COPILoT: Human Collision Prediction and Localization from Multi-view Egocentric Videos

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https://sites.google.com/stanford.edu/copilot

Abstract—To produce safe human motions, assistive wearable exoskeletons must be equipped with a perception system that enables anticipating potential collisions from egocentric observations. However, previous approaches to exoskeleton perception greatly simplify the problem to specific types of environments, limiting their scalability. In this paper, we propose the challenging and novel problem of predicting human-scene collisions for diverse environments from multi-view egocentric RGB videos captured from an exoskeleton. By classifying which body joints will collide with the environment and predicting a collision region heatmap that localizes potential collisions in the environment, we aim to develop an exoskeleton perception system that generalizes to complex real-world scenes and provides actionable outputs for downstream control. We propose COPILOT, a video transformer-based model that performs both collision prediction and localization simultaneously, leveraging multi-view video inputs via a proposed joint space-time-viewpoint attention operation. To train and evaluate the model, we build a synthetic data generation framework to simulate virtual humans moving in photo-realistic 3D environments. This framework is then used to establish a dataset consisting of 8.6M egocentric RGBD frames to enable future work on the problem. Extensive experiments suggest that our model achieves promising performance and generalizes to unseen scenes as well as real world. We apply COPILOT to a downstream collision avoidance task, and successfully reduce collision cases by 29\% on unseen scenes using a simple closed-loop control algorithm.

I. INTRODUCTION

The ability to predict if and where a person may collide with their surroundings from egocentric observations is crucial for assistive wearable exoskeletons [1]–[6]. The exoskeleton must anticipate the actions of its user and react to adjust the human motion to avoid collisions, which may cause falls and injuries to the person. Moreover, to effectively operate in the real world, this collision prediction capability must generalize to diverse and complex real-world environments. Though existing works develop various perceptual capabilities for exoskeletons such as environment classification [1] or obstacle parameter recognition [4], they assume simplified and specific environments and do not explicitly predict collisions, limiting their real-world applicability.

In this work, we aim to equip the exoskeleton with visual perception capabilities that can handle varied and complicated real-world environments, while also providing actionable information for downstream control. To this end, we propose the novel problem depicted in Fig. 1: given multi-view egocentric RGB videos, we aim to classify which body joints will collide in the near future and localize regions in the scene where these collisions are likely to occur. In principle, the ability to predict per-joint collisions along with potential collision locations enables fine-grained downstream control to avoid collisions while being minimally disruptive to the user. To enable such detailed prediction, input videos are captured from cameras mounted to several human body joints, which provide a holistic multi-view context of the human motion and surroundings. Our hardware setup follows that of Chiu et al. [7] with additional visual sensors for full-body collision prediction.

This problem poses significant technical challenges. To predict future collisions and identify collision regions, it is necessary to accurately reason about the user’s body movement and intent along with the surrounding environment geometry. This is especially challenging from egocentric observations: the user’s past body pose is only provided partially and implicitly through videos from cameras mounted on a subset of joints, and it is not trivial to merge visual information from all available camera streams to extract useful features that capture the motion or environment.

To address these challenges, we propose COPILOT, a COllision Predction and LOcalization Transformer that tackles the problem using 4D attention across space-time-viewpoint to leverage information from multi-view video inputs. Our system tackles the collision prediction problem in a multi-task fashion, which is motivated by the key observation that identifying collision regions in an environment helps infer potential collisions on the body. Specifically, we jointly classify collisions and infer collision region maps, which not only improves performance on collision prediction, but also yields actionable information for early collision avoidance. Experiments show our proposed method gives promising results, achieving over 85\% collision prediction accuracy when testing on unseen scenes after training. Moreover, we demonstrate the utility of collision prediction and localization on downstream control through a closed-loop controller that adjusts human motion based on model predictions. In this way, the controller is able to avoid 35\% and 29\% of collision cases on training and unseen scenes, respectively.

To train and evaluate our perception system, we develop a data pipeline that uses simulation [8], [9] to provide large scene diversity, realistic human motion, and accurate
collision checking. We use a pre-trained human motion generation model [10] within 100 large-scale photo-realistic houses [11], [12] to build a dataset containing ~8.6M egocentric RGBD frames with automatically annotated collision labels and heatmaps. This large-scale dataset, along with our proposed approach, establishes a high-quality baseline for further research on this problem.

