FreeMan: Towards Benchmarking 3D Human Pose Estimation in the Wild

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Abstract

Estimating the 3D structure of the human body from natural scenes is a fundamental aspect of visual perception. This task carries great importance for fields like AIGC and human-robot interaction. In practice, 3D human pose estimation in real-world settings is a critical initial step in solving this problem. However, the current datasets, often collected under controlled laboratory conditions using complex motion capture equipment and unvarying backgrounds, are insufficient. The absence of real-world datasets is stalling the progress of this crucial task. To address facilitate the development of 3D pose estimation, we present FreeMan, the first large-scale, real-world multi-view dataset. FreeMan was captured by synchronizing 8 smartphones across diverse scenarios. It comprises $11M$ frames from 8000 sequences, viewed from different perspectives. These sequences cover 40 subjects across 10 different scenarios, each with varying lighting conditions. We have also established an automated, precise labeling pipeline that allows for large-scale processing efficiently. We provide comprehensive evaluation baselines for a range of tasks, underlining the significant challenges posed by FreeMan. Further evaluations of standard indoor/outdoor human sensing datasets reveal that FreeMan offers robust representation transferability in real and complex scenes. FreeMan is now publicly available at `https://github.com/wangjiongw/FreeMan`.

1 Introduction

Estimating 3D human poses from real scene input is a longstanding yet active research topic since its huge potential in real applications, such as animation creation [1, 2], virtual reality [3, 4], the metaverse [5–7] and human-robot interaction [8]. Specifically, it aims to identify and determine the spatial positions and orientations of the human body's parts in 3D space from input data such as the image or the video. Despite numerous models proposed in recent years [9–11], practical implementation in real scenes remains challenging due to the viewpoint variability, occasions, human scale variation and complex background. Some challenges may stem from the disparity between the recent benchmarks and real-world scenarios. As shown in Fig. 1, the widely recognized Human3.6M [12], along with the currently largest dataset HuMMan [13], are usually collected in laboratory settings utilizing intricate equipment, which maintains constant camera parameters and offers minimal variation in background conditions. The effectiveness of the trained models when trained using these datasets often experiences a significant decline in real-world environments.

From a data-oriented perspective, we have identified several constraints that hinder the performance of the existing models. **(1) Insufficient Scene Diversity.** Existing datasets, as shown in Tab. 1, are

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Figure 1: The left displays sample frames from Human3.6M [12] and HuMMan [13], which were collected under laboratory conditions, and contrasted with our FreeMan dataset that was collected in real-world scenarios. Frames from FreeMan have been cropped into a square format for visualization purposes, with the original resolution being 1920×1080 pixels. The right-hand side demonstrates the test results on 3DPW of the HMR model [16] when trained on these three datasets. Notably, the model trained using FreeMan is able to adapt flawlessly to real-world conditions, demonstrating its superior generalization ability.

Dataset	Environment	#Subj	#Action	#Scene	#Seq	#Frame	#Camera	FPS
HumanEva[17]	Laboratory	4	6	1	168	80K	7	30
CMU Panoptic[18]	Laboratory	8	5	1	65	154M	31	30
MPI-INF-3DHP[19]	Real Scene	8	8	1	16	1.3M	14	30
MuCo-3DHP[14]	Real Scene	7	-	4	60	51K	1	30
3DPW[15]	Real Scene	7	47	4	60	51K	1	30
Mirrored Human[20]	Laboratory	-	-	-	-	1.5M	1	30
Human3.6M[12]	Laboratory	9	15	1	840	3.6M	4 (Fixed)	30
AIST++[21]	Laboratory	30	10	1	1408	10.1M	9 (Fixed)	30
HuMMan[13]	Laboratory	1000	500	1	400K	60M†	11 (Fixed)	30
HuMMan-released[13]	Laboratory	132	20	1	4466	278K†	11 (Fixed)	30
FreeMan	Real Scene	40	123	10‡	8000	11.3M	8 (Movable)	30 / 60

Table 1: Comparison of our proposed FreeMan dataset with existing 3D Human Pose datasets. Only HD Cameras counted for CMU Panoptic[18]. † Only 1% of the HuMMan dataset ($600K$ frames) is made publicly available. ‡ FreeMan includes 10 type of scenes that corresponds to 29 locations. *Fixed* means cameras are fixed within the whole dataset, while our cameras are *movable* and camera poses vary among video sequences.

