Playing for 3D Human Recovery

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Abstract—Image- and video-based 3D human recovery (i.e., pose and shape estimation) have achieved substantial progress. However, due to the prohibitive cost of motion capture, existing datasets are often limited in scale and diversity. In this work, we obtain massive human sequences by playing the video game with automatically annotated 3D ground truths. Specifically, we contribute GTA-Human, a large-scale 3D human dataset generated with the GTA-V game engine, featuring a highly diverse set of subjects, actions, and scenarios. More importantly, we study the use of game-playing data and obtain five major insights. First, game-playing data is surprisingly effective. A simple frame-based baseline trained on GTA-Human outperforms more sophisticated methods by a large margin. For video-based methods, GTA-Human is even on par with the in-domain training set. Second, we discover that synthetic data provides critical complements to the real data that is typically collected indoor. We highlight that our investigation into domain gap provides explanations for our data mixture strategies that are simple yet useful, which offers new insights to the research community. Third, the scale of the dataset matters. The performance boost is closely related to the additional data available. A systematic study on multiple key factors (such as camera angle and body pose) reveals that the model performance is sensitive to data density. Fourth, the effectiveness of GTA-Human is also attributed to the rich collection of strong supervision labels (SMPL parameters), which are otherwise expensive to acquire in real datasets. Fifth, the benefits of synthetic data extend to larger models such as deeper convolutional neural networks (CNNs) and Transformers, for which a significant impact is also observed. We hope our work could pave the way for scaling up 3D human recovery to the real world.

Index Terms—Human pose and shape estimation, 3D human recovery, parametric humans, synthetic data, dataset.

I. INTRODUCTION

Image- and video-based 3D human recovery, i.e., simultaneous estimation of human pose and shape via parametric models such as SMPL [1], have transformed the landscape of holistic human understanding. This technology is critical for entertainment, gaming, augmented and virtual reality industries. However, despite that the exciting surge of deep learning is arguably driven by enormous labeled data [2], [3], the same is difficult to achieve in this field. The insufficiency of data (especially in the wild) is attributed to the prohibitive cost of 3D ground truth (such as parametric model annotation) [4]. Existing datasets are either small in scale [5], [6], [7], collected in constrained indoor environment [8], [9], [10], or not providing the 3D parametric model annotation at all [11], [12], [13], [14].

Inspired by the success of training deep learning models with video game-generated data for various computer vision tasks such as instance segmentation [15], 2D keypoint estimation [16], motion prediction [17], mesh reconstruction [18], detection and tracking [19], we present GTA-Human (Fig. 1) in the hope to address the aforementioned limitations of existing datasets. GTA-Human is built by coordinating a group of computational workers (Fig. 2) that simultaneously play the popular video game Grand Theft Auto V (GTA-V), to put together a large-scale dataset (Table I) with 1.4 million SMPL parametric labels automatically annotated in 20 thousand video sequences. Besides the scale, GTA-Human explores the rich resources of the in-game database to diversify the data distribution that is challenging to achieve in real life (Figs. 3, 4 and 5): more than 600 subjects of different gender, age, skin tone, body shape and clothing; 20,000 action clips comprising a wide variety of daily human activities; six major categories of locations with drastically

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different backgrounds from city streets to the wild; *camera angles* are manipulated in each sequence to reflect a realistic distribution; subject-environment interaction that gives rise to *occlusion* of various extents; time of the day that affects *lighting* conditions, and *weather* system that mimics the real climate changes.

Equipped with GTA-Human, we conduct an extensive investigation in the use of synthetic data for 3D human recovery. 1) **Better 3D human recovery with data mixture:** Despite the seemingly unavoidable domain gaps, we show that practical settings that mix synthetic data with real data, such as blended training and pretraining followed by finetuning, are surprisingly effective. First, HMR [23], one of the first deep learning-based methods for SMPL estimation with relatively simplistic architecture, when trained with data mixture, is able to outperform more recent methods with sophisticated designs or additional information such as SPIN [24] and VIBE [25]. Moreover, PARE [26], a state-of-the-art method also benefit considerably from GTA-Human. Second, our experiments on the video-based method VIBE [25] further demonstrate the effectiveness of data mixture: an equal amount of synthetic GTA-Human data is as good as a real-captured indoor dataset as the frame feature extractor is already pretrained on real datasets; the full set of GTA-Human is even on par with in-domain training data.

