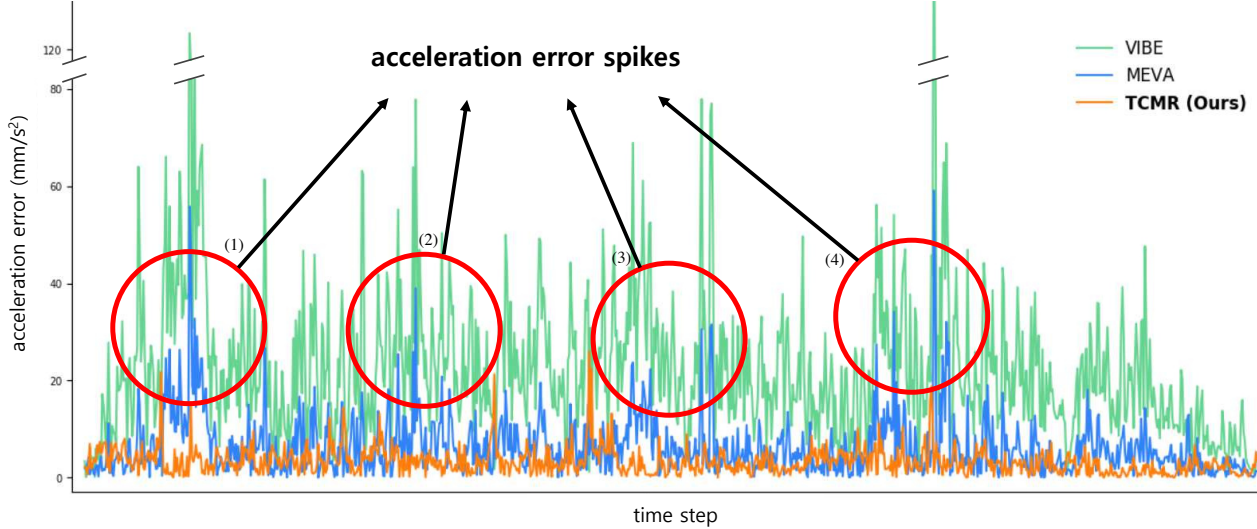
Comparison with video-based methods. We compare our TCMR with previous state-of-the-art video-based methods [12, 14, 19] that report the acceleration error in Table 4.

Table 4: Evaluation of state-of-the-art methods on 3DPW, MPI-INF-3DHP, and Human3.6M. All methods except HMMR [12] do not use Human3.6M SMPL parameters from Mosh [17], but use 3DPW train set for training following MEVA [19].

method	3DPW				MPI-INF-3DHP			Human3.6M			number of input frames
	PA-MPJPE ↓	MPJPE ↓	MPVPE ↓	Accel ↓	PA-MPJPE ↓	MPJPE ↓	Accel ↓	PA-MPJPE ↓	MPJPE ↓	Accel ↓	
HMMR [12]	72.6	116.5	139.3	15.2	-	-	-	56.9	-	-	20
VIBE [14]	57.6	91.9	-	25.4	68.9	103.9	27.3	53.3	78.0	27.3	16
MEVA [19]	54.7	86.9	-	11.6	65.4	96.4	11.1	53.2	76.0	15.3	90
TCMR (Ours)	52.7	86.5	102.9	7.1	63.5	97.3	8.5	52.0	73.6	3.9	16



(a) sampled frames of 'courtyard_basketball_01' in order



(b) acceleration error plot of 'courtyard_basketball_01'

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↓	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
+ Avg. filter	55.0	88.7	6.5

On the basis of the study of Luo *et al.* [19], all methods, except HMMR [12] are trained on the train set including

3DPW [32], but do not leverage Human3.6M [10] SMPL parameters obtained from Mosh [17] for supervision. The numbers of VIBE [14] are from MEVA [19], but we validated them independently. As shown in the table, our proposed system outperforms the previous video-based methods on all 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. Although MEVA [19] also improves the per-frame and temporal metrics, **the model consumes nearly 6 times more input frames during training and testing, and provides worse results than ours.** In addition,

Table 6: Evaluation of state-of-the-art methods on 3DPW, MPI-INF-3DHP, and Human3.6M. All methods do not use 3DPW [32] on training. ‘single image’ or ‘video’ denotes whether the input of a method is a single image or a video.

method		3DPW				MPI-INF-3DHP			Human3.6M		
		PA-MPJPE ↓	MPJPE ↓	MPVPE ↓	Accel ↓	PA-MPJPE ↓	MPJPE ↓	Accel ↓	PA-MPJPE ↓	MPJPE ↓	Accel ↓
single image	HMR [11]	76.7	130.0	-	37.4	89.8	124.2	-	56.8	88.0	-
	GraphCMR [16]	70.2	-	-	-	-	-	-	50.1	-	-
	SPIN [15]	59.2	96.9	116.4	29.8	67.5	105.2	-	41.1	-	18.3
	I2L-MeshNet [22]	57.7	93.2	110.1	30.9	-	-	-	41.1	55.7	13.4
	Pose2Mesh [6]	58.3	88.9	106.3	22.6	-	-	-	46.3	64.9	23.9
	HKMR [8]	-	-	-	-	-	-	-	-	59.6	-
video	HMMR [12]	72.6	116.5	139.3	15.2	-	-	-	56.9	-	-
	Doersch <i>et al.</i> [7]	74.7	-	-	-	-	-	-	-	-	-
	Sun <i>et al.</i> [30]	69.5	-	-	-	-	-	-	42.4	59.1	-
	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	62.8	97.4	8.0	41.1	62.3	5.3

MEVA requires at least 90 input frames, which means that it can not be trained and tested on short videos. 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 a diverse motion.

To further confirm the effectiveness of the proposed system on temporal consistency, we compare our TCMR with VIBE [14] and MEVA [19] with an **average filter** applied as **post-processing** in Table 5. Average filtering is performed by **spherical linear interpolation** in the quaternions of estimated SMPL [18] pose parameters following MEVA. The numbers of other methods are from MEVA. As shown in the table, our system outperforms other methods even when they are applied with the average filtering. Moreover, the results imply that the average filtering can decrease the per-frame 3D pose accuracy by smoothing out the details of 3D human motion. However, each component of our TCMR decreases the acceleration error while improving the per-frame 3D pose accuracy, as shown in Table 1.

In summary, our newly designed system significantly outperforms the previous state-of-the-art methods in temporal consistency and smoothness of 3D human motion without any post-processing while also increasing the per-frame 3D pose accuracy. Note that the comparison in Table 4 and 5 is the fairest comparison between the video-based methods, since all methods, except HMMR [12], used the same training datasets.

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 [32]. For evaluation on Human3.6M [10], we use the frontal view images following [12, 15], whereas 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 per-frame 3D pose accuracy (PA-MPJPE) and temporal consistency. Especially the temporal consistency is largely improved compared with single image-based methods. While VIBE decreases the acceleration error of SPIN [15] by 9% and is defeated by Pose2Mesh [6] in the temporal consistency, our system provides over 3 times better performance than both SPIN and Pose2Mesh in 3DPW. Moreover, VIBE gives a higher acceleration error than I2L-MeshNet [22] but our TCMR outperforms it by a wide margin in Human3.6M.

We provide qualitative comparison with VIBE [14] and MEVA [19] on 3DPW, qualitative results of TCMR on Internet videos, and failure cases in this link 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 the 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. In comparison with the previous video-based methods, the proposed TCMR provides highly temporally consistent 3D motion and a more accurate 3D pose per frame.

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¹<https://www.youtube.com/watch?v=WB3nTnSQDII>

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