Figure 2: Equipment setting of data collection using 8 cameras.

mainly collected in controlled laboratory conditions, which may not be optimal for robust model training due to static lighting conditions and uniform backgrounds. This limitation becomes especially crucial when the objective is to estimate 3D pose in real-world scenarios, where scene contexts exhibit substantial variability. In certain datasets, even though the data is collected from outdoor scenes, *e.g.,* MuCo [14] and 3DPW [15] in Tab. 1, the variety of scenarios remains remarkably limited. This constraint significantly hampers the applicability of trained models across a broader range of situations. **(2) Limited Actions and Body Scales.** In existing datasets, the range of human actions tends to be rather limited. Even in the currently largest dataset, HuMMan [13], the variety of actions in the publicly available data is quite restricted. Additionally, these large datasets typically employ fixed cameras to capture data from various perspectives. The distance from the camera to the actor is relatively constant, which results in a relatively fixed human body scale across different videos. **(3) Restricted Scalability.** The annotation of current datasets primarily relies on expensive manual processing, which greatly restricts the scalability of the datasets. Especially when the camera used for collection is movable, how to effectively align data from different cameras and perform efficient annotation remains an open issue.

To address these above issues, this work presents FreeMan, a novel large-scale benchmark for 3D human pose estimation in the wild. FreeMan contains $11M$ frames in 8000 sequences captured by 8 smartphone cameras from different views simultaneously, as illustrated in Fig. 2. It covers 40 subjects in 10 kinds of scenes. To our best knowledge, it is the current largest multi-view 3D pose estimation dataset, with variable camera parameters and complex background environments. It is $215\times$ of the famous outdoor dataset 3DPW [15]. From a practical perspective, it has several appealing strengths: **Firstly**, a large number of scenes introduce diversity in both backgrounds and lighting, enhancing the generalizability of models trained on FreeMan in real-world scenarios. This makes it particularly suitable for evaluating algorithmic performance in practical applications. **Secondly**, the distances between the 8 cameras and the actors are variant (*i.e.,* 2 to 5.5 meters) both within and among subjects, resulting in significant scale changes in human bodies across different sequences. **Thirdly**, although we employed mobile data collection devices, the annotation of the FreeMan dataset does not rely on

costly manual processes, thereby significantly enhancing the scalability of the dataset. **Lastly**, the proposed FreeMan encompasses a wide range of pose estimation tasks, which include monocular 3D estimation, 2D-to-3D lifting, multi-view 3D estimation, and neural rendering of human subjects. We present thorough evaluation baselines for the aforementioned tasks on FreeMan, highlighting the inherent challenges of such a new benchmark.

In summary, this paper has made three contributions: (1) We have constructed a large-scale dataset for 3D human pose estimation in uncontrolled environments. The impressive transferability of the models trained on this dataset to real-world scenarios has been demonstrated. (2) We have showcased a simple yet effective toolchain that enables the automatic generation of precise 3D annotations from the collected data. (3) We provide comprehensive benchmarks for human pose estimation and modeling on FreeMan, facilitating downstream applications. These baselines highlight potential directions for future algorithmic enhancements.

2 Related Work

Human Pose Datasets. Human modeling is a significant task in computer vision. Existing datasets predominantly rely on 2D and 3D keypoint annotations, with 3D keypoint datasets available in two forms: monocular and multi-view. For 2D keypoint, there are some single-frame datasets such as MPII [22] and COCO [23], which provide diverse images with 2D keypoints annotations, while video datasets such as J-HMDB [24], Penn Action [25] and PoseTrack [26] provide 2D keypoints with temporal information. In contrast, 3D keypoint datasets are often constructed in indoor scenes, such as Human3.6M [12], CMU Panoptic [27], MPI-INF-3DHP [19], AIST++ [28] and HuMMan [13] for multi-view. There also exists some outdoor datasets such as 3DPW [15] for monocular cases. Details of these datasets are shown in Tab. 1. However, the majority of outdoor datasets such as MPI-INF-3DHP, MuCo-3DHP, and 3DPW exhibit a limited variety of acquisition scenes, and the datasets that involve fixed camera poses such as AIST++.