In summary, we contribute (1) a novel problem formulation for egocentric collision prediction and localization, which provides detailed and actionable information for downstream exoskeleton applications; (2) a multi-view and multi-task video transformer-based model to perform collision prediction and localization simultaneously; (3) a synthetic data pipeline with a large-scale dataset for training and evaluation; and (4) extensive experiments that demonstrate our proposed method’s ability to accurately predict and localize collisions, along with an application in collision avoidance assistance through closed-loop control. We plan to make the dataset and all code publicly available.

II. RELATED WORK

Environment perception for exoskeletons. Classical works on exoskeletons mainly rely on locomotion mode transition detection from mechanical measurements, electromyography (EMG) signals, or inertial measurement units (IMU) [13]–[15]. However, these systems ignore the perception of the surrounding environment. More recent works add in perception modules to provide collision avoidance assistance. Several works [1], [16], [17] classify the environment into a small set of cases from egocentric RGB images, while another thread of works rely on a depth sensor to either classify environments [2], [3] or recognize obstacle parameters [4], [5]. These works are limited when deployed in the real world because they assume a simplified environment with either pre-defined scene types or obstacle shapes. Our problem of collision prediction and localization is more general and the proposed transformer model generalizes to complicated scenes with arbitrary obstacle layouts.

Motion prediction for exoskeletons. Another important task for exoskeletons is to predict the motion and intent of the user. Different input modalities have been used to represent motion or intent such as EMG and zero moment point (ZMP) signals [18], eye gaze [19], and optical flow [6]. Prior work has predicted motion classes [18] or joint angles [6], [19]. In this paper, we do not predict motion explicitly but implicitly through future collision prediction and localization.

Affordance prediction as heatmaps. Spatial heatmaps allow for interpretable predictions of affordances that are easy to use in downstream applications. Past works identify various affordances using this idea, such as functional affordances for objects [20]–[22] or scenes [23], risky regions of accidents [24], and important areas in events [25]. In our work, we introduce a novel form of affordance: regions of a scene that are likely to cause collisions. Expressing collision regions as 2D egocentric heatmaps allows them to be directly used by control policies.

General video understanding. Spatio-temporal reasoning is one of the main topics for video understanding. Earlier approaches try to construct hierarchical spatio-temporal understanding by performing 3D convolutions [26]–[31]. More recently, with the success of transformers [32] in the image domain [33], several works have extended the transformer architecture to the video domain. Similar to ViT [33], TimeSformer [34] divides video frames into patches and proposes several strategies to perform spatio-temporal self-attention. MViT [35] learns a hierarchy of features with progressive channel depth and shrinking spatial dimensions. TimeSformer [34] demonstrates strong performance on capturing spatio-temporal patterns in video data, but is only able to handle a single video stream. We further extend it to perform 4D attention over the space-time-viewpoint domain, and use it as our backbone model.

III. PROBLEM FORMULATION AND DATA GENERATION

A. Collision Prediction and Localization Problem Definition

To carry out effective collision avoidance assistance, the exoskeleton must first know if there will be a collision between the person and environment to decide if an intervention is necessary. Second, it must know where a collision will occur, both on the human and in the scene, to decide how to intervene to avoid a collision. Given multi-view egocentric videos, we formulate the problem of (1) classifying if a collision will happen in the near future, (2) pinpointing the body joints involved in the collision, and (3) localizing the
collision region in the scene. Unlike prior works that generally investigate exoskeletons for lower limbs only [1–6, 13–19], we widen our problem scope to full-body collision prediction to allow for collision avoidance assistance for all body joints. Hence, we equip cameras to multiple body joints which gives multi-view inputs that comprehensively capture the full-body motion and environment context. To be more generally applicable, we do not assume access to camera extrinsics or intrinsics, but rather rely solely on visual input.