2) **Closing the domain gap with synthetic data:** We conduct a pioneering study on the root causes behind the effectiveness of game-playing data. An investigation into the domain gaps provides insights into the complementary nature of synthetic and real data: despite the reality gap, the synthetic data embodies the diversity that many real datasets (typically collected indoor) lack. Moreover, we experiment with mainstream domain adaptation methods to further close the domain gaps and obtain improvements.

3) **Dataset scale matters:** We demonstrate that adding game-playing data progressively improves the model performance. Considering the difficulty of collecting real data with ground truth 3D annotations, synthetic data may thus be an attractive alternative. Moreover, a multi-factor analysis reveals that supervised learning leads to severe sensitivity to data density. Amongst factors such as camera angles, pose distributions, and

**TABLE I**

| Dataset       | Year | Type | In-the-Wild | Video | #SMPL | #Sequence | #Subject | #Action |
|---------------|------|------|-------------|-------|-------|-----------|----------|--------|
| HumanEva [5]  | 2009 | Real | -           | ✓     | NA    | 7         | 4        | 6      |
| Human3.6M [8] | 2013 | Real | -           | ✓     | 312K  | 839       | 11       | 15     |
| MPI-INF-3DHP [21] | 2017 | Mixed | ✓           | ✓     | 96K   | 16        | 8        | 8      |
| 3DPW [6]      | 2018 | Real | ✓           | ✓     | 32K   | 60        | 18       | *      |
| Panoptic Studio [9] | 2019 | Real | -           | ✓     | 736K  | 480 ~ 100 | *        |        |
| EFT [20]      | 2020 | Real | ✓           | ✓     | 129K  | NA        | Many     | NA     |
| SMPLy [7]     | 2020 | Real | ✓           | ✓     | 24K   | 567       | 742       |        |
| AGORA [22]    | 2021 | Synthetic | ✓       | ✓     | 173K  | NA >350    | NA        |        |
| GTA-Human     | 2022 | Synthetic | ✓       | ✓     | 1.4M  | 20K >600  | 20K       |        |

We compare GTA-Human with existing real datasets with SMPL annotations and synthetic datasets with highly realistic setups. GTA-Human has competitive scale and diversity. Datasets are divided into three types: real, synthetic and mixed. GTA-Human samples character action sequences from a large in-game database that allows a unique action to be assigned to each video sequence. Note that EFT [20] re-annotates 2D human pose estimation datasets where the number of subjects are difficult to trace. *: 3DPW and Panoptic Studio only have general descriptions of scene activities.

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occlusions, a consistent drop in performance is observed where data is scarce. Hence, our observation suggests that synthetic datasets can play a vital role in supplementing corner case scenarios in real practice.

4) Strong supervision (SMPL) is key: Compared to large-scale pose estimation benchmarks that only provide 3D keypoints, we demonstrate that strong supervision in the form of SMPL parameters may be quintessential for training a strong model. In a greater depth than prior arts, we discuss the potential reasons and reaffirm the value of GTA-Human as a scalable training source with SMPL annotations.

5) Big data benefits big models: Despite recent development in deeper convolutional networks [27], [28] and vision transformers [29], [30] in computer vision research, the mainstream backbone size remains unchanged for 3D human recovery [23], [24], [25]. We extend our study to deeper CNNs and Transformers, and show that training with GTA-Human enables performance boosts for both small and large backbones. Interestingly, smaller, backbones trained with additional GTA-Human could outperform larger counterparts trained with only real data.

II. RELATED WORK

A. 3D Human Recovery

Human Parametric Models: Unlike human pose estimation that uses skeleton (joint keypoints) to represent humans [31], [32], human pose and shape estimation is typically performed with 3D human parametric models, such as SMPL [1], SMPL-X [33] and STAR [34], which take in parameters that represent
pose and shape of the human subject, and output 3D human mesh via linear blend skinning. We base our discussion on SMPL version 1.0 in this work that consists of pose parameters $\theta \in \mathbb{R}^{72}$ and shape parameters $\beta \in \mathbb{R}^{10}$, for its popularity.

