Exploring Versatile Prior for Human Motion via Motion Frequency Guidance

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Abstract

Prior plays an important role in providing the plausible constraint on human motion. Previous works design motion priors following a variety of paradigms under different circumstances, leading to the lack of versatility. In this paper, we first summarize the indispensable properties of the motion prior, and accordingly, design a framework to learn the versatile motion prior, which models the inherent probability distribution of human motions. Specifically, for efficient prior representation learning, we propose a global orientation normalization to remove redundant environment information in the original motion data space. Also, a two-level, sequence-based and segment-based, frequency guidance is introduced into the encoding stage. Then, we adopt a denoising training scheme to disentangle the environment information from input motion data in a learnable way, so as to generate consistent and distinguishable representation. Embedding our motion prior into prevailing backbones on three different tasks, we conduct extensive experiments, and both quantitative and qualitative results demonstrate the versatility and effectiveness of our motion prior. Our model and code are available at https://github.com/JchenXu/human-motion-prior.

1. Introduction

Human motion modeling plays an important role in many applications such as video games and computer animation. Many tasks study the human motion under different circumstances [52, 22, 30, 55, 25]. Most of them ask for the physically plausible human motion, which means that any independent pose of the motion is plausible, as well as the transition between poses is reasonable.

Several works study pose priors by exploring the constraint on human poses \cite{4, 17, 34, 51}. However, a plausible motion asks for both the continuity between poses and the feasibility of the independent pose. Hence, recent works try to design the prior for human motion. Kocabas \textit{et al.} \cite{22} design an adversarial prior to discriminate between generated and real human motions so as to keep the predicted motion plausible. In addition, Holden \textit{et al.} \cite{13} learn a motion manifold, where each motion data is embedded into a low-dimensional representation. However, they design the motion prior only for specific tasks. We argue that a pre-trained and task-agnostic human motion prior is essential for those motion generation tasks because of the insufficient paired 3D motion data. Therefore, we summarize the indispensable properties of the motion prior, and design a versatile motion prior according to these properties.

First, \textit{a tractable and continuous distribution} over the latent representation is required to model the inherent probability distribution of human motions. It is important for solving ambiguity in ill-posed tasks, such as motion infill-
ing and prediction. Because some common motions have a high probability of occurrence, while the probability of rare or impossible motions is lower. For example, in Fig. 1, the full motion (a) and (b) have the same undersampled observation (i.e., start and end position pointed by the blue arrow), leading to the ambiguity in the ill-posed motion infilling. If the prior models the probability distribution of the human motion data, the ambiguity can be solved by offering a more probable solution which is more likely to conform to human behavior. Therefore, we construct a motion prior based on the probabilistic model, variational auto-encoder (VAE) [21], to model the inherent motion distribution.

Second, a complete and efficient space is significant for constructing a versatile prior, since the prior needs to generalize to various tasks and datasets without fine-tuning. Specifically, the complete and efficient space means that we can accurately reconstruct any plausible motion from a low-dimensional representation. A large-scale dataset with a variety of long-term motions is usually adopted for the completeness. However, it leads to a complex data space that is hard to be represented in low dimension. So, we propose to learn an efficient representation space from two aspects: reducing the complexity of the data space to be modeled and encoding each motion data efficiently.

For the reduction of complexity of the data space, Luo et al. [28] resort to shorter-term motions to be modeled. However, more context information provided by long-term motion is beneficial for downstream tasks. By contrast, we introduce a global orientation normalization, which normalizes the global orientation of each motion around yaw axis while retaining the relative orientation transition between frames. Since the direction in which a person moves is related to the environment, the global orientations of motion in the dataset are biased on the environment information. So it is non-trivial to remove the redundant environment information in the data space as well as reducing the complexity.

For the efficient motion encoding, motion segments with slower changes between frames should be efficiently compressed, while motion segments with higher degree of variation deserve more attention. For instance, in a motion sequence, the dancer may stand still for a while before dancing. Compared with standing segments, dancing segments carry more information and details, and deserve to be well retained [46]. Thus, we introduce a two-level motion frequency guidance to efficiently encode the motion into the low-dimensional prior representation. One level is sequence-based and the other is segment-based. The sequence-based frequency guidance captures the difference between frequency patterns of motions and provides category cues from the frequency [14]. The segment-based frequency guidance exploits the frequency difference between segments within a motion to adaptively compress segments with different amount of high-frequency information.

