

Vision as Proprioception: Estimating Humanoid Robot Pose from Video

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<https://github.com/eth-siplab/HumanoidPose>

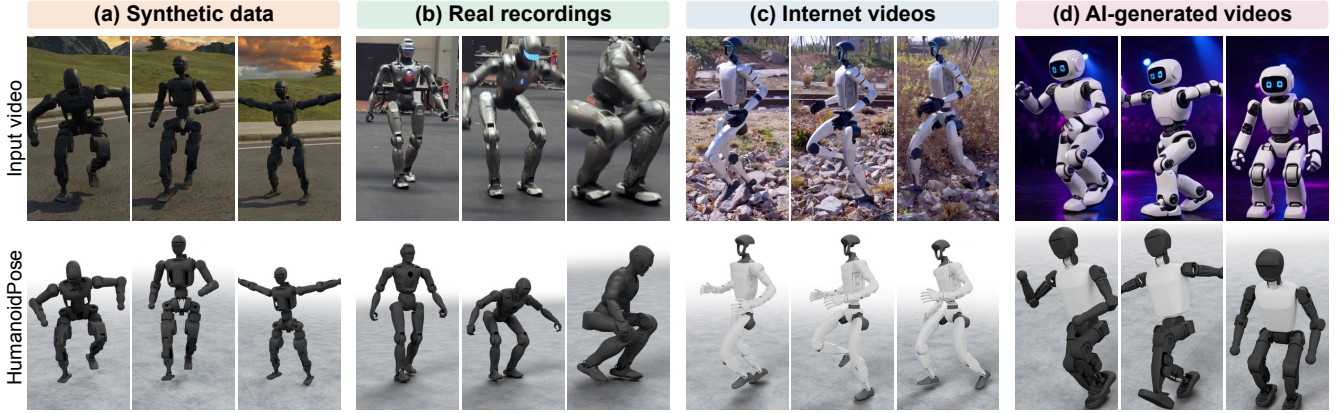


Fig. 1: We present **HumanoidPose**, a new framework that estimates full-body 3D humanoid robot configurations from video alone. Input frames (top) and recovered robot configurations (bottom) are shown for (a) synthetic data, (b) real-robot recordings, (c) internet videos, and (d) AI-generated videos. HumanoidPose is a single shared model that supports multiple robot embodiments without internal state measurements, providing a basis for robot interaction and learning from video.

Abstract—Estimating a humanoid robot’s internal state from video has a wide range of real-world applications but remains unexplored. During interactions with a robot, its onboard state information may be unavailable due to privacy, ownership, or communication constraints. Meanwhile, online and AI-generated robot videos provide rich sources of data but typically lack corresponding joint configurations, limiting their direct use in robot learning. To address these issues, we present **HumanoidPose**, a new framework that treats vision as proprioception to recover full-body joint configurations in world space from video alone. Specifically, we combine pretrained human-pose features with robot kinematics in a unified model that predicts each embodiment’s joint configurations. We retarget human motions to sixteen different humanoid embodiments, enabling scalable learning entirely from synthetic data. To improve real-world generalization, we further leverage unlabeled online videos through self-training to develop a 2D robot-pose detector. In our evaluation, **HumanoidPose** improves joint-angle and joint-position accuracy over the evaluated baselines and reduces joint-angle error by 18–32% relative to the best-performing baseline on each of the three real humanoid platforms. We further show improved global localization and generalization to unseen embodiments. **HumanoidPose** enables visual understanding of other robots during interaction and extraction of robot motion from online and generated videos.

I. INTRODUCTION

Understanding and interacting with humanoid robots requires interpreting how their bodies move. People and other robots may need to anticipate a reaching arm, recognize an action, or coordinate with the robot. Although onboard sensors measure the robot’s configuration, privacy, ownership, or communication constraints may prevent access to these measurements, making vision the primary means for

an external observer to recover it. The same need extends to learning from video: online robot videos capture motion in varied environments without accompanying joint-state logs, while AI-generated videos provide candidate motion demonstrations with no physical robot or encoder measurements at all. Together with real-robot recordings and synthetic videos, these sources motivate recovering articulated robot motion directly from visual observations (Fig. 1). Expressing this motion in the robot’s joint coordinates makes it available for analysis, prediction, and learning.

We study *visual proprioception for humanoid robots*: recovering full-body joint configurations in world space from ordinary video without access to onboard state. This setting introduces several challenges. Humanoids differ in body proportions, joint layouts, and mechanical limits, requiring an estimator that can accommodate different kinematic structures and output spaces. Occlusion and monocular depth ambiguity make articulation underdetermined from appearance alone, calling for learned priors that generalize across embodiments, motions, and visual conditions. Recovering world-space trajectories further requires separating robot motion from camera motion.