Registration-based Methods: As the output of the human parameter model is manipulated by body parameters, SMPLify [35] and the following SMPLify-X [33] are the pioneering works to optimize these parameters to minimize the distance between ground truth 2D keypoints and reprojected human mesh joints. SMPLify is also extended to videos with temporal constraints employed [36]. Although optimization-based methods are able to achieve impressive results, they are slow and typically take more than 60 seconds per frame. Hence, recent work [37] has been proposed to accelerate optimization.

Regression-based Methods: Direct regression of body parameters using a trained deep learning model has gained more popularity due to fast inference. The recent works are categorized into image-based [26], [38], [39], [40], [41], [42], [43], and video-based [44], [45], [46], [47], [48], [49] methods. HMR [23] is a pioneering end-to-end learning-based work, which takes ResNet-50 [27] as its backbone and directly regresses the parameters of $\theta$ and $\beta$. VIBE [25] is a milestone video-based work that leverages temporal information for realistic pose sequences. Recently, a transformer encoder is introduced for vertex-joint reweighting [50], but the method still uses a CNN backbone for feature extraction.

Mixed Methods: There is a line of work that combines optimization-based and regression-based techniques. SPIN [24] adds a SMPLify step to produce pseudo parametric labels to guide the learning of the network. SPIN address the lack of SMPL annotation but the optimization step results in slow training. Others propose to refine the per-frame regression results by bundle adjustment of the video sequence as a whole [51], designing a new swing-twist representation to replace the original axis-angle representation of SMPL [42], and finetuning a trained network to obtain refined prediction [20], and employing a network to predict a parameter update rule in iterations of optimization [52].

B. Datasets

Datasets with 2D Keypoint Annotations: Many datasets contain in-the-wild images, albeit the lack of SMPL annotations, they provide 2D keypoint labels. Datasets such as LSP [11], LSP-Extended [12], COCO [13] and MPII [14] contain images crawled from the Internet, and are annotated with 2D keypoints manually. Such a strategy allows a large number of in-the-wild images to be included in the dataset. To obtain 3D annotations that are crucial to human pose and shape estimation, a common method is to fit an SMPL model on 2D keypoints. SSP-3D [53] and 3DOH50K [54] leverages pre-trained model to perform keypoint estimation as the first step, whereas UP-3D [55] and EFT [20] performs fitting on ground truth keypoints. However, these datasets typically suffer from the inherent depth ambiguity of images and the pseudo-SMPL may not have the accurate scale.

Real Datasets: Motion capture facilities are built to achieve high-accuracy 3D annotations. HumanEva [5] and Human3.6M [8] employ optical motion capture systems, but intrusive markers are needed to be placed on the subjects. Total Capture [56] MuPoTS-3D [57], Panoptic Studio [9], and HUMBI [10] make use of multiple camera views and require no intrusive marker. However, the background is constant and thus lacks diversity. 3DPW [6] combines inertial measurement units (IMUs) and a moving camera to build an in-the-wild dataset with 3D annotations. 3DPW has become an important benchmark for 3D human recovery. Nevertheless, the IMU drift is still an obstacle and the dataset only contains a relatively small number of videos. SMPLy [7] constructs point clouds from multi-view capture of static people and fits SMPL on them. However, the scale of the dataset is limited by the difficulty of collecting videos that meet the special setup requirement. HuMMan [58] is the most recent large-scale multi-modal 4D human dataset.

Synthetic or Mixed Datasets: SURREAL [59], Hoffmann et al. [60] render textured SMPL body models in real-image backgrounds. However, this strategy does not account for the geometry of the clothes, where the mismatch may result in unrealistic subjects. 3DPeople [61] uses clothed human models while MPI-INF-3DHP [21] takes segmented subjects from images and paste them onto new backgrounds in the training set. However, the subject-background interaction is still unnatural. AGORA [22] is a recent synthetic dataset featuring high-quality annotations by rendering real human scans in a virtual world. However, the dataset is image-based and does not support the training of video-based methods. Richter et al. [15], [62], Krähenbühl et al. [63], JTA [16], GTA-IM [17], SAIL-VOS 3D [18], MOTSynth [19] have demonstrated the potential of obtaining nearly free and perfectly accurate annotations from video games for various computer vision tasks. Amongst them, JTA provides 3D keypoint for pedestrian pose estimation (in the form of keypoints) and tracking, SAILVOS3D focuses on object detection and mesh reconstruction (including non-parametric human meshes). However, these datasets do not provide SMPL annotation needed for our investigation. We take inspiration from these works in building GTA-Human specifically for human pose and shape estimation via parametric regression.