Third, a consistent and distinguishable representation should be learnt in the motion prior. As aforementioned, the same motion, consisting of same poses and relative transitions, may have different global orientations as the environment changes. For example, in Fig. 1, (c) and (d) correspond to the same motion with different orientations, but they are supposed to have the consistent representation. A straightforward solution is to take our orientation normalized motions as both input and output of our motion prior, so as to explicitly remove the global orientation for each input motion during training and inference phase. Yet, this solution may cause the prior fail to capture underlying distinguishable features for the motion. Thus, we introduce a denoising training scheme to disentangle the global orientation (environment information) from the human motion data in a learnable way, so as to learn a consistent representation while keeping the representation distinguishable [3, 15].

To demonstrate the versatility and effectiveness, we integrate our pre-trained motion prior into different backbones without fine-tuning for different tasks, such as human motion reconstruction, motion prediction and action recognition. Then, we conduct experiments on 3DPW [45], Human3.6M [16] and BABEL [35] to evaluate the performance on different tasks. Results show that our motion prior improves the baseline and achieves the state-of-the-art performance on all three benchmarks.

In summary, our contributions in this paper are: (1) We first summarize three indispensable properties for the motion prior to achieve versatility, and accordingly, (2) We introduce the global orientation normalization and a two-level motion frequency guidance to learn the versatile motion prior with a denoising training scheme. (3) We integrate the proposed prior into prevailing backbones and achieve the state-of-the-art performance on different benchmarks, which demonstrates the versatility of our motion prior.

2. Related Work

Human pose and motion prior. Constructing a kind of prior is commonly used in pose [4, 17, 34, 51] and motion [43, 13, 22, 28] modeling. Pavlakos et al. [34] utilize VAE [21] to build a non-linear manifold as the human pose prior and provide plausibility constraint. Zanfir et al. [51] construct a wrapped prior space with normalizing flow. Compared with pose priors, motion priors have constraints on both independent poses and transition between poses. Kocabas et al. [22] train an adversarial discriminator as motion prior to discriminate between generated motions and real human motions. Holden et al. [13] employ the autoencoder to encode all plausible motion into a compact manifold, where each latent code can represent a plausible human motion. Luo et al. [28] try to compress a large-scale dataset, AMASS [29], with VAE into a representation space. In this paper, we first analyze the properties of a ver-
satile motion prior and the characteristics of human motion itself. Then, we accordingly propose the global orientation normalization and a two-level motion frequency guidance.

**Frequency in motion modeling.** Previous works convert the motion into frequency domain and take the frequency coefficients as input to combine both spatial and temporal information [31, 5]. Mao et al. [30] represent historical sub-sequences of each motion as frequency coefficients, and aggregate them with attention mechanism to predict the future motion. Zhang et al. [55] encode the motion into different DCT spaces to decompose the motion into several frequency bands. By contrast, we exploit the characteristic of frequency that it represents the amount of information, to adaptively compress the human motion data.

**Human motion reconstruction.** Reconstructing the 3D human pose or motion has attracted significant interest [4, 17, 23, 41, 18, 22, 51]. Compared with poses, reconstructing human motion has more demanding requirements for shape consistency and smoothness. Kanazawa et al. [18] present a temporal encoder to learn 3D human dynamics from video and generate smooth motion. Kocabas et al. [22] design a GRU-based network with the adversarial prior to guide the motion inference. Choi et al. [9] explicitly try to improve the past and future frames to achieve smoother and better results. Meanwhile, [40, 50, 36, 39] try to improve the physical fidelity of generated motion through reinforcement learning and other physical constraints.

**Motion Prediction.** Motion prediction from past pose sequence is studied from two aspects: deterministic [1, 12, 30, 52] and stochastic [54, 47, 49, 2]. Instead of using a sequence of past poses, Chao et al. [6] forecast human dynamics from static images and Yuan et al. [48] predict future motions from egocentric videos. Zhang et al. [52] utilize the SMPL model to represent the human body and predict future motions with pose and shape from videos.