Learning these priors requires large-scale data pairing images with robot configurations across motions, embodiments, and environments. Such data are difficult to obtain: collecting encoder-synchronized footage across many platforms is costly. Existing robot pose estimators address articulated manipulators [1]–[3], but humanoid motion recovery requires full-body estimation across robot designs and appearances. Human mesh recovery offers a way to reuse priors learned

from extensive human imagery [4], [5]: estimate a human pose and retarget it to the robot [6]. However, human articulation differs from robot articulation, and retargeting can amplify prediction errors. We instead transfer pretrained human-pose features to directly predict robot joint poses.

We present **HumanoidPose**, a framework for recovering full-body robot pose and world-space motion from video. Its key design is a shared decoder that combines frozen human-pretrained image features with queries derived from robot kinematics to predict joint configurations and root pose across embodiments. We combine the predicted root pose with estimated camera motion to recover world-space trajectories. Queries follow each robot’s joint layout, allowing a shared decoder and prediction head.

Our synthetic pipeline retargets motions from the Archive of Motion Capture as Surface Shapes (AMASS) [7] to sixteen humanoids using General Motion Retargeting (GMR) [6] and renders paired images and robot states under varied conditions. These data supervise the pose decoder and initialize a YOLO11-based detector for robot boxes and 2D keypoints, and unlabeled online videos further adapt this detector. Across three real platforms, the unified model improves joint-angle and joint-position accuracy over the evaluated baselines.

Our contributions are:

- We formulate visual proprioception for humanoid robots, the problem of recovering full-body joint configurations and world-space motion from video without access to onboard state.
- We introduce a unified, kinematically conditioned model for 3D robot pose estimation that predicts joint configurations and root pose across humanoid embodiments without robot-specific prediction heads.
- We generate 128,000 synthetic images across sixteen humanoids with paired 2D and 3D labels to train the 3D pose model and a 2D detector, further adapting the detector through self-training on online videos.
- We evaluate HumanoidPose on three real humanoid platforms, demonstrating improved joint-angle and joint-position accuracy, improved root translation on G1, and transfer and adaptation to unseen embodiments.

II. RELATED WORK

Robot Pose Estimation. Camera-to-robot calibration methods such as DREAM and PoseFusion combine image keypoints with known 3D robot keypoint locations to estimate the camera transform [8]–[10]. Recovering unknown joint states additionally requires estimating articulation, addressed through rendering-based refinement in RoboPose and GISR [1], [11], [12], geometric lifting [13], [14], and feed-forward regression in HoRoPose [2]. More recent methods such as RoboPEPP and RoboTAG learn visual representations that reflect robot articulation [3], [15], [16]. For humanoids, Amini et al. and Heo et al. [17], [18] estimate 2D image keypoints across robot platforms, without recovering full 3D articulation or actuated joint configurations. In

contrast, HumanoidPose estimates full-body 3D humanoid robot poses in robot coordinates across embodiments.

Human Pose and Motion Estimation. Parametric body models and image fitting [19]–[21] underpin learned body recovery [22]–[24], while kinematic formulations connect joint positions and body rotations [25]–[27]. SAM 3D Body [28] supports keypoint and mask prompts for single-image body recovery. Video methods progress from temporal motion priors [29] to global motion reconstruction [30], [31]. WHAM and TRAM [32], [33] explicitly account for camera motion, while GVHMR [34] uses gravity-view coordinates. PromptHMR [5] incorporates spatial and semantic prompts into full-image SMPL-X recovery and extends to temporally coherent reconstruction from video. Complementary approaches combine egocentric tracking and exocentric observations for full-body motion capture [35]. However, humanoid morphology, joint limits and actuated coordinates make human-body representations indirect for robot-state recovery. HumanoidPose directly estimates robot joint coordinates and world-space motion from video.

Synthetic Data and Sim-to-Real Transfer. Synthetic human data [36] and domain randomization [37] establish rendering as a source of visual supervision. Motion archives [7] and increasingly realistic datasets [38]–[42] broaden coverage of appearance, motion, and scenes, while procedural tools [43] automate rendering and annotation. Rendered robot images and adaptation techniques also support transfer to real robot observations [1], [8], [9], [18]. Motion retargeting [44] further connects human motion resources to new embodiments, supporting humanoid control and imitation [45]–[48]. Recent pipelines such as UH-1 and GMR retarget human motion capture and internet videos into humanoid robot references [6], [49], showing that human motion priors can provide scalable supervision for humanoid behaviors. We combine retargeted motions with robot-specific rendering to pair images with the exact joint configurations used to generate them. This directly supervises actuated coordinates, enabling our decoder to train entirely on synthetic images and transfer to real robot videos.