III. GTA-HUMAN DATASET

A scale comparison between GTA-Human and existing dataset is shown in Table I. GTA-Human features 1.4 million individual SMPL annotations, which is highly competitive compared to other real datasets and synthetic datasets with realist setups. Moreover, GTA-Human consists of diverse (especially outdoor) scenes that are expensive and difficult to collect accurate annotation in real life. Notably, GTA-Human provides video sequences instead of static frames and supports video-based human recovery.

A. Toolchain

Inspired by existing works that use GTA-generated data for various vision tasks [15], [16], [17], [18], [19], [62], [63], our toolchain extracts ground truth 2D and 3D keypoints, semantic
Fig. 6. More examples of GTA-Human. We highlight that GTA-Human is a large-scale, highly diverse (in terms of factors such as subjects, actions, locations, and camera angles) dataset. Each frame of the video clips is annotated with SMPL parameters.

Cloud-based NoSQL Database: The unit of data in GTA-Human is a single video sequence. Hence, we employ a Database that is hosted on the cloud, to track the progress of data generation and processing of each sequence. The status of a sequence is updated at each stage in the toolchain, which we elaborate on the details below.

Scenario File Generator: This tool reads from the Database to retrieve sequence IDs that are either not generated before or failed in previous processing attempts, and produce random scene attributes such as subject ID, action ID, location in the 3D virtual world, camera position and orientation, lighting, and weather settings.

Cloud-based Message FIFO Queue: The Message FIFO Queue parse the scenario files from the Scenario File Generator as text strings, which can be fetched in the first-in-first-out (FIFO) manner by multiple Local GUI Workers. Note that the queue allows for multiple workers to retrieve their next jobs simultaneously.

Local GUI Workers: We purchase multiple copies of GTA-V and install them on regular gaming desktops. We refer to these desktops as Local GUI Workers. Each worker runs three tools: Scenario Controller, Data Collector, and Data Analyser which we elaborate on below.

Scenario Controller: Taking scenario files as the input, Scenario Controller is essentially a plugin that interacts with the game engine via the designated Application Programming Interface (API). It is thus able to control the subject generation and placement, action assignment to the subject, camera placement, in-game time, and weather.

Data Collector: This tool obtains data and some annotations from the API provided by GTA-V. First, it extracts 3D keypoints from each subject via the API provided by GTA-V. In addition to the original 98 3D keypoints available, we further obtain head top [16] and nose from interpolation of existing keypoints. We used the perspective camera model as we have access to the intrinsic and extrinsic parameters of the virtual camera and 3D keypoints of the subjects in world coordinates. Hence, we transform the 3D keypoints in the camera coordinates. We then project 3D keypoints to the image plane to obtain 2D keypoints. Second, we project light rays at each joint to determine if the joint is occluded or self-occluded by checking the entity that the light ray hits first [16]. Third, our tool intercepts the rendering pipeline, powered by DirectX, for depth maps and semantic masks. The pixel-wise depth is directly read from depth buffers. Shader injection enables the segmentation of individual patches, and we manually assign the semantic class to various shaders based on their variable names. We refer interested readers to [63] for more details. Fourth, the collector also records videos.

Data Analyser: To filter out low-quality data in the early stage, Data Analyser imposes several constraints on 3D keypoints obtained. We compute joint movement speed simply as the position different in consecutive frames to filter out less expressive actions (slow-moving or stationary actions). Severely occluded, or out-of-view subjects are also flagged at this stage. If sequences pass the analysis, their data are transferred from the local storage to a centralized storage space on our GPU cluster (Cluster Storage) for further processing. The failed ones, however, are deleted. The Database is notified of the result to get the status updated.