**Action Recognition.** To understand human motion, skeleton-based action recognition attracts much attention [38, 8, 26, 7]. Most of them carefully design and train a GraphConv network in a supervised way on the widely-used NTU-RGBD [37], which has two major problems: the discontinuity of action and the lack of modeling the long-tailed distribution. Recently, the BABEL [35] dataset is proposed to tackle these two problems, which is closer to the real life.

By contrast, we take the learnt prior representation, referring to a plausible motion, as the intermediary to generate the final outputs, which benefits from the context and probability information encoded in the prior.

3. Motion Prior

3.1. Human Motion Representation

We use the parametric human model, SMPL [27], to represent each human pose in the motion. SMPL model, which can be regarded as a differential function $M(\cdot)$, parameterizes the human body pose and shape through $\theta \in \mathbb{R}^{72}$ and $\beta \in \mathbb{R}^{10}$, respectively. Pose parameter $\theta$ consists of global orientation $\theta^g$ and local body pose $\theta^l$ determined by relative rotation of 23 joints in axis-angle format. Given $\theta$ and $\beta$, $M(\theta, \beta)$ outputs a triangulated mesh with $N = 6,980$ vertices. Then, we denote the motion sequence with $K$ frames as $X = \{\Theta_i\}_{i=1}^{K}$, where $\Theta_i = (\theta_i, \beta_i)$ represents the human model for $i$-th frame.

**Global Orientation Normalization.** As aforementioned, the global orientation around yaw axis of each motion in the dataset is related to the environment, while we argue that the motion prior should focus on the human motion itself. Hence, to remove the redundant environment information in the motion data and reduce the complexity of data space, we propose the global orientation normalization.

As shown in Fig. 2, we normalize the orientation of entire motion around yaw axis according to the first frame while remaining the internal relative orientation transition, so as to make all input sequences start in the same forward direction. Specifically, given an input motion sequence $X$, we first normalize the first frame by clipping the yaw rotation and generate normalized orientation $\hat{\theta}^g_1$. Then we generate the correction rotation $R_{cor}$ between the original orientation $\theta^g_1$ and $\hat{\theta}^g_1$ of the first frame, and normalize the global orientation of the motion sequence as follows:

$$R_{cor} = \hat{\theta}^g_{1} \cdot \theta^g_{1}^{-1} = \hat{\theta}^g_{1} \cdot \theta^g_{1}^{*},$$

$$\hat{\theta}^g_{1} = R_{cor} \cdot \theta^g_{1},$$

where $\theta^g$ is the rotation matrix format of $\theta^g$.

3.2. Frequency Guiding Prior Framework

To construct our motion prior, we exploit the variational auto-encoder (VAE) [21] and learn a 256-dimensional latent representation space. We first introduce the input data, then the encoder where we perform the two-level frequency guidance. Finally, we will introduce the decoder.

**Input data.** Given a set of pose and body parameters, $\theta$ and $\beta$, human motion can be expressed through SMPL model. However, the relative rotation and global orientation is less intuitive and straightforward. Therefore, we also take the joint sequence $J \in \mathbb{R}^{K \times J \times 3}$ of each motion as input, where $J$ is the number of body joints. Also, we explicitly calculate velocity $J^{vel}$ and acceleration $J^{acc}$ for each joint to better reveal the dynamic features.

Following [34], we also ignore the variance of shape information and take the same shape for each motion. Therefore, the motion input used to construct our motion prior is denoted as $\Phi = \{(\theta^g_i, \theta^l_i, \beta, J_i, J^{vel}_i, J^{acc}_i)\}_{i=1}^{K}$.

**Encoder.** RNN-based networks, which mainly focus on temporal correlations, usually fail to capture the spatial-temporal dynamics in human motion [24]. Hence, as shown
in Fig. 2, we construct a convolutional encoder, which takes \( \Phi \) as input and consists of three residual blocks to extract both the fine-grained information and global context.

To introduce the sequence-based and segment-based frequency guidance for efficient representation learning, we take the joint sequence \( J \in \mathbb{R}^{N \times J \times 3} \) and further divide \( J \) into \( S \) segments of length \( n \), i.e., \( \tilde{J} \in \mathbb{R}^{S \times n \times J \times 3} \). Then, for each motion, we make use of the discrete cosine transform (DCT) to extract the sequence-based frequency components \( \mathcal{F}_{seq} \in \mathbb{R}^{C_m \times J \times 3} \) from \( \tilde{J} \) and the segment-based frequency \( \mathcal{F}_{seg} \in \mathbb{R}^{S \times C_s \times J \times 3} \) from \( \tilde{J} \), where \( C_m \) and \( C_s \) represent the number of kept frequency components.