III. METHOD

A. Problem Formulation and Overview

HumanoidPose takes an external red–green–blue (RGB) video $\{I_t\}_{t=1}^T$ and a kinematic description in Unified Robot Description Format (URDF) or MuJoCo’s native model format (MJCF). For a robot with n actuated joints, each frame yields a configuration $\hat{\mathbf{q}}_t \in \mathbb{R}^n$ and a root-to-camera transform $\hat{\mathbf{T}}_{C \leftarrow R, t}$. Root estimation uses camera intrinsics and nominal metric robot height. Combining predictions with camera motion recovers world-space trajectories.

Figure 2 shows synthetic supervision, detector adaptation and pose decoding. At inference, the adapted YOLO11 detector crops the robot. A frozen human-pretrained encoder extracts crop features, which the shared decoder combines with kinematic joint queries to predict joint configurations and root pose. Temporal information supports detector self-training and camera estimation. Pose decoding is per-frame.

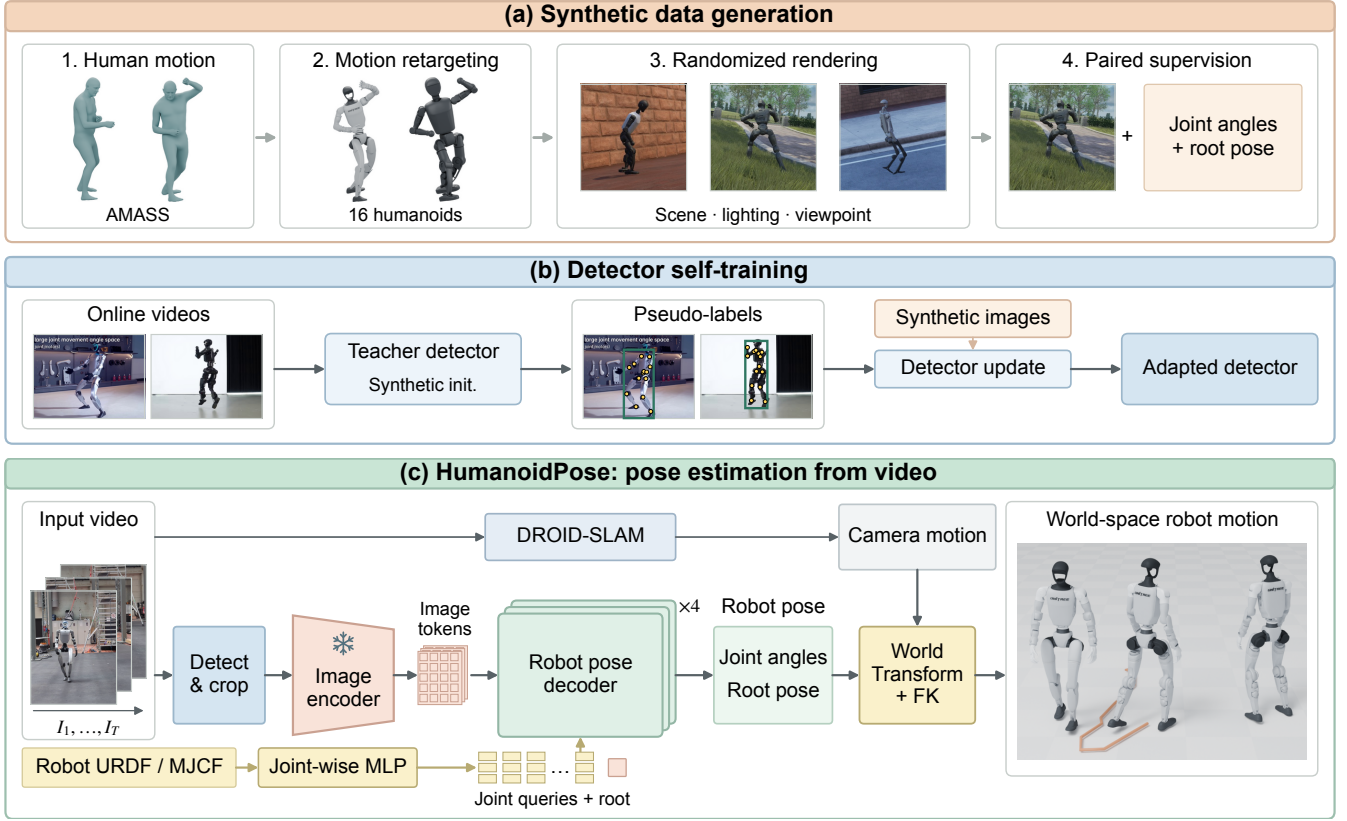


Fig. 2: HumanoidPose overview. (a) Retargeted human motions and randomized rendering provide synthetic robot pose supervision. (b) Pseudo-labels from unlabeled online videos adapt the detector through self-training. (c) Frozen human-pretrained features and kinematic queries drive a shared decoder for joint angles and root pose. Camera motion and forward kinematics place predictions in world coordinates. The pose decoder is trained solely on synthetic data.