Cluster Workers and SMPL Annotator: On each Cluster Worker (a GPU in the cluster), we run an instance of SMPL...
Annotator that takes keypoint annotation from the Cluster Storage. We upgrade SMPLify [35] in two ways to obtain accurate SMPL annotation. 1) we find out that compared to 2D keypoints that have inherent depth ambiguity, exacerbated by weak perspective projection [64], 3D keypoints are unambiguous. Minor modifications are needed to replace the 2D keypoint loss of the original SMPLify with 3D keypoint loss. 2) Taking advantage of the fact that GTA-Human consists of video sequences instead of unrelated images, temporal consistency in the form of rotation smoothing and unified shape parameters are enforced. The SMPL parameters include $\theta$, $\beta$, and an additional translation vector, are optimized at an average of one second per frame. We visualize more examples in GTA-Human that are produced with our SMPL annotation tool in Fig. 6.

B. Data Diversity

Due to the difficulty and cost of data collection and SMPL annotation for the 3D human recovery task, most existing datasets are built at restrictive locations such as indoor studios or laboratory environments. Furthermore, only a small number of subjects are usually employed to perform a limited set of actions. In contrast, GTA-Human is designed to maximize the variety in the following aspects. We demonstrate the diversity in subjects, locations, weather, and time (light conditions) in Fig. 3, actions in Fig. 4, and camera angles in Fig. 5.

**Subjects:** GTA-Human collects over 600 subjects of different genders, ages, skin tones, clothing, and body shapes for a wide coverage of human appearances. In addition, unlike motion capture systems in real life that rely on intrusive markers to be placed on the subjects, accurate skeletal keypoints are obtained directly from the game’s API.

**Actions:** Existing datasets either design a small number of actions [5], [8], [21], or lack a clearly defined action set [6], [9]. In contrast, we gain access to a large database of motion clips (actions) that can be used to manipulate the virtual characters, whose typical length is 30-80 frames at 30 FPS. These actions provide a fairly holistic representation of city-dwellers’ daily activities, and are reasonably realistic because they are originally produced via motion capture of real human actors or actresses. We select 20,000 most dynamic and expressive actions. In Fig. 4, the distribution of GTA-Human poses does not only have the widest spread, but also covers existing poses in the real datasets to a large extent. Note that these actions allows for the study on video-based methods in Section IV-B.

**Locations:** The conventional optical [5], [8] or multi-view motion capture systems [9], [10] require indoor environments, resulting in the scarcity of in-the-wild backgrounds. Thanks to the open-world design of GTA, we have seamless access to various locations with diverse backgrounds, from city streets to the wilderness. Our investigation in Section IV-B highlights these diverse locations are complementary to real datasets that are typically collected indoor.

**Camera Angle:** Recent studies [65], [66] have shown the critical impact of camera angles on model performance, yet its effect in 3D human recovery is not fully explored due to data scarcity: it is common to have datasets with fixed camera positions [5], [8], [9], [21]. In GTA-Human, we choose to sample random camera positions from the distribution of the real datasets [6], [8], [21] to balance both diversity and realness. Our data collection tool enables the control of camera placement position and orientation, thus allowing the study of camera angles that is otherwise difficult in real life. Note that the global orientation of SMPL annotation in the camera coordinates is used to compute an elevation-azimuth representation of the camera angles relative to the subject in the canonical coordinates. We visualize the camera angles in Fig. 5.

**Interaction:** Compared to existing works that crop and paste subjects onto random backgrounds [21], [59], the subjects in GTA-Human are rendered together with the scenes to achieve a more realistic subject-environment interaction empowered by the physics engine. Interesting examples include the subject falling off the edge of a high platform, and the subject stepping into a muddy pond causing water splashing. Moreover, taking advantage of the occlusion culling mechanism [16], we are able to annotate the body joints as “visible” to the camera, “occluded” by other objects, or “self-occluded” by the subject’s own body parts.

**Lighting and Weather:** Instead of adjusting image exposure to mimic different lighting, we directly control the in-game time to sample data around the clock. Consequently, GTA-Human contains drastically different lighting conditions and shadow projections. We also introduce random weather conditions such as rain and snow to the scenes that would be otherwise difficult to capture in real life.

IV. EXPERIMENTS

In this section, we study how to use game-playing data for 3D human recovery for real-life applications.