More formally, given a set of multi-view time-synchronized egocentric RGB videos \(X = \{X_1, X_2, \ldots, X_V\}\) captured from \(V\) viewpoints where each \(X_v = \{x_v^1, x_v^2, \ldots, x_v^T\}\) consists of a history of \(T\) frames, our goal is to predict:

1) An overall binary prediction \(y_{\text{col}}\) of whether any collision will happen in the next \(H\) (prediction horizon) time steps. This determines whether an exoskeleton should intervene;

2) For each body joint \(j \in J\), a per-joint binary prediction \(y_{j,\text{col}}\) of whether joint \(j\) will be involved in a collision. Note that \(J \neq V\) because it is hard to attach cameras to some joints (e.g. elbows). Therefore, we must predict collisions for joints that do not have mounted cameras. This indicates where to intervene;

3) A set of per-frame collision region heatmaps \(y_{\text{map}} = \{P_1, P_2, \ldots, P_V\}\) corresponding to the input videos, where \(P_v = \{p_v^1, p_v^2, \ldots, p_v^T\}\) is the heatmap sequence corresponding to \(X_v\). The sum of all values in one heatmap \(\sum_{ij} p_{ij}^v = 1\), so that \(p_{ij}^v\) is a probability distribution over all spatial locations in that frame. This indicates the likelihood that a collision may occur at each location. This tells the exoskeleton how to intervene. Importantly, in practice, \(y_{j,\text{col}}\) and \(y_{\text{map}}\) are not used unless \(y_{\text{col}}\) is true, which indicates a collision is close and an intervention should be made. Besides, although the above formulation specifies RGB inputs, the problem, along with our model detailed later, is agnostic to the input modality (i.e. RGB or depth). If available, depth can be easily leveraged, and we present results using depth in Sec. V-A. We choose RGB as our primary setting as it is a more practical setup that avoids potentially cumbersome depth cameras.

B. Large-Scale Data Generation

To facilitate the study of egocentric collision prediction, we require a large and high-quality dataset for training and evaluating models. Due to the anomalous nature of collision events, it is unclear how to collect real-world data for this purpose, let alone the required fine-grained supervision for collision regions and colliding joints. Hence, we build a pipeline that leverages a simulated environment to generate a large-scale high-quality synthetic dataset containing \(\sim 8.6\)M egocentric RGBD frames with automatically annotated collision labels and heatmaps.

Our data pipeline places virtual humans in synthetic scenes and renders egocentric videos as they perform realistic motions. To get a diverse set of environments, we pick 100 scenes from the Matterport3D [11] and Gibson [12] datasets, with each scene containing several rooms. We leverage HuMoR [10] to randomly generate sequences of realistic walking motions within each scene using the SMPL human body model [36]. During sequence rollout, we perform collision checking between the human and scene meshes to get the overall collision label \(y_{\text{col}}\). We then assign each colliding vertex to the closest one of 10 human body joints (head, torso, elbows, hands, legs, and feet), which results in a set of per-joint collision labels \(y_{j,\text{col}}\). Collision checking is efficiently implemented using PyBullet [37] by segmenting the body into convex parts; when a collision is detected, the sequence is terminated.

For each generated sequence, we slide a window at 1 sec step size, and save the first 1 sec of observations as the past (i.e. model input) with its corresponding collision annotations, if a collision occurs within the next 1 sec (i.e. \(H = 30\), at 30 fps). Otherwise, this window is marked as non-colliding. We found empirically (see Sec. V-C) that 1 sec is often enough to intervene and avoid collisions given the slow moving speed of humans. Past observations are rendered from egocentric viewpoints with the AI-habitat simulator [8], [9] by placing cameras at 6 body joints (head, pelvis, wrists, and knees) as shown in Fig. 1. Finally, collision region heatmaps \(y_{\text{map}}\) are annotated for each sequence with a future collision by projecting the collision vertices to each egocentric viewpoint, setting these pixels to 1 and others to 0, and applying a Gaussian kernel to smooth the heatmap before normalizing it to a proper distribution.

IV. COLLISION PREDICTION AND LOCALIZATION TRANSFORMER

We propose COPILOT to jointly solve collision prediction and collision region localization. Since these tasks are deeply connected and all require learning useful features of motion and environment geometry, it makes sense to learn them together, which we confirm experimentally in Sec. V-A. As shown in Fig. 2, the architecture consists of a backbone and two subsequent branches. The backbone transformer first performs 4D attention over space, time, and viewpoint across all video streams. Then the upper branch up-samples features to produce collision region heatmaps for each viewpoint, while the lower branch pools features globally to make the overall and per-joint collision predictions. The details of each component are described next.