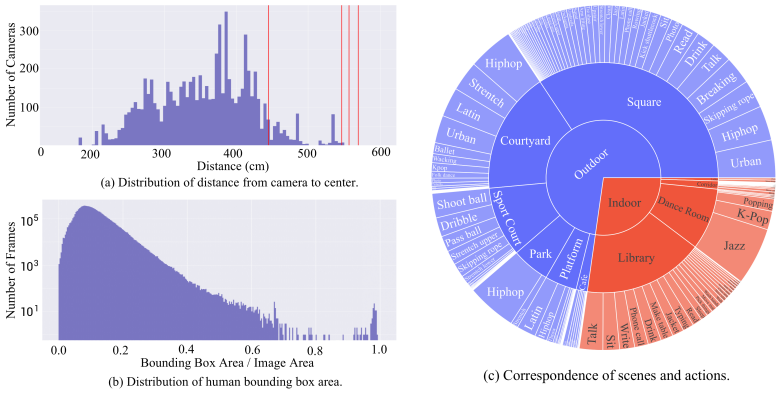
3D Human Pose Estimation. The present study categorizes the task of 3D pose estimation into three distinct types, namely 2D-to-3D pose lifting, monocular 3D pose estimation, and multi-view 3D pose estimation. In the 2D-to-3D pose lifting task, Martinez [29] proposed a simple baseline to regress the 3d keypoints based on a convolutional neural network from 2D keypoints. While Pavllo[30], Zheng[31] and Li[10]'s work better incorporated temporal information in this task. In monocular 3D pose estimation task, HMR[16], SPIN[32] takes a single RGB image as input to perform 3D huna pose estimation, which is often used as baselines for comparison with other algorithms, such as PARE[9], SPEC[33] and HybrIK[34]. Additionally, multi-view methods are proposed to accommodate potential body parts overlapping in monocular view. Iqbal's [35] and MCSS [36] adopt weak supervision to reduce the dependence on the 3D annotated pose, while Wandt et al. [37] and Kocabas et al. [38] turned to self-supervise fashion to deal with multi-view data.

Neural Rendering of Human Subjects. With the development of NeRF[39] in dynamic scene rendering, people also focus on the dynamic rendering of humans. Compared to dynamic scenes, the non-rigid property of humans has more challenges. The prior knowledge of body movements can provide a good prior for rendering, and many methods use SMPL[40] as a prior for body rendering. Most methods reconstruct human bodies through multi-view videos[41–43], while recent works have also employed single-view videos, such as HumanNeRF[44], FlexNeRF[45], YOTO[46].

3 FreeMan Dataset

FreeMan is a large-scale multi-view dataset in the wild, offering precise 3D pose annotations. It comprises $11M$ frames from 1000 sessions, featuring 40 subjects across 10 types of scenes. The dataset includes $10M$ frames recorded at 30FPS and an additional $1M$ frames at 60FPS. Next, we highlight the diversity of FreeMan, from various camera settings and scenario selections

Scenarios. We design 10 types of real-world scenes, comprising 4 indoor and 6 outdoor scenes, for our data collection. Fig. 3 illustrates the scene diversity of our FreeMan. The blue section



(a) Distribution of distance from camera to center.

(b) Distribution of human bounding box area.

(c) Correspondence of scenes and actions.

Figure 3: (a) Distribution of distance from the camera to the center of the system, indicated by translation along the z-axis in camera parameters. Four vertical red lines represent the distance of 4 cameras in Human3.6M [12]. (b) Distribution of human bounding box areas. The horizontal axis represents the ratio of the bounding box area over the image area. The vertical axis is in log scale. (c) Correspondence of scenes and actions. Areas of blocks represent the scale of the respective frame number. The outmost circle shows actions and the circle in the middle present 10 type of scenes in our dataset. Zoom in $10\times$ for the best view.

represents the data collected outdoors, while the red sector refers to frames captured in indoor scenes. Specifically, there are 2.76 million frames captured indoors and 8.45 million frames captured outdoors. Additionally, there are different frame numbers collected under varying lighting conditions, with 1 million frames captured at night and 7.45 million frames captured during the day outdoors. Moreover, the central block of the circle denotes different scenarios, while the blocks on the outermost circle refer to actions. The areas of the blocks are proportional to the corresponding frame numbers. For more details about the distribution of scenarios, please refer to the supplementary material.

Action Set. Following the popular action recognition dataset NTU-RGBD120[47], we compose our action set with several common actions corresponding to scenes in daily life, $e.g.$, drinking and talking in a cafe and reading in the library. Also, subjects interact with real objects to make actions as close to real life as possible. As shown in the topmost row of Fig. 4, interaction with objects brings complicated occlusions, making our data more challenging. For outdoor scenarios, we set the data collection field as large as possible to help subjects perform actions with little restriction.