B. Training Data and Detector Adaptation

Synthetic data generation. Our synthetic pipeline turns human motion archives into paired robot images and states across diverse mechanisms. We first retarget AMASS human motions [7] to sixteen humanoid URDF/MJCF models using GMR [6], producing robot joint trajectories and root poses in each embodiment’s own coordinates. We render these configurations in Unreal Engine [50] with randomized scenes, lighting, camera viewpoints and robot appearances [37]. For each rendered frame, we project a shared set of robot body landmarks through the rendering camera to obtain 2D keypoint annotations and derive bounding boxes for detector training. Each RGB image is paired with its camera intrinsics, root pose, exact joint configuration and corresponding 2D annotations. These pairs supervise robot configurations and 2D pose across different heights, proportions and joint counts. A common compiled robot model defines coordinate conventions, joint limits and forward kinematics (FK), keeping labels, descriptors and training losses consistent.

2D robot pose estimation and self-training. To localize humanoids across embodiments, we finetune a YOLO11 pose model [51], initialized from human keypoint weights, on the paired images and 2D annotations generated by our synthetic pipeline. The model learns to predict a robot bounding box and 15 shared body landmarks: pelvis, neck, head, and

the left and right hips, knees, feet, shoulders, elbows and wrists. This common landmark definition supports robots with different actuated joint layouts.

We further adapt the model to real-world appearances through self-training on unlabeled online videos. Confident detections with sufficient visible keypoints serve as temporal anchors, and expanded keypoint extents define their bounding boxes. We fill short detection gaps by interpolating jointly visible keypoints between nearby anchors, retaining only single-robot pairs with overlapping boxes and excluding ambiguous detections. The resulting pseudo-labeled frames are mixed with synthetic images to finetune the model. We repeat pseudo-label generation and training for two rounds, excluding evaluation recordings. The 3D decoder trains solely on synthetic poses.

At inference, the adapted model localizes the robot and defines a square RGB crop with robot-height fraction $\rho = 0.55$. The 3D decoder predicts robot pose from the crop’s visual features and robot descriptors. The predicted 2D landmarks also provide the observations for the geometric fitting baseline in our experiments.

C. Kinematics-Conditioned 3D Pose Estimation

Joint queries. A shared encoder maps each actuated joint’s description to a query, allowing one decoder to handle



Fig. 3: The training corpus. Human motion capture retargeted onto sixteen humanoids spanning $3.0\times$ in height (0.60–1.78 m) and 19–43 degrees of freedom, rendered in Unreal Engine under randomized scene, illumination and viewpoint. One sample is shown per robot, paired with the configuration used to render it.

variable joint layouts. Building on per-joint representations in morphology-conditioned control [52]–[54], each query encodes geometry, motion range and kinematic-tree position.

For joint j , let $\mathbf{a}_j$ and $\mathbf{c}_j$ denote its axis and anchor in the local body frame, and $\mathbf{o}_j$ and $\mathbf{r}_j$ the body’s rest offset and quaternion relative to its parent. Let $\bar{\mathbf{c}}_j$ and $\bar{\mathbf{a}}_j$ be the rest anchor and axis expressed in the robot base frame. We form

$$\mathbf{v}_j = [\mathbf{a}_j, \mathbf{c}_j/s_R, \mathbf{o}_j/s_R, \mathbf{r}_j, \|\mathbf{o}_j\|_2/s_R, \ell_j, u_j, u_j - \ell_j, d_j/10, \eta_j, \log s_R, \bar{\mathbf{c}}_j/s_R, \bar{\mathbf{a}}_j, m_j], \quad (1)$$

where $[\ell_j, u_j]$ is the joint range, d_j the depth in the compiled body tree, s_R the robot’s zero-pose vertical extent measured from body origins in meters, and $\eta_j = \text{sign}(\bar{\mathbf{c}}_{j,y})$ a base-frame side indicator, with a small zero tolerance. The flag m_j indicates whether the joint has finite limits. A shared multilayer perceptron (MLP) maps the 27-dimensional descriptor to a query $\mathbf{t}_j = \phi(\mathbf{v}_j)$. Local geometry describes how a joint moves, while the base-frame anchor, axis and side fields encode its spatial identity, distinguishing left–right counterparts and otherwise symmetric joints without relying on joint names. Normalizing offsets expresses geometry relative to body size, while $\log s_R$ preserves absolute scale. For a new embodiment, we supply its joint descriptors and output ranges while reusing all learned weights.

Visual features and shared decoder. PromptHMR’s frozen image and camera encoders [5] provide visual features conditioned on crop intrinsics. We pool features to 32×32 image tokens $\mathbf{X}$ and initialize the decoder as

$$\mathbf{H}^0 = [\mathbf{e}_{\text{root}}, \mathbf{e}_{\text{aux}}, \mathbf{t}_1, \dots, \mathbf{t}_n], \quad (2)$$

where the learned root and auxiliary tokens are shared across robots. The root token predicts root pose. The auxiliary token has no separate prediction target. Four pre-normalized transformer blocks combine token self-attention, cross-attention to $\mathbf{X}$ and feed-forward updates with residual connections. A shared linear head maps each normalized joint token to a scalar z_j , decoded as

$$\hat{q}_j = \ell_j + (u_j - \ell_j) \sigma(z_j). \quad (3)$$

Here σ is sigmoid. For continuous joints, $\hat{q}_j = \text{wrap}(z_j)$.