A. Experiment Details

**Datasets:** We follow the original training convention of our baseline methods [23], [24], [26], we define the “Real” datasets used in the experiments to include Human3.6M [8] (with SMPL annotations via MoSh [67]), MPI-INF-3DHP [21], LSP [11], LSP-Extended [12], MPII [14] and COCO [13]. “Real” datasets consist of approximately 300K frames. “Blended” datasets are formed by simply mixing GTA-Human data with the “Real” data. Amongst the standard benchmarks, 3DPW [6] has 60 sequences (51k frames) of unconstrained scenes. In contrast, MPI-INF-3DHP [21] has only two sequences of real outdoor scenes (728 frames) and Human3.6M [8] is fully indoor. Hence, we follow the convention [24], [25], [26] to evaluate models mainly on 3DPW test set to gauge their in-the-wild performances. Nevertheless, we also provide experiment results on Human3.6M and MPI-INF-3DHP.

**Metrics:** The standard metrics are Mean Per Joint Position Error (MPJPE), and Procrustes-aligned [68] Mean Per Joint Position Error (PA-MPJPE), i.e., MPJPE evaluated after rigid alignment of the predicted and the ground truth joint keypoints, both in millimeters (mm). We highlight that PA-MPJPE is the
primary metric [20], [24], on which we conduct most of our discussions.

**Training Details:** We follow the original paper in implementing baselines [23], [24], [25], [26] on the PyTorch-based framework MMHuman3D [69]. HMR+ is a stronger variant of the original HMR, for which we remove all adversarial modules from the original HMR [23] for fast training and add pseudo SMPL initialization (“static fits”) for keypoint-only datasets following SPIN [24] without further in-the-loop optimization. For the Blended Training (BT), since GTA-Human has a much larger scale than existing datasets, we run all our experiments on 32 V100 GPUs, with the batch size of 2,048 (four times as SPIN [24]). The learning rate is also scaled linearly by four times to 0.0002. The rest of the hyperparameters are the same as SPIN [24]. For the Finetuning (FT) experiments, we use the learning rate of 0.00001 with the batch size of 512, on 8 V100 GPUs for two epochs.

**Domain Adaptation Training Details:** We use the same training settings as Blended Training, except that an additional domain adaptation loss is added in training. CycleGAN [70], we first train a CycleGAN between real data and our synthetic GTA-Human data. Then we use a trained sim2real generator from the CycleGAN to transform the input GTA-Human image into a real-style image during training. For JAN [71], we use the default Gaussian kernel with a bandwidth 0.92, and set its loss weight to 0.001. For Chen et al. [72], we use a 3-layer MLP to classify the domain of given features extracted from the backbone. The loss weight of the adversarial part is progressively increased to 0.1 for more stable training.

**B. Better 3D Human Recovery With Data Mixture**

Despite that GTA-Human features reasonably realistic data, there inevitably exists domain gaps. Surprisingly, intuitive methods of data mixture are effective despite the domain gaps for both image- and video-based 3D human recovery.

**Image-based 3D Human Recovery:** We evaluate the use of synthetic data under two data mixture settings: blended training (BT) and finetuning (FT). Results are collated in Table II. In blended training (BT), synthetic GTA-Human data is directly mixed with a standard basket of real datasets [24] (Human3.6M [8], MPI-INF-3DHP [21], LSP [11], LSP-Extended [12], MPII [14] and COCO [13]). Compared with the HMR and HMR+ baselines, blended training achieves 7.0mm and 5.7mm improvements in PA-MPJPE, surpassing methods such as SPIN [24] that requires online registration or VIBE [25] that leverages temporal information (Video); State-of-the-art method PARE [26] also benefit from data mixture. We also conduct further experiments on video-based human recovery with VIBE in Table III. Mixture: data mixture strategies. Real: real datasets.