Camera Poses. Cameras in previous 3D human pose datasets [13, 12, 18] are fixed during data collection, resulting that only a few camera poses being included. As shown in Fig. 2, Our cameras are attached to lightweight tripods and are newly placed from time to time, and translation from the center of the system to camera d, which is the physical distance between the camera and the system center, can vary from 2m to 5.5m. Fig. 3 (a) shows the distribution of d and the corresponding number of cameras. Most cameras are located around 4 meters far away from the system center. Besides, we show the distribution of the human bounding box area in Fig. 3 (b), in a unit of ratio to the whole image area, to demonstrate the variation of human size. With variations in camera translation and human actions, the area of human bounding boxes varies from 0.01 to 0.7 of the whole image area.

Subjects. There are 40 subjects participating in the construction of FreeMan and recruitment is completely based on voluntary. All of them are well-informed and signed the agreement to make the data public for research purposes only.

4 Data Acquisition & Annotation Pipeline

Overview. To collect a large-scale dataset from real-world environments, we developed a comprehensive toolchain, as shown in Fig. 5. Unlike previous toolchains used in controlled or idealized conditions, we carefully accounted for potential challenges in outdoor settings, including calibration and synchronization errors. To overcome these issues, we incorporated automated correction procedures to ensure efficient data collection.

Figure 4: The diverse frames in FreeMan. The topmost two rows illustrate a range of indoor and outdoor scenes, highlighting the diversity of scene contexts, lighting conditions, and subjects. The third row exhibits frames from different cameras, showcasing the variance across views. The final row illustrates the temporal variation of human poses from a consistent viewpoint, emphasizing the dynamism of motion capture.

4.1 Hardware Setup

Cameras. We collect FreeMan via 8 Mi11 phones [48] indexed from 1 to 8 as our data collection devices. ***Note** 8 **collection of one action as one session, which corresponds to RGB sequences from 8 views.*** and each phone is attached to a tripod to keep stable within each data collection session.

As shown in Fig. 2, all devices are positioned in a circle around a human at a height of approximately 1.6 meters above the ground, with the distance from the camera to the system center varying from 2 to 5.5 meters. which is similar to real-life usage scenarios. Each smartphone captures RGB sequences using the main camera at 1920×1080 resolution and $30/60$ FPS. During the data collection process, actors perform actions facing the device with odd-numbered indices. As shown in Fig. 5(a), the only requirement beyond devices is to connect all devices to the same server stably.

Camera Calibration. At the beginning of each session, we calculate the intrinsic and extrinsic camera parameters in two steps with a chessboard tiled at the center of the system, following the standard implementation in OpenCV[49, 50]. We attach cameras to tripods and collect tiled chessboards from each view. In this phase, chessboard frames from all views are sent to the server and the server detects corner points, calculates camera extrinsic parameters of each device, and sends parameters back to cameras. Cameras are allowed for the next step only if extrinsic parameters are received.

Device Synchronization. Previous works [13, 12, 18] have synchronized devices using wired interfaces in a laboratory. However, the complexity of the entire system coupled with the difficulty in deploying it in real-world environments, has prompted us to consider alternative methods. To address issues related to usability and device constraints, we connect all devices wirelessly to a single server and developed an Android app that utilizes the Network Time Protocol (NTP) [51] to calculate the time difference between each device and the server's clock. During the capture process, time information is stored locally on each device as a timecode, while the server records the synchronized capture interval for all devices. The starting frame is determined by matching the timecode to the frame closest to the server's clock time. This approach ensures device synchronization, with synchronization errors limited to smaller than a single frame during our testing. At frame rates of 30FPS and 60FPS, this corresponds to 33ms and 16ms, respectively.

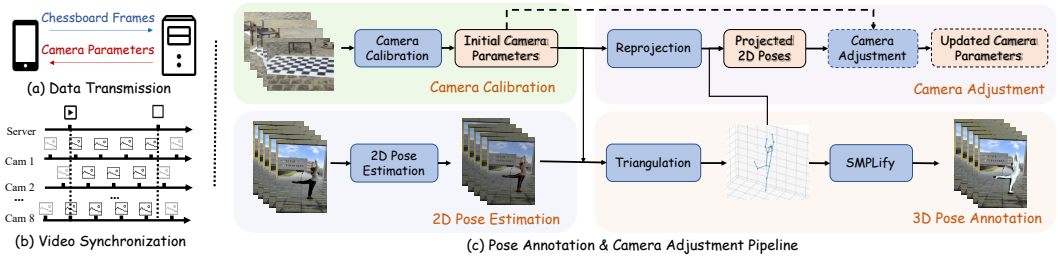


Figure 5: The illustration of data collection and annotation toolchain: (a) depicts the transmission of signals between cameras and servers for camera calibration, where chessboard frames are sent to the server, and camera parameters are returned. (b) demonstrates the synchronization process among devices. (c) showcases the pipeline for annotation and camera adjustment.