A. Video Transformer Backbone

Our backbone is based on TimeSformer [34], which was originally introduced to process a single video. Here we describe the key differences to TimeSformer, and refer the reader to the original paper for full details. The model first splits each frame spatially into an \(H \times W\) grid of non-overlapping patches, which are then passed through a sequence of space-time-viewpoint attention blocks. Each block encodes the patches to query, key, and value vectors and performs space-time-viewpoint self-attention. In particular, we extend the joint space-time attention [34] to handle the multi-view inputs: for each patch, the model first attends to all patches across different viewpoints at the same time step
Fig. 2. **COPILOT** architecture. Videos taken from different viewpoints are fed into a backbone model, from which we obtain a set of feature maps after 4D space-time-viewpoint attention. The upper branch gradually up-samples the features to the original image resolution via the up-sampling module, which are then used to generate the collision region heatmaps. The lower branch pools the features globally to predict the overall and joint-level collisions.

(i.e. cross-view attention), then attends to all patches within the same viewpoint (i.e. spatio-temporal attention).

The output of the backbone is a sequence of discretized feature tokens $F = \{ f_1, f_2, \ldots, f_{HWTV} \}$, where $H = W = 14$ is the spatial dimension of a discretized feature map. Note that we discard the class embedding token pre-pended to each sequence [34] and only use the feature maps where each feature $f$ has a dimension of $D = 768$.

**B. Collision Region Localization**

The first branch takes in the feature grid from the backbone and is responsible for predicting per-frame spatial heatmaps corresponding to the input videos. High values in the heatmap correspond to a viewed region of the scene where there is likely to be a collision in the near future. Inferring spatial collision heatmaps requires per-pixel predictions, so this branch of the model must up-sample the discretized feature maps back to the original image resolution. Inspired by the scheme introduced in FPN [38], we use a sequence of up-sampling modules, each doing $2 \times$ nearest-neighbor up-sampling followed by a $3 \times 3$ convolution, GroupNorm layer, and ReLU activation. Different from FPN, the feature dimension is reduced by half in each spatial up-sampling to avoid an excessive memory footprint. Following up-sampling, we use a one-layer multi-layer perceptron (MLP) to project the feature dimension at each pixel down to 1. And finally, similar to Demo2Vec [20], we apply a **softmax** function over each frame, such that each heatmap is a proper distribution representing collision probability, namely

$$\hat{y}_{\text{map}}^v = \text{softmax}(\text{MLP}(\text{up}(F_v))) \in [0, 1]^{H \times W \times T}$$  \hspace{1cm} (1)

where $F_v$ is the $v$-th slice of $F$ on the viewpoint dimension.

**C. Overall and Per-Joint Collision Prediction**

Given the features $F$ from the backbone, the second branch predicts (1) an **overall** binary classification of whether any part of the human will collide within the next $H$ timesteps, and (2) a **per-joint** binary classification of whether each joint will collide. Features are first pooled globally using average-pooling across space-time-viewpoint to get a condensed feature vector. Then, this feature vector is fed to an MLP to produce the final overall and per-joint collision predictions. This architecture can be summarized as:

$$\hat{y}_{\text{joint}}^j, \hat{y}_{\text{col}} = \text{sigmoid}(\text{MLP}(\text{pool}(F))) \in [0, 1]^{J+1}$$  \hspace{1cm} (2)

where the first $J$ outputs from the MLP are used for joint collision prediction $\hat{y}_{\text{joint}}^j$ while the last value is used for overall collision prediction $\hat{y}_{\text{col}}$.

**D. Training**

The model is trained in a fully-supervised manner using the synthetic dataset described in Sec. III-B. Collision heatmap prediction is supervised using the KL divergence between the predicted collision heatmap and the ground-truth as $L_{\text{map}} = D_{\text{KL}}(\hat{y}_{\text{map}}^v || y_{\text{map}}^v)$. For overall collision prediction, we compute a binary cross-entropy loss (BCE) with the overall collision label as $L_{\text{col}} = \text{BCE}(\hat{y}_{\text{col}}, y_{\text{col}})$. Similarly, for per-joint collision prediction we sum over all $J$ joints as $L_{\text{joint}} = \sum_{j=1}^J \text{BCE}(\hat{y}_{\text{joint}}^j, y_{\text{joint}}^j)$. Then the final loss is the weighted summation of these losses:

$$L = \lambda_{\text{map}} L_{\text{map}} + \lambda_{\text{col}} L_{\text{col}} + \lambda_{\text{joint}} L_{\text{joint}}$$  \hspace{1cm} (3)

Throughout our experiments, $\lambda_{\text{map}} = \lambda_{\text{col}} = \lambda_{\text{joint}} = 1$. 


