

Pose-Oriented Transformer with Uncertainty-Guided Refinement for 2D-to-3D Human Pose Estimation

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Abstract

There has been a recent surge of interest in introducing transformers to 3D human pose estimation (HPE) due to their powerful capabilities in modeling long-term dependencies. However, existing transformer-based methods treat body joints as equally important inputs and ignore the prior knowledge of human skeleton topology in the self-attention mechanism. To tackle this issue, in this paper, we propose a Pose-Oriented Transformer (POT) with uncertainty guided refinement for 3D HPE. Specifically, we first develop novel pose-oriented self-attention mechanism and distance-related position embedding for POT to explicitly exploit the human skeleton topology. The pose-oriented self-attention mechanism explicitly models the topological interactions between body joints, whereas the distance-related position embedding encodes the distance of joints to the root joint to distinguish groups of joints with different difficulties in regression. Furthermore, we present an Uncertainty-Guided Refinement Network (UGRN) to refine pose predictions from POT, especially for the difficult joints, by considering the estimated uncertainty of each joint with uncertainty-guided sampling strategy and self-attention mechanism. Extensive experiments demonstrate that our method significantly outperforms the state-of-the-art methods with reduced model parameters on 3D HPE benchmarks such as Human3.6M and MPI-INF-3DHP.

Introduction

3D human pose estimation (HPE) aims to obtain the 3D spatial coordinates of body joints from monocular images or videos. It has attracted extensive attention in a wide range of applications such as autonomous driving, augmented/virtual reality (AR/VR) and virtual avatar. The 2D-to-3D pipeline is prevailing in recent works (Martinez et al. 2017; Zhao et al. 2019; Cai et al. 2019; Li et al. 2021), where 2D joint coordinates are taken as the inputs to directly regress the 3D pose target. Despite its promising performance, the 2D-to-3D pipeline is restricted by depth ambiguity caused by the many-to-one mapping from multiple 3D poses to one same 2D projection.

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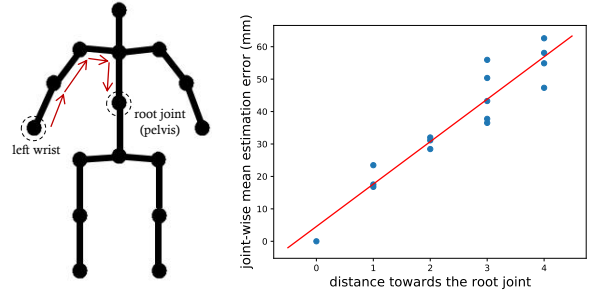


Figure 1: **Left: Human skeleton topology.** We consider the distance for each joint towards the root joint (pelvis) based on the human skeleton topology. **Right: Impact of distance towards the root joint on the joint-wise estimation error.** Based on a baseline model, we empirically find that joints far from the root joint tend to have large prediction errors. This inspires us to introduce targeted designs for these joints.

Considering that the human body can be modeled as a highly structured graph, the problem of depth ambiguity can be alleviated by exploiting the interactions between body joints. Graph convolution networks (GCNs) have been naturally adopted to exploit these interactions (Zhao et al. 2019; Cai et al. 2019; Li et al. 2021). However, GCNs are usually limited in receptive fields and impede the relationship modeling. Inspired by the success of Transformer (Vaswani et al. 2017), the self-attention mechanism is leveraged in recent works (Zheng et al. 2021; Zhu et al. 2021; Zhao, Wang, and Tian 2022; Zhang et al. 2022) to facilitate global interactions for 3D HPE and yield state-of-the-art performance. **However, these methods treat body joints as input tokens of equal importance but ignore the human body priors (e.g., human skeleton topology) in designing the self-attention mechanism.**

In this paper, we argue that introducing pose-oriented designs to the transformer is important for 3D HPE and thereby propose a Pose-Oriented Transformer (POT) for reliable pose prediction. We design a novel pose-oriented self-attention (PO-SA) mechanism for POT that is the first to ex-

explicitly exploit human skeleton topology without implicitly injecting graph convolutions. The relative distance is computed for each joints pair and is encoded as attention bias into the self-attention mechanism to enhance the ability of modeling the human skeleton dependence. Furthermore, as shown in Figure 1, we empirically find that joints far from the root joint (pelvis) tend to have large prediction errors. To better model these difficult joints, we split body joints into several groups according to their distance toward the root joint and assign additional distance-related position embeddings to different groups.