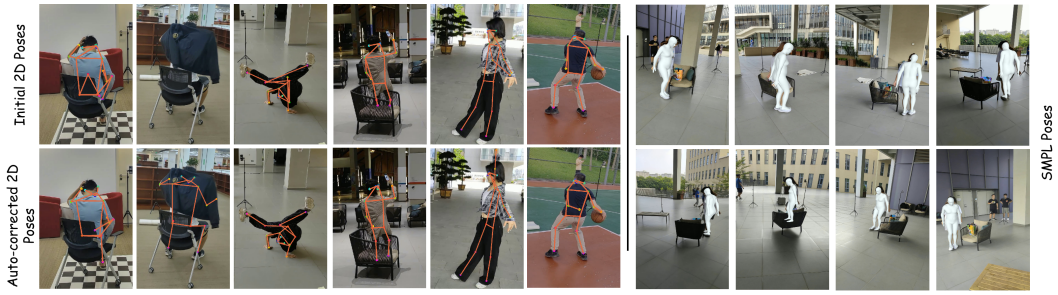


Figure 6: The examples of human pose annotations are presented as follows. In the left part, the first row displays 2D keypoints directly generated by HRNet-w48 [53], while the second row illustrated the re-projected 2D poses. When HRNet fails to deal with occlusions, our toolchain automatically corrects annotations by incorporating multi-view priors. The right part showcases the SMPL annotation examples for each view in our dataset.

4.2 Pose Annotation.

After camera calibration, subjects enter the capture area to perform actions. Once videos are collected, we use a state-of-the-art detector YOLOX[52] to detect human locations and HRNet-w48[53] to detect 2D keypoints of 8 views $K_{2D} \in \mathbb{R}^{8\times17\times2}$ in COCO[23] format. To eliminate the effect of potential wrong keypoints output, keypoint predictions with confidence lower than a threshold ϕ are removed. Then remaining 2D keypoints are used for triangulation to get 3D human pose $K_{3D} \in \mathbb{R}^{17\times3}$ with pre-computed camera parameters. Here, we set ϕ to be 0.5. Furthermore, we optimize K_{3D} with smoothness constraints and bone length constraints introduced in HuMMan[13] resulting in optimized 3D pose $\tilde{K}_{3D} \in \mathbb{R}^{17\times3}$. Then we fit a standard SMPL[40] model to the estimated 3D skeleton by SMPLify [54] to produce a rough mesh annotation. After that, we project 3D keypoints to 2D image planes of each view using corresponding camera parameters. With regularization in triangulation and optimization along the temporal axis, the re-projected 2D poses $\tilde{K}_{2D}$ is a refined version compared with K_{2D}. Comparison between original K_{2D} and $\tilde{K}_{2D}$ are shown in the left part of Fig. 6.

Camera Adjustment. Finally, for cameras that failed in calibration accidentally, we adjust camera parameters through pose computation[55] if needed. If more than two cameras failed in calibration, the session is discarded directly. Otherwise, we ignore the uncalibrated views first, then triangulate the remaining 2D poses into 3D poses. We can obtain the camera parameters of uncalibrated cameras by minimizing the re-projection error of 2D-3D point correspondences.

4.3 Annotation Quality Assessment

To demonstrate the effectiveness of our toolchain, we test the toolchain on Human3.6M[12]. We select 3 different actions of each subject in the training set, which covers 10% sequences of the whole training set and all kinds of actions. Performance is assessed by Euclidean distance between estimated 2D poses and ground truth 2D poses in units of pixels. The error results in 9.9 pixels for images with the size of 1000×1000, demonstrating that our toolchain can generate accurate annotations.

To validate the effectiveness of camera adjustment for failure cases in calibration, we randomly mask a camera for all sessions and use the other 3 views to get 3D poses, then compute the parameters of the missing one via pose computation. Then 3D poses are projected to the corrupted view by estimated camera parameters, mean error between resulting 2D poses and ground truth is 7.42 pixels.