Camera-relative root pose. Nominal robot height sets metric depth, and the crop-center ray sets a lateral reference. A linear root-token readout predicts 6D orientation [55] and dimensionless corrections (p_x, p_y, p_z) to account for posture and image evidence. Let H_R denote robot height, S the square crop size, ρ the reference robot-height fraction, and $(f_x, f_y), (c_x, c_y)$ the focal lengths and principal point in crop pixels. With $u_0 = S/2$, translation is

$$\begin{aligned} \hat{z} &= \frac{f_x H_R}{S \rho} \exp(\text{clip}(p_z, -3, 3)), \\ \hat{t}_x &= \left(\frac{u_0 - c_x}{f_x} + p_x \right) \hat{z}, \\ \hat{t}_y &= \left(\frac{u_0 - c_y}{f_y} + p_y \right) \hat{z}. \end{aligned} \quad (4)$$

The offsets p_x, p_y adjust the crop-center ray in normalized camera coordinates, while p_z corrects log-depth, preserving positive depth. The metric height prior H_R is distinct from the body-origin extent s_R used to normalize joint descriptors.

Training objective. We supervise joint coordinates, their induced body poses, and the root transform. Let $\mathcal{B}_R$ be the robot’s body set and $P_R(\mathbf{q})_b$ the position of body b in the robot base frame. The objective is

$$\begin{aligned} \mathcal{L}_q &= \frac{1}{n} \sum_j |\text{wrap}(\hat{q}_j - q_j)|, \\ \mathcal{L}_{\text{FK}} &= \frac{1}{|\mathcal{B}_R|} \sum_b \|P_R(\hat{\mathbf{q}})_b - P_R(\mathbf{q})_b\|_2, \\ \mathcal{L} &= \mathcal{L}_q + \lambda_{\text{FK}} \mathcal{L}_{\text{FK}} + \lambda_{\text{end}} \mathcal{L}_{\text{end}} \\ &\quad + \lambda_{\text{root}} \left(\mathcal{L}_{\text{rot}} + \frac{\|\hat{\mathbf{t}} - \mathbf{t}\|_1}{\tau} \right). \end{aligned} \quad (5)$$

The angle difference is wrapped to $(-\pi, \pi]$, $\mathcal{L}_{\text{rot}}$ is geodesic rotation error, and $\tau = 5$ m scales translation loss. Differentiable FK [2], [16], [25] propagates body-position errors to joint predictions in the robot base frame, separating articulation from root motion. For terminal actuated bodies, $\mathcal{L}_{\text{end}}$ averages $1 - \langle \hat{\mathbf{u}}_b, \mathbf{u}_b \rangle^2$, where the unit quaternions $\hat{\mathbf{u}}_b, \mathbf{u}_b$ are predicted and target FK orientations. This supervises rotations that leave terminal body origins unchanged. We set $\lambda_{\text{FK}} = 1$, $\lambda_{\text{end}} = 0.1$ and $\lambda_{\text{root}} = 0.5$.

Implementation. The decoder has width 256, eight attention heads and approximately 4.55M active parameters. We train with AdamW, learning rate 4×10^{-4} , effective batch size 48 and a one-cycle schedule, keeping the visual encoder frozen and grouping each device’s mini-batch by embodiment. Training uses 8000 synthetic images per embodiment for twenty epochs, selecting the checkpoint by the mean synthetic-validation objective. The root decoder uses reference crop size $S = 480$, with intrinsics rescaled from encoder pixels to this crop resolution. Nominal robot heights are estimated from zero-pose geometry bounds using a common scale factor calibrated to G1’s known height.

D. World-Space Motion Recovery

To express the recovered poses in a common world frame, we combine each predicted root-to-camera transform with the camera-to-world transform. Here $\mathbf{T}_{A \leftarrow B}$ maps coordinates from frame B to frame A :

$$\hat{\mathbf{T}}_{W \leftarrow R, t} = \mathbf{T}_{W \leftarrow C, t} \hat{\mathbf{T}}_{C \leftarrow R, t}. \quad (6)$$

Together with $\hat{\mathbf{q}}_t$, this transform places the articulated robot in world coordinates through forward kinematics. For a fixed camera, the camera-to-world transform is constant. For a moving camera, we mask the robot to exclude its motion from camera estimation and use the PromptHMR camera pipeline [5] with DROID-SLAM [56]. Metric depth supplies the translation scale. The world frame is defined independently for each continuous shot.