V. Experimental Results

We evaluate COPILOT on overall and per-joint collision prediction (Sec. V-A) along with collision region localization (Sec. V-B). Additionally, we show proof-of-concept collision avoidance assistance using the model’s predictions (Sec. V-C), and evaluate how well our model generalizes to real-world data, after training on synthetic data (Sec. V-D). We strongly encourage the reader to check the accompanying video and webpage for additional visualizations and analysis.

A. Overall and Per-Joint Collision Prediction

The overall and per-joint collision outputs of COPILOT are quantitatively evaluated on held-out sequences from the synthetic dataset described in Sec. III-B. Results for multiple variations of the method are reported in Tab. I for sequences containing novel human motions in training scenes (Unseen Motions) and for new motions in 5 unseen scenes (Unseen Motions & Scenes). COPILOT No Map does not predict the collision region while Root-Only uses the input video from the root joint (pelvis) instead of all input views. We then compare to two other ways of leveraging multi-view inputs. ST-Attn only performs attention over space-time and concatenates features from all viewpoints (same as No Map). Divided extends divided attention [34] (instead of joint attention) by attending only to patches at the same spatial location across viewpoint and time, followed by a spatial self-attention across its own frame. We also compare to vanilla TimeSformer [34], which operates on a single view and does not predict collision heatmaps. Our evaluation metrics include binary classification accuracy (Col) for overall collision prediction, and for per-joint classification we report precision (Prec), recall (Rec), and F1-score (F1).

Collision localization improves prediction. Training our model with the auxiliary task of collision region localization improves prediction performance on both overall and per-joint collisions. This holds across all input variations, which supports our intuition that learning to spatially localize collisions helps extract features useful for collision prediction. **Multiple viewpoints are better than single-view.** Using input observations from all viewpoints performs better than using the root video by itself. This is true with or without collision map prediction. This supports the proposed problem formulation that uses all input viewpoints to adequately capture the whole-body movement and environment context.

**Depth improves accuracy.** As noted before, depth can be easily used, if available, by only changing the input layer. We observe that using depth as input, rather than RGB, improves performance both with and without collision region learning. This is expected because depth provides direct information on scene proximity, which is essential for our task. **Joint 4D attention best leverages multi-view inputs.** Our joint space-time-viewpoint attention performs significantly better than the other two ways of fusing multi-view inputs. This makes sense as the joint attention has a larger window of attention compared to divided attention, and fuses cross-view information at an earlier stage compared to ST-Attn.

B. Collision Region Localization

Multiple predicted collision region heatmaps are visualized in Fig. 3. In Fig. 3(a), we use the COPILOT Root-only RGB model to infer the collision region heatmaps on two sequences. We compare to the TimeSformer baseline, which does not predict a heatmap; to get a proxy for a collision heatmap in this case, we visualize the model’s spatial attention map using Attention Rollout [39]. We observe that COPILOT predicts concentrated heatmaps around reasonable risky regions. Moreover, the model is accounting for the motion of the human: in Scene 2, the left side of the oven is closer to the person but only the right side is highlighted since the person moves in that direction.

In Fig. 3(b), the same timestep is visualized from multiple viewpoints along with the collision region localization from the full COPILOT RGB model. The localization is consistent across viewpoints, suggesting the model has learned a useful representation of the surrounding environment that enables spatial correspondence of the same region across viewpoints.