In addition to POT, a second stage of pose refinement is developed to further improve the prediction of difficult joints. Specifically, we propose a transformer-based Uncertainty-Guided Refinement Network (UGRN) for pose refinement by explicitly considering the prediction uncertainty. The proposed UGRN comprises an uncertainty-guided sampling strategy and an uncertainty-guided self-attention (UG-SA) mechanism. The uncertainty-guided sampling strategy incorporates the estimated uncertainty for each joint (that implies the difficulty of prediction) into the learning procedure. The joint coordinates are sampled around the prediction from POT following a Gaussian distribution with the estimated uncertainty as variance. Then, we use the sampled coordinates as the input of UGRN to make the model more robust to errors. Subsequently, the UG-SA is developed in UGRN to reduce the contribution of the joints with high uncertainty during learning.

This paper makes the following contributions:

- We propose a novel pose-oriented transformer for 3D HPE with the self-attention and position embedding mechanisms explicitly designed to exploit human skeleton topology.
- We present an uncertainty-guided refinement network to further improve pose predictions for difficult joints with uncertainty-guided sampling strategy and self-attention mechanism.
- We demonstrate our method achieves SOTA performance on the Human3.6M and MPI-INF-3DHP benchmarks and shed light on the task-oriented transformer design for single-frame input human pose estimation.

Related Work

3D Human Pose Estimation

The methods of 3D human pose estimation can be divided into two categories: one-stage methods and two-stage methods. The one-stage methods take RGB image as input and directly predict the 3D pose. Thanks to the development of deep learning, recent works (Zhou et al. 2017; Shi et al. 2020; Pavlakos, Zhou, and Daniilidis 2018; Moon, Chang, and Lee 2019; Lin and Lee 2020; Sun et al. 2017) can leverage the advantages of Convolutional Neural Networks (CNNs) to obtain promising results for image-to-3D human pose estimation. In which (Zhou et al. 2017) built a weakly-supervised transfer learning framework to make full use of mixed 2D and 3D labels, and augmented the 2D pose estimation sub-network with a 3D depth regression sub-network

to estimate the depth. (Pavlakos, Zhou, and Daniilidis 2018) represented the space around the human body discretely as voxel and used 3D heatmaps to regress 3D human pose. Taking the feature extracted by CNNs as input, (Lin, Wang, and Liu 2021) further proposed a graph-convolution-reinforced transformer to predict 3D pose. (Wehrbein et al. 2021) proposed a normalizing flow method that can generate a diverse set of feasible 3D poses.

The second category of methods first estimate the 2D position of human joints from the input image, and then regress the 3D pose in the camera coordinate system. Pioneering work (Martinez et al. 2017) revealed that only using 2D joints as input can also get highly accurate results, and proposed a simple yet effective baseline for 3D HPE. Since the human body can be regarded as a highly structured graph, (Zhao et al. 2019) proposed Semantic Graph Convolution (SemGConv) for 3D HPE, it added a parameter matrix to learn the semantic relations among body joints. (Zou et al. 2020) further extended SemGConv to a high-order GCN to learn long-range dependencies among body joints. Nevertheless, GCN-based methods still suffer from limited receptive field. In this work, we leverage the powerful long-term modeling capability of transformer to construct our model.

Transformer and Self-Attention Mechanism

Transformer was firstly introduced in (Vaswani et al. 2017) for the natural language processing (NLP) tasks such as machine translation, whose core component is the self-attention mechanism that can model the long-term dependence of the input sequential data. Recently, with the appearance of ViT (Dosovitskiy et al. 2020), transformer also attracted much attention in various visual tasks. In addition, (Ying et al. 2021) also generalized transformer to graph-structured data for graph-level predictions tasks including link prediction and knowledge graphs. For the 3D HPE, PoseFormer (Zheng et al. 2021) first built a transformer-based model to sequentially capture the temporal and spatial dependency of the input 2D pose sequence. PoseGTAC (Zhu et al. 2021) and Graformer (Zhao, Wang, and Tian 2022) both injected graph convolution into transformer in different ways to exploit the structure information of human skeleton topology. However, we argue that simply stacking self-attention and graph convolution can not fully utilize the human skeleton topology and propose our pose-oriented transformer to take the topology information into account in the self-attention mechanism.

Uncertainty Estimation

Uncertainty in the deep learning models can be categorized into two types: aleatoric uncertainty and epistemic uncertainty. It can be estimated by sampling-based method (Glorot and Bengio 2010) and dropout method (Gal and Ghahramani 2016). (Kendall and Gal 2017) further revealed that the heteroscedastic uncertainty dependent on the input data is vitally important for computer vision application. For example, (Song et al. 2021) considered the uncertainty of the noisy input data and proposed the uncertain graph neural networks for facial action unit detection. (Wang et al.