Then, to perform the segment-based frequency guidance, we extract the segment attention value \( \alpha_{seg} \in \mathbb{R}^S \) from \( \mathcal{F}_{seg} \) and re-weight the segment features \( f_{seg} \) extracted by the residual block for each segment, so as to adaptively compress the information according to the frequency:

\[
f'_{seg} = f_{seg} \cdot \alpha_{seg} = f_{seg} \cdot \sigma(\phi(\mathcal{F}_{seg})),
\]

where \( f'_{seg}, f_{seg} \in \mathbb{R}^{S \times n \times c} \), \( n \) and \( c \) are the length of each segment and the channel number of the feature. \( \sigma(\cdot) \) and \( \phi(\cdot) \) are the softmax function and multi-layer perceptron and are used to predict the segment attention value \( \alpha_{seg} \). Besides, this compressing process is conducted in the first layer for efficient compression for the entire motion.

Furthermore, we combine features from different scales as the motion dynamic feature to keep both the global context information and the fine-grained local pose information. Also, we exploit the sequence-based frequency \( \mathcal{F}_{seq} \) and introduce the global motion category information from \( \mathcal{F}_{seq} \) into the dynamic feature. Finally, we encode both category information and dynamic feature into the latent representation \( z_{mot} \in \mathbb{R}^{256} \) with re-parameterization trick [21].

**Decoder.** Different from the encoder, an overly complex decoder may hurt the test log-likelihood and cause the overfitting [11, 44]. Therefore, as shown in Fig. 2, our decoder consists of two residual blocks containing one fully connected layer each. The final layer outputs the reconstructed normalized global orientation \( \phi^g \) represented by 6D continuous rotation feature [56] and a latent local pose representation \( \varphi' \in \mathbb{R}^{32} \), in VPoser latent space [34], which is a reasonable sub-manifold for human pose. Furthermore, \( D_{cont} \) converts \( \phi^g \) to the axis-angle format and the decoder \( D_{vp} \) of VPoser [34] with pre-trained and fixed weights decodes \( \varphi' \) into predicted local body pose \( \theta^v \) in axis-angle format.

### 3.3. Denoising Training Scheme

To learn a consistent and distinguishable representation for the same motion, we design a denoising training scheme. Given a motion sample \( \Phi \) after orientation normalization, we randomly apply a rotation around yaw axis to it, which can be regarded as an inverse process of normalization in Sec. 3.1 with random degree, and generate a corrupted sample \( \Phi^c \). Then, our prior is trained to reconstruct normalized motion \( \{ \theta^g, \theta^v \} \) from \( \Phi \) instead of \( \Phi \) as follows:

\[
\mathcal{L} = \lambda_{rec} \mathcal{L}_{rec} + \lambda_{kl} \mathcal{L}_{kl} + \lambda_{vposer} \mathcal{L}_{vposer},
\]

where \( \mathcal{L}_{rec} = \mathcal{M}(\hat{\theta}^g || \theta^g, \beta) - \mathcal{M}(\mathcal{D}_{cont}(\hat{\phi^g}) || \mathcal{D}_{vp}(\hat{\varphi}), \beta), \)

\[
\mathcal{L}_{kl} = KL(q(z_{mot} || \hat{\Phi}) || N(0, I)),
\]

and \( \mathcal{L}_{vposer} = || \varphi' ||^2 \).

### 4. Versatility of Motion Prior

To demonstrate the versatility and effectiveness of our proposed motion prior, in this section, we integrate our motion prior into several prevailing backbones in different human motion modeling tasks.
4.1. Human Motion Reconstruction

**Problem definition.** Given a video sequence \( \{I_t\}_{t=1}^T \), we reconstruct the 3D human pose and shape \( \{\Theta_t\}_{t=1}^T \) (defined the same as Sec. 3.1) from each frame. It is noteworthy that the reconstructed shape parameter \( \beta_t \) should be consistent across the whole sequence for a person.