IV. EXPERIMENTS

Our experiments assess HumanoidPose as an external source of robot-state information, evaluating its ability to recover joint configurations and global motion from visual observations. We examine accuracy and generalization across embodiments and domains, the contribution of the main design choices, and adaptation with additional visual data.

A. Experimental setup

Data and metrics. We use our sixteen-robot synthetic dataset (Sec. III-B) with separate training and test images. Real evaluation uses held-out, encoder-synchronized videos of Unitree G1, EngineAI PM01 and Fourier N1 performing locomotion, arm movements, crouching and supported poses, with synchronized optical motion capture on G1 for global root motion. Mean per-joint angle error (MPJAE, $^\circ$) averages absolute wrapped joint-angle errors. Mean per-joint position error (MPJPE, cm) averages Euclidean FK body-origin errors in the robot base frame, with both root poses fixed to zero translation and identity rotation. We pool real frames within each robot and average synthetic metrics equally across robots. Global root translation is evaluated separately in Sec. IV-B.

Baselines. Since full-body 3D humanoid pose estimation from RGB images or videos remains underexplored, we construct and adapt the following baselines for this task: PromptHMR [5] followed by GMR [6], the same pipeline

with synthetic finetuning (SynFT) on our data, keypoint fitting, HoRoPose [2], and RoboPEPP [3].

Finetuning updates PromptHMR’s SMPL-X decoder and camera embedding with its image encoder frozen. The training configuration for HumanoidPose is given in Sec. III-C. Synthetic finetuning uses the corresponding AMASS source labels for supervision. Synthetic retargeting receives the source global pose and body shape. On real data, all methods use square crops with robot-height fraction 0.55, and GMR receives predicted SMPL-X body rotations with a fixed canonical body shape and zero global orientation and translation. Retargeting solves each frame independently with the same GMR call for every method.

Keypoint fitting is inspired by keypoint-based pose estimation [3], [8]. For each image, it fits joint angles and base pose to the 15 2D keypoints predicted by our robot-adapted YOLO11 model. The optimization minimizes confidence-weighted reprojection error through forward kinematics, subject to joint limits, and starts from the zero configuration and a box-based translation estimate. It shares detections, crops and frames with all other methods and requires no training.

We adapt HoRoPose [2] and RoboPEPP [3], originally evaluated on robot manipulators, to humanoids and train a separate model for each robot using their original code. HoRoPose retains its original losses and uses a joint-angle branch registered for each humanoid. RoboPEPP pretrains its embedding on our renders before finetuning.

B. Comparisons with Baselines

Pose estimation on synthetic data. All methods share a held-out synthetic test set excluded from training. HumanoidPose achieves the lowest average MPJAE and MPJPE (Table I), reducing MPJAE by 35% relative to RoboPEPP, the strongest joint-angle baseline on synthetic data. The shared model also leads both metrics on each reported embodiment, supporting recovery across robot structures.

Real-robot pose estimation. The shared decoder transfers to all three real platforms without real pose supervision, achieving the lowest MPJAE and MPJPE on each platform (Table I). Relative to the best-performing baseline on each platform, MPJAE decreases by 18–32%, with the largest gain on G1. Figure 4 shows recovered locomotion, arm movements and supported poses across robot geometries, including side and rear views.

Root and world-space recovery. Table II evaluates global root position against motion capture on G1 recordings captured with phone cameras. We compare against keypoint fitting and PromptHMR with box prompts and camera intrinsics. PromptHMR is evaluated at native scale and with translation scaled per sequence by robot height divided by median predicted mesh height. Each trajectory receives one rigid alignment without rescaling, refined on the lowest 90% of initial residuals. Errors are pooled over all matched frames shared by the methods. HumanoidPose achieves the lowest error on all metrics and reduces root-mean-square error (RMSE) by 40% relative to height-scaled PromptHMR.

TABLE I: POSE ESTIMATION ON SYNTHETIC DATA AND REAL ROBOTS. MPJAE ($^{\circ}$) and base-frame MPJPE (cm). All (16) averages robots equally. One HumanoidPose model serves all robots and both domains. Best in bold and second best underlined.