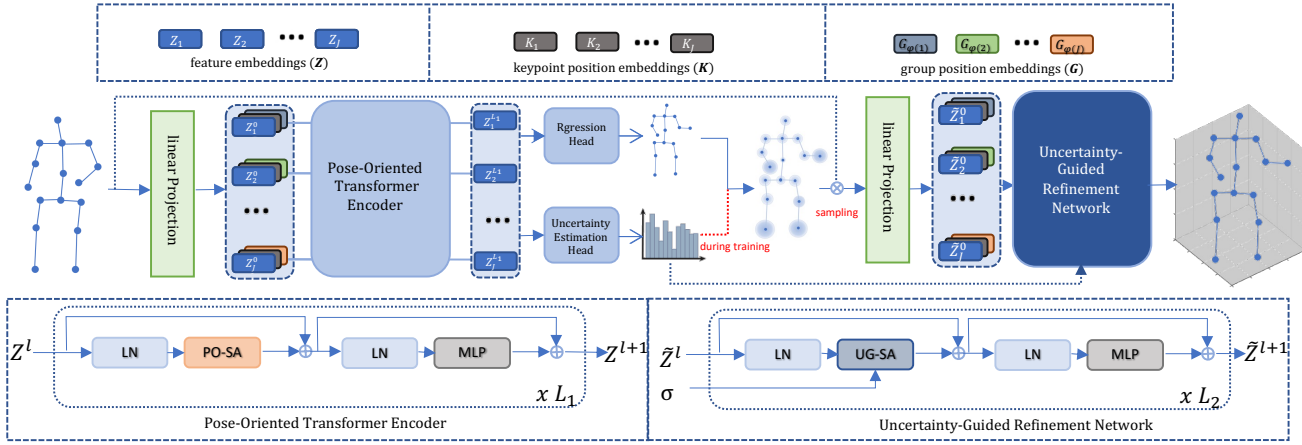


Figure 2: The overview of proposed method, which contains two major module: pose-oriented transformer (POT) and uncertainty-guided refinement network (UGRN). Given the 2D pose $X \in R^{J \times 2}$ estimated by an off-the-shelf 2D pose detector, POT with pose-oriented attention and position embedding designs are first used for pose-related feature extracting and first-stage 3D pose predicting. Then, UGRN leverage uncertainty information $\sigma \in R^{J \times 3}$ to generate refined pose $\hat{Y} \in R^{J \times 3}$.

2021) utilized the data-uncertainty as guidance to propose a multi-phase learning method for semi-supervised object detection. (Yang et al. 2021) combined the benefits of Bayesian learning and transformer-based reasoning, and built an uncertainty-guided transformer for camouflaged object detection. However, previous 2D-to-3D HPE methods did not take uncertainty information of human pose into account in the training and inference procedure. For our work, we estimate the uncertainty for each joint of first-stage 3D pose and propose our UG-sampling and UG-SA to obtain the refined 3D pose.

Method

The overview of the proposed method is depicted in Figure 2. Our method is a two-stage framework which consists of two major module: pose-oriented transformer (POT) and uncertainty-guided refinement network (UGRN). Given the 2D pose $X \in R^{J \times 2}$ estimated by an off-the-shelf 2D pose detector from an image, POT is designed by utilizing human skeleton topology for better pose-related feature extracting and first-stage 3D pose predicting, while UGRN leverages uncertainty information $\sigma \in R^{J \times 3}$ to further refine the predicting pose. Details are included in the following.

Preliminaries

In this work, we leverage transformer to model the long-distance relationship between body joints. We first briefly introduce the basic components in the transformer, including multi-head self-attention (MH-SA), position-wise feed-forward network (FFN) and position embeddings.

MH-SA The basic self-attention mechanism transfers the inputs $Z \in R^{N \times C}$ into corresponding *query* Q , *key* K and *value* V with the same dimensions $N \times C$ by projection matrices $P^Q, P^K, P^V \in R^{C \times C}$ respectively, where N denotes the sequence length, and C is the number of hidden

dimension.

$$Q = ZP^Q, \quad K = ZP^K, \quad V = ZP^V, \quad (1)$$

Then we can calculate self-attention by:

$$A = QK^T / \sqrt{d}, \quad MH-SA(X) = softmax(A)V, \quad (2)$$

where $A \in R^{N \times N}$ denotes the attention weight matrix. Based on the basic self-attention, MH-SA further splits the Q, K, V for h times to perform attention in parallel and then the outputs of all the heads are concatenated.

FFN position-wise FFN is used for non-linear feature transformation and it contains two Multilayer Perceptron (MLP) and an GELU activation layer. This procedure can be formulated as follows:

$$FFN(X) = MLP(GELU(MLP(X))) + X. \quad (3)$$

Position Embeddings As MH-SA and FFN in transformer are permutation equivariant operation, additional mechanisms are required to encode the structure of input data into model. In particular, we can utilize sine and cosine functions or learnable vectors as the position embeddings, which can be formulated as

$$P_t = PE(t) \in R^C, \quad (4)$$

where t denotes the position index.