5 Benchmarks

We have constructed four benchmarks utilizing images and annotations derived from our dataset. The data is subdivided based on subjects, allocating 18 subjects for training, 7 for validation, and 15 for testing purposes. This partitioning results in three subsets composed of $5.87M$, $700K$, and $3.69M$ frames, respectively. For each benchmark, subject lists of each subset are shared, and only views selected from the session vary for each task. **(1) Monocular 3D Human Pose Estimation (HPE).** This task involves taking an RGB image or sequence from a monocular view as input and predicting 3D coordinates relative to the camera. For this benchmark, we randomly select one view from each session to construct the dataset. The performance of algorithms is measured by widely used Mean Per Joint Position Error (MPJPE)[12] and Procrustes analysis MPJPE (PA-MPJPE)[40]. **(2) 2D-to-3D Lifting.** Given that 2D human poses can be predicted using existing 2D keypoint detectors [56–58, 53], the primary goal of this task is to effectively elevate these 2D poses into the 3D space within the camera coordinate system. The evaluation metrics are the same as HPE. **(3) Multi-View 3D Human Pose Estimation.** Due to occlusions in motion capture, monocular methods often encounter difficulties. Estimating the 3D human pose from multiple views presents a natural solution to overcome this problem. For this task, models are provided with images or videos from multiple views, along with corresponding camera parameters. The objective is to predict the 3D coordinates of human joints in the same world coordinate system as the cameras. The performance is measured by MPJPE and average precision (AP) following previous work[59]. **(4) Neural Rendering of Human Subjects.** The free-viewpoint rendering of humans is a significant issue in human modeling. With the rise in popularity of neural radiance fields (NeRF) [39] for the novel view rendering task, several methods, including HumanNeRF [44], have emerged. These methods utilize monocular human motion videos as input to synthesize novel views of dynamic humans through NeRF. The widely used metrics of prediction are PSNR, SSIM[60] and LPIPS[61].

6 Experiments

We experiment with the four benchmarks. In human 3D pose estimation tasks, we conduct several transfer tests with other standard datasets to evaluate the effectiveness and transferability of our proposed FreeMan dataset. Existing similar datasets, Human3.6M[12] & HuMMan[13], are used for comparison. Since *HuMMan only releases 1% of data*, we only involve it in monocular 3D human pose estimation and 2D-to-3D lifting. In the neural rendering of human subjects tasks, we train the model from one of the 8 views and test from the rest of the views in selected sessions.

6.1 Monocular 3D Human Pose Estimation

Method			HMR		PARE	
Train	Supervision	Test	MPJPE	PA	MPJPE	PA
Human3.6M	2D+3D KPTs	3DPW	279.92	133.13	118.54	81.22
HuMMan	2D+3D KPTs	3DPW	407.57	192.75	110.99	63.11
HuMMan	2D KPTs+SMPL	3DPW	475.73	184.15	114.20	66.19
HuMMan	2D+3D KPTs+SMPL	3DPW	437.52	203.17	114.33	72.12
FreeMan	2D+3D KPTs	3DPW	157.46	87.93$\uparrow_{33.95\%}$	118.31	68.72$\uparrow_{15.39\%}$
FreeMan	2D KPTs+SMPL	3DPW	151.85	88.85$\uparrow_{51.75\%}$	94.27	60.39$\uparrow_{8.76\%}$
FreeMan	2D+3D KPTs+SMPL	3DPW	159.31	91.33$\uparrow_{55.04\%}$	98.33	64.51$\uparrow_{10.55\%}$

Table 2: Monocular 3D HPE performance of HMR[16] and PARE[9] trained on different dataset for monocular Human Pose Estimation. PA stands for PA-MPJPE and both metrics are in unit of millimeters. The lower metrics is, the better performance model obtains. All released part of HuMMan is used for training. $\uparrow$ refers to the improvement relative to HuMMan and $\uparrow$ refers to the improvent relative to Human3.6M.