**Architecture.** We utilize the VIBE [22] as our backbone and embed our motion prior into it as shown in Fig. 3. VIBE extracts temporal feature for each frame through Gated Recurrent Units (GRU). Then, for each frame, they produce pose \( \theta_t \), shape \( \beta_t \), and scale and translation \([s; t]\) of camera using a shared regressor [17] from each temporal feature.

However, we predict the pose for each frame in the sequence at once from our motion prior, instead of predicting frame-wisely through the regressor. As illustrated in Fig. 3, we construct a motion encoder \( E_{\text{mot}} \), consisting of two convolutional layers and a fully-connected layer, to predict the motion representation \( z_{\text{mot}} \in \mathbb{R}^{256} \). Then, the pre-trained motion prior decodes \( z_{\text{mot}} \) into the motion with \( K \) frames. However, the length \( T \) of input video is required to be less than \( K \) and we use the first \( T \) poses \( \{(\theta^p_t, \theta^l_t)\}_{t=1}^T \) as the output. Compared with producing poses for consecutive frames one by one, our motion prior provides more context information between poses for accurate prediction. Also, we discard the motion discriminator in VIBE, which acts as a prior to generate plausible motion but fails to solve ambiguity. By contrast, our motion prior generates more probable motion to solve ambiguity while keeping plausibility.

In addition, due to the global orientation normalization (see Sec. 3.1), the predicted global orientation sequence \( \{\theta^g_t\}_{t=1}^T \) has been normalized according to the first frame. Therefore, we construct another branch to predict the residual rotation \( R_{\text{res}} \) around yaw axis for the first frame and rectify the \( \{\theta^e_t\}_{t=1}^T \) by \( \bar{\theta}^e_t = R_{\text{res}} \cdot \theta^e_t \).

Furthermore, we also introduce a branch to directly predict the \( \beta \) from the first frame and use the predicted \( \beta \) for all rest frames to ensure the shape consistency across a video, where the regressor in VIBE may fail. However, given the 2D keypoints supervision, the camera model for each frame is still needed and we keep regressing \([s; t]\) based on predicted shape and pose from each temporal feature.

4.2. Motion Prediction

**Problem definition.** In this task, we aim to predict the future 3D human motion \( \{\Theta_{T+1}, \Theta_{T+2}, \ldots, \Theta_{T+N}\} \) conditioning on a past 2D video sequence \( \{I_1, I_2, \ldots, I_T\} \).

**Architecture.** An auto-regressive framework PHD [52] is taken as our backbone. It conducts auto-regressive prediction in the feature space, where each feature is regularized by an adversarial pose prior [17]. Given a video, PHD first extracts the temporal feature \( \{f^i_t\}_{t=1}^T \) for each input frame, and then predicts \( \{f^i_{T+1}\}_{i=1}^{T+N} \) in an auto-regressive manner, and accordingly generate poses for future motion.
Table 2. Evaluation on 3DPW and Human3.6M dataset with the SMPL annotations of Human3.6M. “Ours‡” denotes that we directly take the orientation normalized motion as input and output without denoising training scheme.

| Method          | MPJPE ↓ | PA-MPJPE ↓ | MPVPE ↓ | Accel Error ↓ | MPJPE ↓ | PA-MPJPE ↓ | Accel Error ↓ |
|-----------------|---------|------------|---------|---------------|---------|------------|---------------|
| Frame-based     |         |            |         |               |         |            |               |
| SPIN [23]       | 96.9    | 59.2       | 116.4   | 29.8          | -       | 41.1       | -             |
| I2L-MeshNet [33]| 93.2    | 58.6       | 110.1   | 30.9          | 55.7    | 41.7       | -             |
| Pose2Mesh [10]  | 88.9    | 58.3       | 106.3   | -             | 64.9    | 46.3       | -             |
| Video-based     |         |            |         |               |         |            |               |
| HMNR [18]       | 116.5   | 72.6       | 139.3   | 15.2          | -       | 56.9       | -             |
| Sun et al. [42] | -       | 69.5       | -       | -             | 59.1    | 42.4       | -             |
| VIBE [22]       | 93.9    | 55.9       | 112.6   | 27.0          | 65.6    | 41.4       | 27.3          |

“Ours‡” means without denoising training scheme.