![Table II](image)

**TABLE II**

GTA-HUMAN’S IMPACT ON MODEL PERFORMANCE

| Method | Mixture | Registration | Video | Pretrain | Train | Finetune | MPJPE ↓ | PA-MPJPE ↓ |
|--------|---------|--------------|-------|----------|-------|----------|---------|------------|
| HMR    | -       | -            | ImageNet Real | 0.0175  | 67.5  |
| HMR+   | -       | -            | ImageNet Real | 0.0175  | 67.5  |
| SPIN   | -       | -            | ImageNet Real | 0.0175  | 67.5  |
| VIBE   | -       | -            | ImageNet Real | 0.0175  | 67.5  |
| PARE   | -       | -            | ImageNet Real | 0.0175  | 67.5  |

The values are reported on 3DPW test set in mm. We employ two strategies: blended training (BT) that directly mixes GTA-Human data with real data to train an HMR model; finetuning (FT) that finetunes pretrained models with mixed data. Significant performance improvements are achieved with both settings. Including GTA-Human in the training boosts the HMR [23] baseline to outperform much more sophisticated methods such as SPIN [24] that leverages in-the-loop optimization (Registration) and VIBE [25] that utilizes temporal information (Video); State-of-the-art method PARE [26] also benefit from data mixture. We also conduct further experiments on video-based human recovery with VIBE in Table III. Mixture: data mixture strategies. Real: real datasets.

**Table III**

VIDEO-BASED 3D HUMAN RECOVERY

| Mixture | 3DPW | GTA-Human | MPJPE ↓ | PA ↓ | Accel ↓ |
|---------|------|----------|---------|------|---------|
| ✔️      | ✔️   | ✔️       | 95.0    | 58.5 | 27.3    |
| ✔️      | ✔️   | ✔️       | 87.9    | 54.7 | 23.2    |
| ✔️      | ✔️   | ✔️       | 93.9    | 55.9 | 27.0    |
| ✔️      | ✔️   | ✔️       | 93.7    | 53.0 | 26.3    |
| ✔️      | ✔️   | ✔️       | 91.3    | 54.1 | 24.7    |
| ✔️      | ✔️   | ✔️       | 85.2    | 52.4 | 24.2    |
| ✔️      | ✔️   | ✔️       | 86.0    | 51.9 | 23.3    |

The values are reported on 3DPW [6] test set with VIBE as the base model. M3: MPI-INF-3DHP, GTA: GTA-Human. PA: PA-MPJPE. Accel: acceleration error (mm/s). *: downsampled GTA-Human data to match the size of MPI-INF-3DHP (96K SMPL poses).

We obtain the following observations. First, when training alone, GTA-Human outperforms MPI-INF-3DHP with an equal number of training data. Second, the full set of GTA-Human is comparable with the

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*https://github.com/mkocabas/VIBE/issues/99#issuecomment-708351802
in-domain training source (3DPW train set), even slightly better in PA-MPJPE. Third, GTA-Human is complementary to real datasets as blended training leads to highly competitive results in all metrics.

**Comparison with Other Data-driven Methods:** We highlight that GTA-Human is a large-scale, diverse dataset for 3D human recovery. In Table IV, we compare GTA-Human with several other recent works that provide additional data for human pose and shape estimation. We show that GTA-Human is a practical training source that improves the performance of various base methods. Notably, GTA-Human slightly surpasses AGORA, which is built with expensive industry-level human scans of high-quality geometry and texture. This result suggests that scaling with game-playing data at a lower cost achieves a similar effect.

### C. Closing the Domain Gap With Synthetic Data

After obtaining good results under both image- and video-based settings on 3DPW, an in-the-wild dataset and the standard test benchmark, we extend our study to answer *why is game playing data effective at all?* We highlight that this investigation holds more significance to the community as it provides fundamental reasons for the use of synthetic data. To this end, we also evaluate models on other datasets that provide additional data for human pose and shape estimation.

**Table IV**

**Comparison With Other Data-driven Methods**

| Dataset            | Method | MPJPE | PA-MPJPE |
|--------------------|--------|--------|----------|
| Arnab et al. [51]  | HMR    | 72.2   |          |
| EFT [20]           | SPIN   | -      | 54.2     |
| AGORA [22]         | SPIN   | 85.7   | 55.3     |
| AGORA* [22]        | SPIN   | 84.4   | 54.9     |
| GTA-Human (BT)     | HMR    | 98.7   | 60.5     |
| GTA-Human (FT)     | HMR    | 91.4   | 55.5     |
| GTA-Human (FT)     | SPIN   | 83.1   | 52.0     |

GTA-Human data effectively improves the base method performance. The numbers are reported on 3DPW test set, without using 3DPW in the training. *Blended AGORA and real data for a fair comparison.