Pose-oriented Transformer

POT aims at better utilizing the human skeleton information for feature extracting. It includes target position embedding and self-attention design for 3D HPE. Specifically, given the input 2D joints $X \in R^{J \times 2}$, we first project it into high-dimensional feature embeddings $Z \in R^{J \times C}$, where J denotes the number of human body joints and C denotes the embedding dimension. Then we add keypoint position embeddings K and our proposed group position embeddings G to Z as the input of POT encoder. In POT encoder, we also design pose-oriented self-attention (PO-SA) which takes the topological connections of body joints into consideration.

Keypoint and Group Position Embeddings Following previous design (Zheng et al. 2021; Zhang et al. 2022), we first introduce a learnable keypoint position embeddings $K \in R^{J \times C}$ to represent the absolute position of each body joint. In addition, as shown in Figure 3, according to the distance between each joint and the root joint (Pelvis), we split body joints into five groups and design another learnable embeddings called group position embeddings, *i.e.*, $G \in R^{5 \times C}$. Therefore, additional distance-related knowledge can be encoded into model, helping transformer better model the difficult body joints that are far from the root. In this way, the input of pose-oriented transformer encoder, $Z^{(0)}$, can be obtained by:

$$Z_i^{(0)} = Z_i + K_i + G_{\varphi(i)}, \text{ for } i \in [1, \dots, J], \quad (5)$$

where i is the joint index and $\varphi(i) = \mathcal{D}(i, 1)$ represents the shortest path distance between i -th joint and the root joint.

Pose-Oriented Self-Attention (PO-SA) We also propose our pose-oriented self-attention (PO-SA) that explicitly modeling the topological connections of body joints. Specifically, we compute the relative distance for each joints pair (i, j) , and encode it as the attention bias for the self-attention mechanism. In this way, we rewrite the self-attention in Eq (2), in which the (i, j) -th element of attention matrix A can be computed by:

$$A_{i,j} = (Z_i P^Q)(Z_j P^K)^T / \sqrt{d} + \Phi(\mathcal{D}(i, j)), \quad (6)$$

where Φ is a MLP network which projects the relative distance (1-dimension) to an H-dimension vector where H is the number of heads in the SA mechanism, it makes each PO-SA have the ability to adjust the desired distance-related receptive field and the additional parameters can be ignored.

POT Encoder Based on the PO-SA, we can obtain output features by sending $Z^{(0)}$ to a cascaded transformer with L_1 layers. These procedure can be formulated as :

$$Z^l = PO-SA(LN(Z^{l-1})) + Z^{l-1}, \quad (7)$$

$$Z^l = FFN(LN(Z^l)) + Z^l, \quad (8)$$

where $LN(\cdot)$ represents the layer normalization and $l \in [1, 2, \dots, L_1]$ is the index of POT encoder layers.

Regression Head In the regression head, we apply a MLP on the output feature Z^{L_1} to perform pose regression, generating the first-stage 3D pose $\tilde{Y} \in R^{J \times 3}$.

Uncertainty-guided Refinement

Taking the first-stage 3D pose \tilde{Y} from POT, we further send it together with the input 2D pose X to another Uncertainty-guided Refinement Network (UGRN) for pose refinement. The proposed UGRN contains the following components.

Uncertainty Estimation We first model the uncertainty for each joint. Specifically, features of POT encoder Z^{L_1} are sent to another uncertainty estimation head, producing the uncertainty $\sigma \in R^{J \times 3}$ of the first-stage 3D poses by using an uncertainty estimation loss \mathcal{L}_σ (Kendall and Gal 2017).

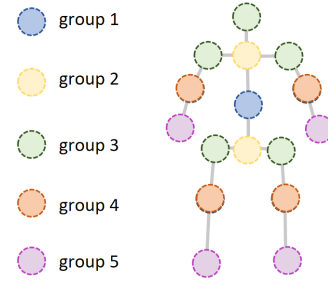


Figure 3: The depiction of distance-related group for human body joints.

Uncertainty-Guided Sampling Instead of directly utilizing the first-stage 3D predictions \tilde{Y} , we randomly sample 3D coordinates \bar{Y} around \tilde{Y} according to a Gaussian distribution $\mathcal{N}(\tilde{Y}, \sigma)$ with the predicted uncertainty σ as variance, and send the sampled coordinates to UGRN. This uncertainty-guided sampling strategy ensures that the sampled coordinates have large variance on difficult joints, which requires the model to focus more on making use of context from other joints to compensate for the difficult joint predictions, thus further enhancing the model robustness.