C. Collision Avoidance Assistance using COPILOT

Next, we show that our model’s predictions are useful for downstream control tasks by providing collision avoidance assistance to a virtual human in a simulated environment. Our control experiment setup follows that of a hip exoskeleton emulator with actuation to adjust foot placement and center-of-mass states [7]. We approximate center-of-mass as the root joint and directly control its orientation. We leave more fine-grained controller design as future work. Given the past 1 sec of video observations, COPILOT Root-Only predicts if there will be a collision in the next 1 sec. Based on the aggregated probabilities in the left and right halves of the predicted

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| Method              | Inputs Views | Modality | Output Col Map? | Unseen Motions | Unseen Motions & Scenes |
|---------------------|--------------|----------|-----------------|----------------|-------------------------|
|                     |              |          |                 | Col | Prec | Rec | F1 | Col | Prec | Rec | F1 |                     |
| TimeSformer [34]    | Root         | RGB      |                 | 75.3 | 33.4 | 33.5 | 32.4 | 78.1 | 23.9 | 23.6 | 22.9 |                     |
| COPILOT No Map      | All          | RGB      |                 | 77.7 | 37.1 | 40.9 | 37.4 | 78.4 | 26.6 | 27.0 | 25.4 |                     |
| COPILOT Root-Only   | Root         | RGB      |  ✓              | 74.9 | 36.9 | 36.8 | 35.5 | 79.9 | 31.1 | 29.7 | 29.3 |                     |
| COPILOT ST-Attn     | All          | RGB      |  ✓              | 81.4 | 46.6 | 48.9 | 45.9 | 83.4 | 31.1 | 34.2 | 31.0 |                     |
| COPILOT Divided     | All          | RGB      |  ✓              | 81.7 | 48.5 | 49.5 | 47.4 | 80.2 | 31.2 | 31.5 | 30.0 |                     |
| COPILOT             | All          | RGB      |  ✓              | 86.5 | 53.5 | 58.4 | 53.6 | 85.5 | 41.1 | 45.4 | 41.1 |                     |
| COPILOT No Map      | All          | Depth    |                 | 83.1 | 49.9 | 53.3 | 49.8 | 84.8 | 45.5 | 47.3 | 44.5 |                     |
| COPILOT             | All          | Depth    |  ✓              | 88.3 | 63.8 | 66.9 | 63.2 | 89.3 | 56.7 | 60.1 | 56.1 |                     |

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**TABLE I:** COLLISION PREDICTION RESULTS. ALL RESULTS ARE PERCENTAGES (%).
collision region localization results. (a) Two examples comparing COPILOT Root-Only RGB (Pred map) to the spatial attention map [39] from TimeFormer [34] (Attention). (b) Three examples from the full COPILOT model. All examples are on scenes unseen during training.

Control sequence result. Grey meshes indicate the history trajectory, orange is the original future without intervention, and blue is the future using collision avoidance assistance.

Fig. 5. Predictions from COPILOT Root-Only for two real-world videos. The heatmap, the controller slightly rotates the hip by 5 degrees to the left or the right about the z-axis to avoid the higher-probability region. Observations are then sampled at the new rotated pose and the control loop repeats autoregressively.

The policy avoids 35% of collision cases on training scenes and 29% on unseen scenes. Two such cases are visualized in Fig. 4. For example, in the left example, the person originally walks into the vanity, but after intervention they instead gradually turn left to avoid the collision.

D. Generalization to Real-World Videos

Finally, we demonstrate that our model trained on synthetic data effectively transfers to the real world. Since deploying a full exoskeleton system in unconstrained settings is itself a challenging and open problem, we instead apply COPILOT Root-Only to real-world videos captured from a chest-mounted camera as a person moves in a cluttered office building. As shown in the left example of Fig. 5, as the person passes the trash bin on the right, our model reasonably predicts a potential collision with the right hand and the heatmap highlights the protruding object. Extensive examples in the accompanying video demonstrate COPILOT’s sim-to-real transfer ability, despite motion blur in the real-world videos and being trained on a different viewpoint.

VI. LIMITATIONS AND DISCUSSION

We have shown promising results on effectively predicting and localizing collisions from ego-centric observations with the goal of providing exoskeletons with generalizable perception capabilities useful for downstream control. However, our model does suffer some limitations, leaving room for future work. Since generating scene-aware 3D human motion sequences is an open research problem [40], the motions in our dataset are scene-agnostic, which does not always accurately reflect real-world scenarios. Another limitation is that our model can have trouble dealing with ambiguous futures due to unclear motion patterns, as shown in Fig. 6. Finally, developing more sophisticated control algorithms that leverage the detailed per-joint outputs of our model is another important direction for future work.
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