Table 3. Evaluation on 3DPW without the SMPL annotations of Human3.6M. “Ours‡” means without denoising training scheme.

| Method          | MPJPE ↓ | PA-MPJPE ↓ | MPVPE ↓ | Accel Error ↓ |
|-----------------|---------|------------|---------|---------------|
| VIBE [23]       | 91.9    | 57.6       | -       | 25.4          |
| MEVA [28]       | 86.9    | 54.7       | -       | 11.6          |
| TCMR [9]        | 86.5    | 52.7       | 103.2   | 6.8           |
| Ours‡           | 85.5    | 53.6       | 102.6   | 15.9          |
| Ours            | 85.2    | 53.2       | 102.1   | 14.3          |

5.2. Motion Prior Evaluation

To demonstrate the effectiveness of our proposed methods, we conduct experiments on the test set of 3DPW. The VAE reconstruction error reported in Tab. 8 shows that our prior generalizes well from AMASS to the unseen 3DPW, which is important for the versatility. Then, we train a vanilla VAE with the global orientation normalization. As shown in Tab. 8, compared with MEVA [28] which reduces the complexity of data space by resorting to shorter-term motions, we achieve the better performance and it demonstrates the effectiveness of our global orientation normalization. Also, the proposed frequency guidance further improves the performance of vanilla VAE, and it proves that sequence-based and segment-based frequency guidance are effective. Compared with sequence-based frequency that indicates the category information mainly determined by the local poses, segment-based frequency focuses on both
orientation transition and local poses compression, leading to better tradeoff between MPJPE and PA-MPJPE.

To qualitatively show that we construct an expressive prior space for plausible motions, we randomly sample the latent variable $z_{mot} \in \mathbb{R}^{256}$ from the normal distribution and generate the human motion. The top and bottom rows in Fig. 4 show two motions generated from sampled latent variables $z_{mot}^{\alpha}$ and $z_{mot}^{\beta}$. Also, we average these two variables and get the interpolated motion in the middle row of Fig. 4. These reasonable results demonstrate our prior is plausible while tractably and continuously distributed.

### 5.3. Human Motion Reconstruction

**Dataset.** Following [22], in training phase, we use the InstaVariety [18] dataset to provide pseudo ground-truth 2D annotations. Also, we utilize 3DPW and Human3.6M [16] for SMPL parameters supervision, while employing MPI-INF-3DHP [32] for 3D joints supervision. For evaluation, we show results on the test set of 3DPW and Human3.6M. Specifically, on Human3.6M, we use [S1, S5, S6, S7, S8] as the training set and [S9, S11] as the test set.

**Experimental results.** As introduced in Sec. 4.1, we take the VIBE [22] as our backbone while keeping the same setting, e.g., the length of video $T = 16$. Tab. 2 shows the quantitative results compared with the state-of-the-art methods on 3DPW and Human3.6M. Compared with VIBE, our motion prior improves the smoothness and reduces the acceleration error from 27.0 mm/s$^2$ to 12.7 mm/s$^2$ on 3DPW and from 27.3 mm/s$^2$ to 13.9 mm/s$^2$ on Human3.6M. Also, because our motion prior naturally encodes the reasonable transition between poses and provides the context information, the reconstruction error (e.g., MPJPE, PA-MPJPE and MPVPE) is also improved. Fig. 5 illustrates the qualitative results in presence of occlusion. Compared with the adversarial prior in VIBE, which only offers a plausible prediction, our motion prior generates a predicted motion with higher probability and achieves better results. More qualitative results are provided in Sup. Mat.

Furthermore, following [28], we also show the performance without SMPL parameters of Human3.6M and the results are shown in Tab. 3. Compared with previous works which are carefully designed for reconstruction task and output the prediction in a frame-wise manner, the MPJPE and MPVPE are improved. Specifically, compared with MEVA [28] that constructs the motion prior with more complex latent space and shorter-term motion, the improvement also demonstrates the efficiency of our motion prior.