To enable correct back-propagation, we employ a re-parameterization trick to draw a sample ϵ from the standard Gaussian distribution $\mathcal{N}(\mathbf{0}, \mathbf{1})$ randomly, *i.e.*, $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{1})$. In this way, we can obtain the sampled 3D coordinates by:

$$\bar{Y} = \tilde{Y} + \sigma \cdot \epsilon. \quad (9)$$

Note that this sample strategy is only implemented in the training stage. In the inference stage, we set $\bar{Y} = \tilde{Y}$ directly.

Uncertainty-guided Refinement Network After obtaining the sampled 3D pose \bar{Y} , we first concatenate it with the input 2D pose X and obtain \tilde{X} , *i.e.*, $\tilde{X} = \text{Concat}(\bar{Y}, X)$. Then we project \tilde{X} to feature embeddings \tilde{Z} and equip them with keypoint position embeddings K and group position embedding G :

$$\tilde{Z}_i^{(0)} = \tilde{Z}_i + K_i + G_{\varphi(i)}, \text{ for } i \in [1, J]. \quad (10)$$

Next, $\tilde{Z}_i^{(0)}$ is sent to the following L_2 transformer layers of UGRN to perform uncertainty-guided refinement. The transform layers of UGRN is similar to those of POT, but we replace the distance-related term of Eq. 6 with uncertainty guidance to dynamically adjust the attention weights:

$$A_{i,j} = (Z_i P^Q)(Z_j P^K)^T / (\sqrt{d} \cdot \text{Sum}(\sigma_j)), \quad (11)$$

where $\sigma_j \in R^3$ is the predicted uncertainty of j -th joint. The above uncertainty-guided self-attention (UG-SA) ensures that the body joints with high uncertainty will contribute less in the self-attention mechanism, which can not only alleviate the error propagation, but also enhance the context understanding ability of the model.

Finally, we apply another regression head to \tilde{Z}^{L_2} and generate our second-stage refined 3D pose $\hat{Y} \in R^{J \times 3}$.

Table 1: Quantitative evaluation results using MPJPE in millimeter on Human3.6M . No rigid alignment or transform is applied in post-processing. We split this table into 2 groups. The inputs for the top group methods are the detection 2D pose, SH denotes the 2D pose detected by Stacked Hourglass network (Newell, Yang, and Deng 2016), and CPN denotes the cascaded pyramid network (Chen et al. 2018). The inputs for the bottom group are ground truth (GT) of 2D pose. Best results are showed in bold.

Methods	Dire.	Disc.	Eat	Greet	Phone	Photo	Pose	Puch.	Sit	SitD.	Smoke	Wait	WalkD	Walk	WalkT	Avg.
(Martinez et al. 2017) (SH)	51.8	56.2	58.1	59.0	69.5	78.4	55.2	58.1	74.0	94.6	62.3	59.1	65.1	49.5	52.4	62.9
(Zhao et al. 2019) (SH)	48.2	60.8	51.8	64.0	64.6	53.6	51.1	67.4	88.7	57.7	73.2	65.6	48.9	64.8	51.9	60.8
(Liu et al. 2020) (CPN)	46.3	52.2	47.3	50.7	55.5	67.1	49.2	46.0	60.4	71.1	51.5	50.1	54.5	40.3	43.7	52.4
(Zou et al. 2020)(CPN)	49.0	54.5	52.3	53.6	59.2	71.6	49.6	49.8	66.0	75.5	55.1	53.8	58.5	40.9	45.4	55.6
(Xu and Takano 2021)(CPN)	45.2	49.9	47.5	50.9	54.9	66.1	48.5	46.3	59.7	71.5	51.4	48.6	53.9	39.9	44.1	51.9
Ours (CPN)	47.9	50.0	47.1	51.3	51.2	59.5	48.7	46.9	56.0	61.9	51.1	48.9	54.3	40.0	42.9	50.5
(Martinez et al. 2017) (GT)	37.7	44.4	40.3	42.1	48.2	54.9	44.4	42.1	54.6	58.0	45.1	46.4	47.6	36.4	40.4	45.5
(Zhao et al. 2019) (GT)	37.8	49.4	37.6	40.9	45.1	41.4	40.1	48.3	50.1	42.2	53.5	44.3	40.5	47.3	39.0	43.8
(Liu et al. 2020) (GT)	36.8	40.3	33.0	36.3	37.5	45.0	39.7	34.9	40.3	47.7	37.4	38.5	38.6	29.6	32.0	37.8
(Xu and Takano 2021) (GT)	35.8	38.1	31.0	35.3	35.8	43.2	37.3	31.7	38.4	45.5	35.4	36.7	36.8	27.9	30.7	35.8
(Zhao, Wang, and Tian 2022) (GT)	32.0	38.0	30.4	34.4	34.7	43.3	35.2	31.4	38.0	46.2	34.2	35.7	36.1	27.4	30.6	35.2
Ours (GT)	32.9	38.3	28.3	33.8	34.9	38.7	37.2	30.7	34.5	39.7	33.9	34.7	34.3	26.1	28.9	33.8

Table 2: Results on the test set of MPI-INF-3DHP (Mehta et al. 2017) by scene. The results are shown in PCK and AUC.