Method	Synthetic								Real Robot							
	MPJAE $\downarrow_{\circ}$				MPJPE $\downarrow_{\text{cm}}$				MPJAE $\downarrow_{\circ}$				MPJPE $\downarrow_{\text{cm}}$			
	All (16)	G1	PM01	N1	All (16)	G1	PM01	N1	G1	PM01	N1	G1	PM01	N1		
Keypoint fitting	21.21	19.86	27.86	20.32	10.84	9.85	15.27	8.74	10.52	<u>6.99</u>	14.70	5.93	6.14	<u>5.63</u>		
PromptHMR [5] + GMR [6]	18.03	20.37	24.05	18.26	8.78	10.17	12.82	7.45	12.50	16.11	19.57	5.31	<u>6.02</u>	7.46		
PromptHMR [5] + GMR [6] + SynFT	16.82	19.39	22.83	17.04	<u>7.98</u>	10.03	12.85	<u>6.99</u>	<u>10.46</u>	16.45	15.42	<u>4.88</u>	11.88	6.33		
HoRoPose [2]	15.09	14.21	<u>20.60</u>	16.19	9.61	10.05	<u>12.06</u>	8.91	12.98	15.36	13.72	13.24	11.01	7.24		
RoboPEPP [3]	<u>14.49</u>	<u>13.62</u>	20.91	<u>15.86</u>	8.68	<u>8.84</u>	14.23	8.06	10.72	13.96	<u>10.52</u>	7.97	8.40	6.00		
HumanoidPose (Ours)	9.48	9.03	11.15	8.80	4.49	4.99	5.57	3.66	7.10	5.65	8.62	3.81	2.60	5.18		

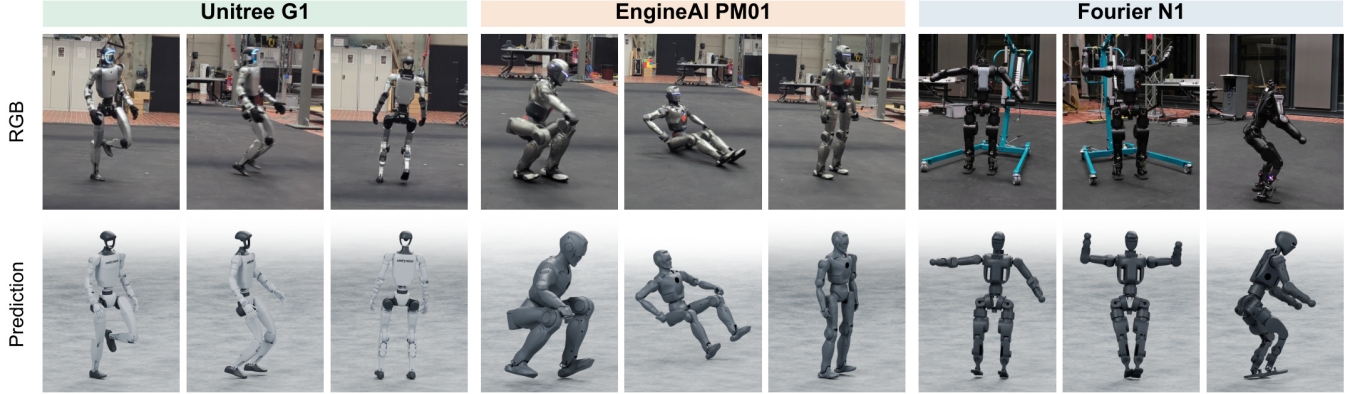


Fig. 4: Pose recovery across real humanoid platforms. Self-recorded RGB frames (top) and predicted 3D configurations (bottom) for G1, PM01 and N1. The same HumanoidPose model recovers locomotion, arm movements, crouching and supported poses across different robot structures and appearances.

Our root estimator uses known robot size and learns image-dependent position corrections from synthetic robot poses, helping account for posture changes beyond a fixed height-based scale adjustment.

TABLE II: Global root-translation errors on G1 (cm) after fixed-scale rigid alignment. P90 denotes the 90th percentile.

Method	RMSE $\downarrow$	Median $\downarrow$	P90 $\downarrow$
Keypoint fitting	42.2	21.3	56.3
PromptHMR [5]	66.2	37.4	96.2
PromptHMR [5] + height scaling	39.0	16.8	51.1
HumanoidPose (Ours)	23.4	11.3	21.7

C. Ablation studies

Table III evaluates the main design choices on the same test sets. Synthetic metrics average robots equally. Real metrics are frame-weighted averages over G1, PM01 and N1. **w/o joint identity.** This variant removes the base-frame rest anchor $\bar{\mathbf{c}}_j/s_R$, axis $\bar{\mathbf{a}}_j$ and side indicator η_j from the joint descriptor in Eq. 1. Errors increase in both domains, with a larger effect on synthetic data. Base-frame geometry helps associate visual evidence with the corresponding joints, including symmetric left-right counterparts.

w/o direct robot decoding. This variant replaces direct prediction of robot configurations with synthetic-finetuned PromptHMR followed by GMR retargeting. This produces

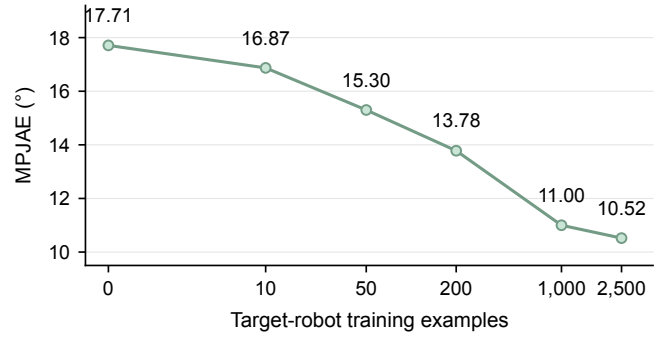


Fig. 5: Few-shot adaptation to a held-out embodiment. G1 test error decreases with more synthetic training examples. The horizontal axis uses $\log(1 + N)$.