**Effectiveness of denoising scheme.** Furthermore, we also conduct experiments to prove the effectiveness of our proposed denoising training scheme. From Tab. 2 and 3, we can see that the performances are improved on both two settings, especially in MPJPE, which shows that the denoising scheme of rotation noise helps to learn a better representa-

### Table 4. Results of motion prediction from video without Dynamic Time Warping. We report the PA-MPJPE for the 1th, 5th, 10th, 20th, 30th frame in the future motion.

| Method   | PA-MPJPE ↓ |
|----------|------------|
|          | 1th | 5th | 10th | 20th | 30th |
| Zhang et al. [52] | 57.7 | 61.2 | 64.4 | 67.1 | 81.1 |
| Ours     | **51.9** | **61.1** | **63.3** | **63.9** | **80.2** |

### Table 5. Evaluation on BABEL dataset. “Ours” means that we only train the MLP and freeze the pre-trained encoder. “Ours†” denotes that we train the whole framework from scratch.

| Loss     | Method     | BABEL-60  | BABEL-120 |
|----------|------------|-----------|-----------|
|          | Top1       | Top1-norm | Top1       | Top1-norm |
| CE       | 2s-AGCN [35] | 44.9 | 17.2 | 43.6 | 11.3 |
|          | Ours†      | 38.6 | 22.4 | 36.0 | 17.4 |
|          | Ours       | 40.3 | **23.6** | 37.8 | **18.2** |
| Focal    | 2s-AGCN [35] | 37.6 | 25.7 | **31.7** | 19.2 |
|          | Ours†      | 32.7 | 26.2 | 30.4 | 22.3 |
|          | Ours       | **38.1** | **27.2** | 31.5 | **25.5** |

### 5.4. Motion Prediction

**Dataset.** Following [52], we train our network on the combination of InstaVariety, PennAction [53] and Human3.6M. Specifically, the Human3.6M is split into train/val/test set as [S1, S6, S7, S8]/[S5]/[S9, S11].

**Experimental results.** In Sec. 4.2, we introduce that PHD [52] is taken as our backbone and we also use the past $T = 15$ frames as input and train the network to predict future 25 frames. Then, we discard the Dynamic Time Warping in [52] and compare with them under the same setting. As shown in Tab. 4, the performance of first 20 frames are improved with our prior. Following [52], we also report result of the 30th frame, which is not supervised in the training phase and directly taken from the motion generated by $z_{mot}$, and we can see that our motion prior still improve the result, because it naturally encodes a sequence of plausible motion starting from the given frames.

### 5.5. Action Recognition

**Dataset.** As introduced in Sec. 2, BABEL [35] provides more diversity and long-tailed distribution of samples, that is more close to real-world applications. Therefore, we conduct experiments on BABEL dataset and follow the official split in [35] to use the long-tailed BABEL-60 and BABEL-120, containing 60 and 120 action categories, respectively.

**Experimental results.** In Tab. 5, we report two metrics: Top1 and Top1-norm accuracy (the mean Top1 across categories). Compared with Top1, Top1-norm better reveals the performance of tackling the long-tailed distribution prob-
Figure 5. Qualitative comparison between VIBE (top) and our method (bottom) on the in-the-wild 3DPW.

| Method          | 60 Frames ↓ | 120 Frames ↓ |
|-----------------|-------------|--------------|
| Interpolation   | 10.45 (± 15.5) | 17.04 (± 24.4) |
| Holden et al. [13] | 15.28 (± 19.1) | 18.26 (± 24.5) |
| Kaufmann et al. [20] | 4.96 (± 8.5)  | 12.00 (± 19.5) |
| Ours            | 2.01 (± 2.15) | 2.51 (± 2.52) |

Table 6. Results of motion infilling tasks. 3D joint errors are reported by the mean and standard deviation in cm computed over all joints and frames on the validation set.

lem. In addition, following [35], we use both cross-entropy and focal loss in the training phase. On BABEL-60 and BABEL-120, our method achieves better performance in Top1-norm compared with the baseline, which is end-to-end trained on the dataset. It demonstrates the effectiveness and generalization ability of learnt representation. Also, we retrain the skeleton encoder together with MLP in Sec. 5.5 from scratch in an end-to-end way. As shown in Tab. 5, the result is worse, and it is because, decoupling representation learning may help to retain more distinguishable information and lead to more generalizable representation [19].

5.6. Motion Infilling

To show that our prior encodes the transition between poses, we exploit the motion filling task, which aims to fill in missing frames in a human motion. Instead of designing a network, we utilize our pre-trained decoder with fixed weights and perform the motion infilling in an optimizing manner. We refer the reader to Sup. Mat. for more details.