Methods	Training data	GS	noGS	Outdoor	ALL (PCK \uparrow)	ALL (AUC \uparrow)
(Martinez et al. 2017)	H36M	49.8	42.5	31.2	42.5	17.0
(Mehta et al. 2017)	H36M	70.8	62.3	58.8	64.7	31.7
(Yang et al. 2018)	H36M+MPII	-	-	-	69.0	32.0
(Zhou et al. 2017)	H36M+MPII	71.1	64.7	72.7	69.2	32.5
(Luo, Chu, and Yuille 2020)	H36M	71.3	59.4	65.7	65.6	33.2
(Ci et al. 2019)	H36M	74.8	70.8	77.3	74.0	36.7
(Zhou et al. 2019)	H36M+MPII	75.6	71.3	80.3	75.3	38.0
(Xu and Takano 2021)	H36M	81.5	81.7	75.2	80.1	45.8
(Zhao, Wang, and Tian 2022)	H36M	80.1	77.9	74.1	79.0	43.8
Ours	H36M	86.2	84.7	81.9	84.1	53.7

Loss Function

Stage I We first train our POT for the first-stage 3D pose regressing. The objective function can be formulated as :

$$\mathcal{L}_{\text{stageI}} = \frac{1}{J} \sum_{i=1}^J \left(\left\| \tilde{Y}_i - Y_i \right\|^2 \right), \quad (12)$$

where \tilde{Y}_i and Y_i are the estimated first-stage 3D positions and the ground truth of i -th joint respectively.

Stage II We aim to predict the uncertainty correctly as well as estimate an accurate refined 3D pose in Stage II. During this stage, we freeze the model parameters of POT and only train the UGRN for stable results. Following (Kendall and Gal 2017), we set our uncertainty estimation loss as:

$$\mathcal{L}_{\sigma} = \frac{1}{J} \sum_{i=1}^J \left(\left\| \frac{\tilde{Y}_i - Y_i}{\sigma_i} \right\|^2 + \log(\|\sigma_i\|^2) \right). \quad (13)$$

In addition, we also apply L2 loss to minimize the errors between the refined 3D poses and ground truths:

$$\mathcal{L}_{\text{refine}} = \frac{1}{J} \sum_{i=1}^J \left(\left\| \hat{Y}_i - Y_i \right\|^2 \right), \quad (14)$$

The final loss function of Stage II is computed by $\mathcal{L}_{\text{stageII}} = \mathcal{L}_{\text{refine}} + \lambda \mathcal{L}_{\sigma}$, where λ is the trade-off factor. We set λ to 0.001 such that the two loss terms are of the same order of magnitude.

Experiments

Experimental Setups

Dataset Human3.6M dataset (Ionescu et al. 2013) is widely used in the 3D HPE task which provides 3.6 million indoor RGB images, including 11 subjects actors performing 15 different actions. For fairness, we follow previous works (Martinez et al. 2017; Zhao et al. 2019; Xu and Takano 2021) and take 5 subjects (S1, S5, S6, S7, S8) for training and the other 2 subjects (S9, S11) for testing. In our work, We evaluate our proposed method and conduct ablation study on the Human3.6M dataset. Besides, the MPI-INF-3DHP (Mehta et al. 2017) test set provides images in three different scenarios: studio with a green screen (GS), studio without green screen (noGS) and outdoor scene (Outdoor). We also apply our method to it to demonstrate the generalization capabilities of our proposed method.

Evaluation metrics For Human3.6M, we follow previous works (Martinez et al. 2017; Zhao et al. 2019) to use the

Table 3: Ablation Study on different pose-oriented design in the pose-oriented transformer.

position embeddings		PO-SA	MPJPE(mm)	#Param
keypoint	group			
✓			37.57	0.97M
✓	✓		36.69	0.97M
✓		✓	36.43	0.98M
✓	✓	✓	35.59	0.98M

Table 4: Ablation Study on Uncertainty-Guided Refinement.

Method	MPJPE(mm)	#Param
POT	35.59	0.79M
POT+UGRN	34.72	0.98M
POT+UGRN+UG-Sampling	33.82	0.98M

mean per-joint position error (MPJPE) as evaluation metric. MPJPE computes the per-joints mean Euclidean distance between the predicted 3D joints and the ground truth after the origin (pelvis) alignment. For MPI-INF-3DHP, we employ 3D-PCK and AUC as evaluation metrics.