Implementation details. For the Human3.6M [12] and HuMMan [13] datasets, all views in their training set are utilized. In contrast, for FreeMan, we randomly sample a single view from sessions

Train	Test	AP@25mm (%) ↑	AP@50mm (%) ↑	AP@75mm (%) ↑	AP@100mm (%) ↑	Recall@500mm (%) ↑	MPJPE@500mm (mm) ↓
Human3.6M	Human3.6M	32.32	97.47	98.61	98.99	100.00	25.95
Human3.6M	FreeMan	0.00	0.00	0.00	0.00	0.06	89.85
Human3.6M	FreeMan (w/ GT Root)	0.00	1.27	11.44	21.40	96.20	154.41
FreeMan	FreeMan	43.38	88.77	97.73	99.12	99.97	26.61
FreeMan	Human3.6M	0.00	5.77	82.85	92.62	96.68	62.37
FreeMan	Human3.6M (w/ GT Root)	0.00	6.60	87.91	95.38	100.00	58.30

Table 3: Multi-View 3D Pose Estimation results of VoxelPose[59] . Ground truth root position (GT Root) is not used if not specified. Recall@$500mm$ shows the percentage that falls within the threshold, and the MPJPE@$500mm$ indicates the average MPJPE values within the threshold. Rows highlighted shows the best setting in cross-domain test.

in the training split, resulting that the frame numbers of all three datasets being $312K$, $253K$, and $233K$, respectively. To enhance efficiency, videos of all three datasets are downsampled to 10FPS, following the implementation of MMPose [62]. We trained HMR[16] and PARE[9] models on different datasets using configurations open-sourced by [63]. Please refer to Appendix for more.

Results. We perform testing on the test set of 3DPW [15]. The performance of the models trained on different datasets, with varying types of supervision, are reported in Tab. 2. Notably, the HMR models trained on FreeMan exhibit significantly better performance on the 3DPW test set compared to those trained on Human3.6M and HuMMan. The PA-MPJPE scores are 42.59mm and 112.63mm, respectively, indicating that our dataset demonstrates superior generalizability compared to the others. The same results are obtained with PARE, further confirming that our FreeMan outperforms even in more advanced algorithms. This can be attributed to the diversity of scene contexts and human actions present in our dataset, which provides better transferability in real-world scenarios.

6.2 Multi-View 3D Human Pose Estimation

Implementation Details. We conduct in-domain and cross-domain tests between Human3.6M and FreeMan to evaluate the effectiveness and generalization ability. We conduct the experiments of multi-view 3D human pose estimation with VoxelPose[64], which locates the human root first and then regresses 3D joint location accordingly. COCO-format poses in FreeMan are transformed to match that in Human3.6M via interpolation. We trained VoxelPose[64] on the two datasets following official implementation. For Human3.6M, bounding box annotations are from [65] and its validation set is used for the test. For FreeMan, we only use videos of odd-indexed views from the training set.

Results. Results of all experiments are reported in Tab. 3. For in-domain testing, the model trained on FreeMan achieves MPJPE@500mm of 26.61mm on test set consisting of *odd-indexed* views. For cross-domain testing, the model trained on FreeMan achieves Recall@500mm of 96.68% while MPJPE@500mm is 62.37mm on Human3.6M validation set. However, the model trained on the Human3.6M dataset fails to locate human on FreeMan test set. To get rid of the effects of root location, we input the ground truth root locations to model directly. With this setting, the model trained on Human3.6M obtains MPJPE@500mm of 154.41mm on FreeMan test set, while the model trained on FreeMan can obtain MPJPE@500mm of 58.30mm on Human3.6M validation set. Results show that the model trained on FreeMan has a much better generalization ability, while that on Human3.6M struggles in transfer testing.

6.3 2D-to-3D Pose Lifting

Implementation Details. We employ four methods, either CNN-based or Transformer-based, including SimpleBaseline[29], VideoPose3D[30], PoseFormer[31] and MHFormer[10] in this task, and all the methods follow the corresponding official implementation. The results of VideoPose3D and PoseFormer can be found in Appendix. For training set in this task, we select one view from every session and down-sample the videos to 15FPS, resulting in the frame number to be $350K$, which is similar to the amount of released part of HuMMan ($253K$) and much smaller than Human3.6M ($1500K$). In order to verify the generalization across datasets, we unify the test set to be AIST++[28]. To verify the effect of the dataset scale, we also train our model on the whole training set.