**Dataset.** We use the dataset released by [13], where each pose is represented as 22 joints. Following [20], we evaluate the performance on the validation set, and T frames are randomly selected as the missing frames in each motion.

**Experimental results.** Because the data is represented in skeleton, we regress the 22 joints from predicted SMPL model so as to optimize the z_mot. Tab. 6 shows the results in two settings: i) T = 60 and ii) T = 120. We outperform previous methods trained on this dataset, which shows the generalization ability of our motion prior and proves that it naturally represents the inherent transition between poses. Also, Fig. 10 illustrates the qualitative results and the comparison between ground truth is in Sup. Mat.

6. Conclusion

In this paper, we summarize the indispensable properties of a motion prior and propose a versatile motion prior which models the inherent probability distribution of motions. To keep the learnt representation space efficient, we introduce a global orientation normalization and a two-level frequency guidance. Then, we adopt a denoising training scheme to provide the consistent and distinguishable representation for each motion. Finally, we embed our proposed motion prior into different prevailing backbones and conduct extensive experiments on different tasks. The results show that the motion prior can improve the baseline and achieve the state-of-the-art performance, and it demonstrates the versatility and effectiveness of our prior.

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Appendix

7. Data Preparation

Because AMASS [29] consists of diverse motion capture data with SMPL [27] parameters. Therefore, to provide a unified training and validation set, we first downsample the original sequence into 30 fps and divide each sequence into sub-sequence with $K = 128$ frames. The overlap between every two sub-sequences is 30 frames. Second, we randomly select 15% of the sub-sequence dataset as the validation set to evaluate the performance of our proposed motion prior, and ensure that there are no overlapping sub-sequences with the training set.

| Method    | Parameters (M) |
|-----------|----------------|
| VIBE [22] | 21.31          |
| MEVA [28] | 58.74          |
| TCMR [9]  | 81.91          |
| Ours      | 28.14          |

Table 7. The amount of network parameters compared with the state-of-the-art methods.

8. Model Complexity

Here, we compare the model complexity of our method and previous works in Tab. 7. As we can see, we achieve the better performance as well as maintain the low complexity of network.

9. Number of Representation Dimension

To show the impact of the number of representation dimension, we conduct the ablation study and results are shown in Tab. 8. As we can see, compared with the 256-dimensional space that we adopt in our motion prior, the 128-dimensional latent space has the inferior performance. Because the expressive ability is limited. Furthermore, the 512-dimensional representation space does not significantly improve the performance. Because it is hard for the high-dimensional latent space to balance between maintaining favorable performance and following the normal distribution regularization. Therefore, we choose to construct our motion prior with the 256-dimensional latent space which provides both satisfied performance and compact representation space.

10. Implementation in Motion Infilling

In the motion infilling task, a 3D human motion sequence $X'$ with missing frames is given. Using our pretrained decoder with fixed weights, we aim to complete the missing frames by directly optimizing a zero-initialized latent variable $z_{mot}$ to generate the human motion. Then, we use the available frames in $X$ to supervise the corresponding frames in the output motion and optimize for 30 iterations with learning rate $0.2$.

11. Qualitative Results

Fig. 7 visualizes the motion randomly sampled from our motion prior. Then, in Fig. 8, we compare the visualization results with VIBE [22] on 3DPW [45] dataset, so as to show that embedding our motion prior to VIBE can improve the performance. We suggest that you can zoom in for more details. Additionally, we upload some video demo here. For fair comparison, we use the same roughly estimated camera for 2D rendering of both VIBE and our results. In Fig. 9, we visualize the predicted future motion results given $T = 15$ past frames on the Human3.6M dataset [16]. Fig. 10 illustrates the comparison between ground truth and predicted results of motion infilling. Note that, even given the known frames as the supervision, the predicted poses in the known frames may still different from the ground truth.
Figure 8. Qualitative comparison between VIBE and our method on the in-the-wild 3DPW.

Figure 9. Visualization of motion prediction results on the Human3.6M dataset. Results are shown at every 5 frames.
Figure 10. Illustration of motion infilling. We visualized six consecutive poses, with an interval of ten frames. Poses in gray mean the known frame and green ones denote the generated pose.