Implement details In our experiment, we set the dimension of embeddings to 96 and adopts 6 heads for self-attention with a dropout rate of 0.25. The MLP ratio of FFN is set to 1.5 to reduce the model parameters. We implement our method within the PyTorch framework. During the training stage, we adopt the Adam (Kingma and Ba 2014) optimizer. For both Stage I and Stage II, the learning rate is initialized to 0.001 and decayed by 0.96 per 4 epochs, and we train each stage for 25 epochs using a mini-batch size of 256. We initialize weights of the our model using the initialization method described in (Glorot and Bengio 2010). We also adopt Max-norm regularization to avoid overfitting.

Comparison With the State-of-the-Art

The performance compared with the state-of-the-art are shown in Table 1. In the top group, following the setting of previous works (Pavlo et al. 2019; Zhou et al. 2017; Cai et al. 2019), We use the cascaded pyramid network (CPN) (Chen et al. 2018) as 2D pose detector to obtain 2D joints for benchmark evaluation. In the bottom group, we take the ground truth (GT) 2D pose as input to predict the 3D human pose. It can be seen that, our method outperforms all other methods with both GT and detected 2D pose as input, demonstrating the effectiveness of our method.

Generalization Ability

We further apply our model to MPI-INF-3DHP to test the generalization abilities. As shown in Table 2, our model achieves 84.1 in PCK and 53.7 in AUC while only using Human3.6M dataset for training, which outperforms all the previous SOTA by a large margin. These results verify the strong generalization capability of our method.

Ablation Study and Discussion

We conduct a series of ablation studies to better understand how each component affects the performance. The 2D

Table 5: Ablation study on UG-SA

Method	MPJPE(mm)	#Param
POT+UGRN (MH-SA)	35.22	0.98M
POT+UGRN (PO-SA)	35.07	0.98M
POT+UGRN (UG-SA)	34.72	0.98M

Table 6: Ablations on different parameters of POT and UGRN. L_1 and L_2 are the number of layers of POT encoder and UGRN, respectively. C is the embedding dimension.

L_1	L_2	C	MPJPE(mm)	#Param
4	1	96	37.08	0.33M
8	2	96	35.20	0.66M
12	3	96	33.82	0.98M
16	4	96	34.47	1.31M
12	3	48	34.20	0.25M
12	3	96	33.82	0.98M
12	3	144	34.68	2.20M

Table 7: Comparison on model complexity.

Method	MPJPE(mm)	#Param
Pre-Aggr (Liu et al. 2020)	37.80	4.22M
Graph SH (Xu and Takano 2021)	35.80	3.70M
Modulated GCN (Zou and Tang 2021)	37.43	1.10M
Graformer (Zhao, Wang, and Tian 2022)	35.20	0.62M
Our-S	34.20	0.25M
Our-L	33.82	0.98M

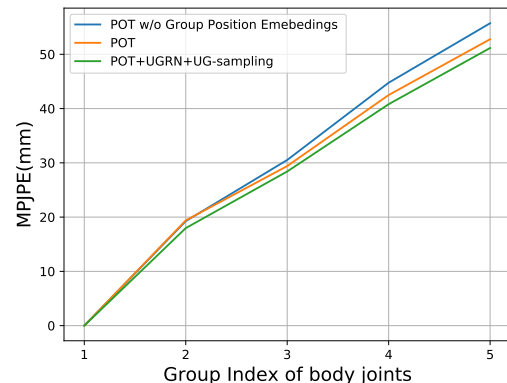


Figure 4: Analysis on difficult joints. Our proposed group position embeddings and uncertainty-guided refinement mainly benefit the difficult joints in group 4 and 5.

ground truth (GT) is taken as input in the ablation.

Effect on different pose-oriented design We first diagnose how each pose-oriented design in the POT affects the performance. In this section, the UGRN is excluded and the first stage 3D pose \tilde{Y} is used for evaluated. As shown in Table 3, our method achieves the best performance when all the pose-oriented designs are included. Compared with only using keypoint position embeddings, we achieve 0.88mm (37.57mm to 36.69mm) improvement by adding the