Results. The experimental results are shown in Tab. 4. Results of the in-domain test on FreeMan are provided as a baseline for future work. For in-domain testing, the MPJPE of SimpleBaseline trained on FreeMan, 79.22mm, is larger than that on HuMMan[13] (78.5mm) and Human3.6M[12]

(53.4mm), demonstrating that FreeMan is a more challenging benchmark. Besides, all the methods trained on FreeMan tend to generalize better than that on HuMMan and Human3.6M when testing on AIST++ under the same setting. Although the scale of FreeMan training set is of a similar magnitude as HuMMan's, which is much smaller than Human3.6M's, models trained on FreeMan outperform models trained on the other two by a large margin. Furthermore, when the training set is expanded to all frames in training split, FreeMan can further boost models to achieve better performance, proving that our large-scale data helps to improve model performance.

6.4 Neural Rendering of Human Subjects.

Implementation Details. We employ 10 scenes captured by FreeMan to train HumanNeRF[44], a deep neural network that aims to achieve high-quality human-centric new synthesis. To obtain human body segmentation annotations, we utilize the SAM (Segment Anything)[66] algorithm using our bounding boxes as prompts. Throughout the training step, we randomly select one view for each session and render the rest 7 view as novel views for testing. We then calculate metrics including PSNR, SSIM, and LPIPS, to evaluate the performance of the model. Please refer to Appendix for results of data at 60FPS.

Results. The reconstruction results in 10 scenes are shown in Tab. 5. The best reconstruction achieves a high PSNR of 30.11 which indicates FreeMan contains contents that the model can learn and fit very well. While the performance varies, the lowest PSNR of 23.86 shows FreeMan also contains contents that are outside of model's learning scope and challenging. Additionally, the results in 10 scenes including both familiar contents that the model can handle well and more challenging new contents demonstrates the diversity of our dataset.

Algorithm	Train	Test	MPJPE (mm)	PA (mm)
SimpleBaseline	FreeMan	FreeMan	90.53	54.17
	FreeMan†	FreeMan	79.22	49.11
	Human3.6M	AIST++	212.57	138.98
	HuMMan	AIST++	255.5	116.86
	FreeMan	AIST++	156.96	105.85↑10.30%
	FreeMan†	AIST++	126.23	88.07↑24.64%
MHFormer	FreeMan	FreeMan	93.00	63.50
	FreeMan†	FreeMan	77.06	53.38
	Human3.6M	AIST++	171.19	133.37
	HuMMan	AIST++	188.73	101.52
	FreeMan	AIST++	132.99	88.79↑12.54%
	FreeMan†	AIST++	124.34	79.22↑21.97%

Table 4: Performance of methods with different training and testing datasets in 2D-to-3D Pose Lifting. PA stands for PA-MPJPE. † refer to experiments with the whole training set of FreeMan. Smaller MPJPE and PA-MPJPE indicate better performance. Highlighted rows show training on our dataset achieves the best performance in the transfer test. ↑ refers to the improvement relative to HuMMan.

Scene	PSNR↑	SSIM↑	LPIPS*↓
Square	25.98	0.9501	58.38
Corridor	24.57	0.9340	81.39
Sports Port	26.33	0.9662	30.09
Park	23.86	0.9439	73.61
Courtyard	28.56	0.9630	53.99
Dance Room	30.11	0.9658	43.34
Library	29.41	0.9665	31.53
Platform	26.79	0.9439	70.01
Lobby	25.41	0.9387	78.80
Cafe	27.32	0.9644	37.88

Table 5: Neural rendering results by using HumanNeRF[44] on 10 scenes of FreeMan. Note that $\texttt{LPIPS}^* = \texttt{LPIPS} \times 10^3$.

7 Conclusion

We present FreeMan, a novel large-scale multi-view 3D pose estimation dataset with comprehensive tasks and 3D human pose annotations. We elaborately develop a simple yet effective annotation pipeline to automatically annotate frame-level 3D landmarks and precise 3D human motions at a much lower cost. We establish benchmarks covering multiple tasks in human modeling, including monocular and multi-view 3D human pose estimation, 2D-to-3D pose lifting, and neural rendering of human subjects. Extensive experimental results demonstrate the strengths of the proposed FreeMan.

Limitation and future work. While we have validated the superiority of our dataset on numerous in-domain and cross-domain cases, there is still a wide range of potential applications that are worth exploring. Additionally, since the data is automatically annotated, more evaluation schemes for the accuracy of annotations and understanding their potential impact on downstream applications remain open issues. We consider these aspects as future work for further investigation. As a large-scale human motion dataset, our FreeMan addresses the existing gap between the current datasets and real-scene applications, and we are optimistic that it will catalyze the development of algorithms designed to model and sense human behavior in real-world scenes.

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1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [N/A]
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2. If you are including theoretical results...
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