the largest increase in both errors among the compared variants, highlighting the value of direct robot-state prediction.

w/o kinematic conditioning. This variant replaces the descriptor-generated queries $\mathbf{t}_j = \phi(\mathbf{v}_j)$ with learned embeddings for each robot’s joints while retaining a shared decoder. Both metrics worsen in both domains, supporting the combined use of geometric descriptors.

w/o human-pretrained encoder. This variant replaces the human-pretrained PromptHMR image encoder with a generic DINOv2 [57] encoder. Both errors increase on synthetic and real data, indicating that human-pretrained features provide a useful prior for robot articulation.

TABLE III: Core design comparisons on synthetic data from sixteen robots and real data from three platforms. MPJAE ($^{\circ}$) and MPJPE (cm).

Variant	Synthetic		Real	
	MPJAE $\downarrow$	MPJPE $\downarrow$	MPJAE $\downarrow$	MPJPE $\downarrow$
Ours	9.48	4.49	7.09	3.82
w/o joint identity	10.94	5.05	7.15	4.02
w/o direct robot decoding	16.82	7.98	12.12	6.19
w/o kinematic conditioning	12.43	6.67	7.62	4.15
w/o human-pretrained encoder	11.14	5.57	7.95	4.65

TABLE IV: Robot-adapted 2D pose detector stages: synthetic detection rate and PCK (%), and real coverage (%) and MPJAE ($^{\circ}$) of our fixed pose decoder.

Detector	Synthetic		G1		PM01		N1	
	Det. $\uparrow$	PCK $\uparrow$	Cov. $\uparrow$	MPJAE $\downarrow$	Cov. $\uparrow$	MPJAE $\downarrow$	Cov. $\uparrow$	MPJAE $\downarrow$
YOLO11	56.8	38.6	98.6	7.82	96.5	5.89	77.8	17.65
YOLO11 + SynFT	100	93.6	81.1	8.65	75.6	5.87	99.3	8.98
YOLO11 + SynFT + ST	100	92.1	98.8	7.11	96.8	5.36	99.4	8.90

D. Transfer to new embodiments

We evaluate pose-decoder transfer while retaining the trained detector, whose training includes the target robots’ synthetic images and public videos. We separately train decoders with a frozen PromptHMR encoder, holding out both G1 variants or PM01 and leaving fourteen or fifteen training robots. At test time, the target’s kinematic description supplies joint queries without learning new embeddings. Pooled real MPJAE is 11.27 $^{\circ}$ on G1 and 11.44 $^{\circ}$ on PM01, with median root errors of 8–16 cm across their sequences.

Finetuning the G1-held-out decoder on increasing amounts of synthetic G1 data reduces synthetic test error (Fig. 5), with the image encoder frozen and no real pose labels.

E. Self-training from online videos

Table IV evaluates detector stages before and after self-training (ST). On the sixteen-robot synthetic test set, percentage of correct keypoints (PCK) uses a 5% box-height threshold for visible landmarks. Real coverage is the detection rate over all sampled frames with a visible robot. Pose errors use frames detected by all three stages, with a fixed pose decoder. The human-pose model’s PCK uses the twelve shared landmarks. It detects robots on G1 and PM01 but poorly localizes keypoints on N1. Synthetic finetuning improves keypoint localization, and subsequent self-training improves real-video coverage while retaining keypoint accuracy and yielding the lowest pose error across platforms.

V. LIMITATIONS

HumanoidPose supports shared pose estimation across embodiments and transfer from synthetic images to real observations. Our evaluation focuses on individual robots while multi-robot scenes with sustained mutual occlusion remain to be explored. Such scenes require maintaining robot identities and pose consistency as visual evidence becomes intermittent, motivating temporal modeling and tracking. Downstream interaction and learning from demonstrations

require further evaluation to establish how pose errors affect motion prediction, coordination and learned behaviors.

VI. CONCLUSION

We presented HumanoidPose, a framework for recovering humanoid joint configurations in world space from video. Combining pretrained human-pose features with robot kinematics allows one model to learn across embodiments from synthetic data, while self-training on unlabeled videos adapts the detector to real appearances. Experiments demonstrate improved pose accuracy over the evaluated baselines on real humanoids and support transfer and adaptation to new embodiments. These findings support vision as an external source of robot-state information when onboard measurements are inaccessible. HumanoidPose provides a basis for understanding other humanoids during interaction and for extracting internal states from online and generated videos.

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