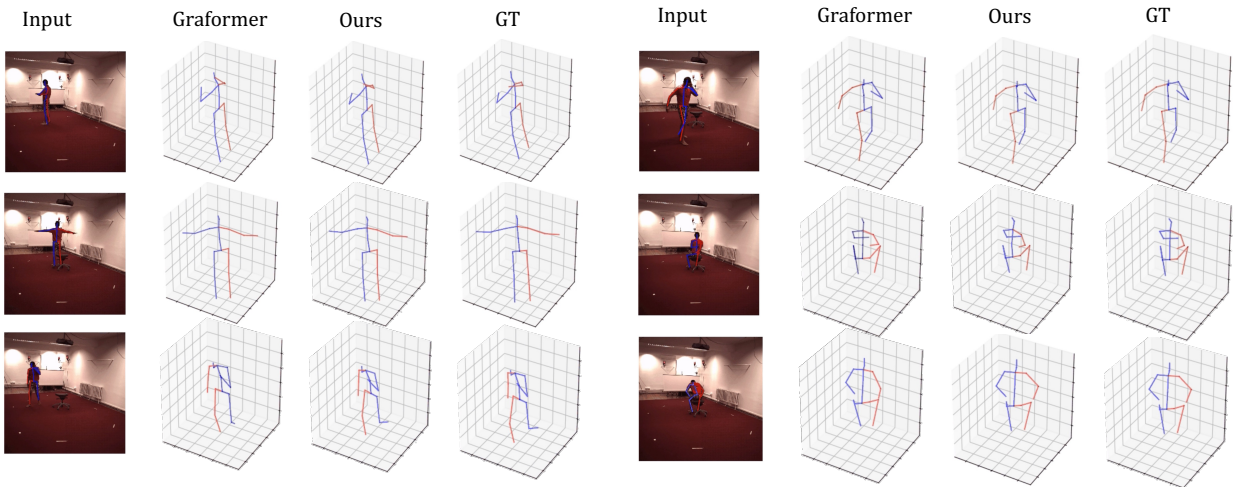


Figure 5: Qualitative results on Human3.6M.

distance-related group position embeddings, proving that the representation of difficult joints is effectively facilitated. In addition, by replacing the standard self-attention with our PO-SA, we also achieve 1.10mm (36.69mm to 35.59mm) improvement with only 0.01M model parameters increase, which reflects the benefits of enhancing the ability of modeling the topological interactions.

Effect on uncertainty-guided refinement We then inspect how uncertainty-guided refinement benefits performance. It can be seen from Table 4 that our first-stage prediction obtained directly by POT can achieve 35.59 mm in MPJPE, while adding UGRN for refinement can bring 0.83mm (35.59mm to 34.72mm) performance improvement, and UG-sampling can facilitate the learning procedure and further bring 0.9 mm (34.72mm to 33.82mm) gains. To demonstrate that the performance improvement is not brought by the increased model parameters, we also test other refinement model design using other kinds of self-attention, and the results are shown in Table 5. When we replacing UG-RA with standard MH-SA, the performance degrades from 34.72mm to 35.22mm. In addition, when using the proposed PO-SA in the UGRN, the performance also degrades (34.72mm to 35.07mm), which reflects that the uncertainty-related information is more important than distance-related information in the second refinement stage.

Comparison on different parameters in POT and UGRN Table 6 reports how different parameters impact the performance and the complexity of our model. The results show that, enlarging the embedding dimension from 48 to 96 can boost the performance, but using dimensions larger than 96 cannot bring further benefits. In addition, we observe the best performance when using 12 and 3 transformer layers in POT encoder and UGRN, respectively, and no more gains can be obtained by stacking more layers. Therefore, we set the basic setting to $L_1 = 12$, $L_2 = 3$, and $C = 96$.

Comparison on model complexity In Table 7, We compare both the accuracy and the model complexity with other

benchmarks on the Human3.6M dataset. We provide two configurations of our method, in which the embedding dimension of Our-S is 48 while that of Our-L is set to 96. Results show that our method can achieve better results with even much fewer parameters.

Understanding the performance improvement In Figure 4, we present the average estimation errors of different body joints according to its group index. It can be seen that, both our group position embedding and UGRN bring more performance improvement for group 4 and 5, in which joints are far from the root joint. The results confirm that our benefit mainly comes from the difficult joints.

Qualitative results Figure 5 demonstrates some qualitative results on the Human3.6M dataset compared with Graformer (Zhao, Wang, and Tian 2022). It can be seen that our method can make accurate pose prediction, especially for the difficult joints that are far from the root.

Conclusion

In this paper, we proposed a two-stage transformer-based framework for 3D HPE. First, we introduce targeted improvements for the basic components of transformers and fabricate Pose-Oriented Transformer (POT). Specifically, we design a novel self-attention mechanism in which the topological connections of body joints can be well considered. We also split body joints into several groups according to their distance toward the root joint and provide additional learnable distance-related position embedding for each group. Then, the second stage Uncertainty-Guided Refinement Network (UGRN) is introduced to further refine pose predictions, by considering the estimated uncertainty of each joint with uncertainty-guided sampling strategy and self-attention mechanism. Extensive results on Human3.6M and MPI-INF-3DHP reveal the benefits of our design.

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