**Table V**

**More Benchmarks**

| Method | Human3.6M | MPI-INF-3DPH |
|--------|-----------|--------------|
|        | MPJPE ↓  | PA ↓         | MPJPE ↓  | PA ↓         |
| HMR    | 77.9      | 55.8         | 107.2    | 74.1         |
| SPIN   | -         | 41.1         | 105.2    | 67.5         |
| HMR    | 74.3      | 52.3         | 103.4    | 71.3         |
| HMR    | -         | 73.2         | 102.9    | 71.0         |
| SPIN   | -         | 60.9         | 96.4     | 67.0         |

We evaluate image-based methods trained with data mixture strategies on Human3.6M and MPI-INF-3DPH. We observe that the performance boosts are smaller than that on 3DPW. This may be attributed to the indoor-outdoor domain gaps that we discuss in Section IV-C.

In Fig. 7, we visualize the feature distribution of various datasets. We discover that there are indeed some domain gaps between real indoor data and real outdoor data. Hence, models trained on real indoor data may not perform well in the wild. We observe that in Fig. 7(a), indoor data has a significant domain shift away from in-the-wild data. This result implies that models trained on indoor datasets may not transfer well to in-the-wild scenes. In Fig. 7(b), blended training achieves better results as 3DPW test data are well-covered by mixing real data or GTA-Human data. Specifically, even though the domain gap between GTA-Human and real datasets persists, the distribution of 3DPW data is split into two main clusters, covered by GTA-Human and real datasets separately. Hence, this novel observation may explain the effectiveness of GTA-Human: albeit synthetic, a large amount of in-the-wild data provides meaningful knowledge that is complementary to the real datasets.

Moreover, we further validate the synergy between real and synthetic data through domain adaptation in Table VI. We select and implement several mainstream domain adaptation methods [74], and evaluate them on an HMR model under BT with an equal amount of real data and GTA-Human (1 x). We discover that learned data augmentation such as CycleGAN [70] may not be effective, whereas domain generalization techniques (JAN [71] and Ganin et al. [73]) and domain adaptive regression such as Chen et al. [72] further improves the performance. In Fig. 7(c), domain adaptation (Ganin et al. [73]) pulls the distributions of both real and GTA-Human data together, and they jointly establish a better-learned distribution to match that of the in-the-wild 3DPW data.
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D. Dataset Scale Matters

We study the data scale in two aspects. 1) Different amounts of GTA-Human data are progressively added in the training to observe the trend in the model performance. 2) The influence of a lack of data from the perspectives of critical factors such as camera angle, pose, and occlusion.

Amount of GTA-Human Data: In Fig. 8, we delve deeper into the impact of data quantity on 3DPW test set. HMR is used as the base model with BT setting. The amount of GTA-Human data used is expressed as multiples of the total quantity of real datasets (~300K [24]). For example, 2× means the amount of GTA-Human is twice as much as the real data in the BT. A consistent downward trend in the errors (~6mm decrease) with increasing GTA-Human data used in the training is observed. Since real data is expensive to acquire, synthetic data may play an important role in scaling up 3D human recovery in real life.

Synthetic Data as a Scalable Supplement: We collate more experiments with different real-synthetic data ratios in Table VII, using HMR+ as the base method and BT as the data mixture strategy. We observe that 1) Adding more data, synthetic and real alike, generally improve the performance. 2) Mixing 75% real data with 25% synthetic data performs well (200K to 400K data). 3) When the data amount increases, high ratio of real data cannot be sustained beyond 300K data due to insufficient real data. However, additional synthetic data still improves model performance. These experiments reaffirm that synthetic data complements real data. More importantly, in real practice, synthetic data can serve as an easily scalable training source to supplement typically limited real data that is too expensive to accumulate further.

Impact of Data Scarcity: In Fig. 9, we systematically study the HMR+ model trained with BT and evaluate its performance on GTA-Human, subjected to different data density for factors such as camera angle, pose, and occlusion. We disentangle all examples evaluated to obtain and plot the data density with bins, and compute the mean error for each bin to form the curves. A consistent observation across factors is that the model performance deteriorates drastically when data density declines, indicating high model sensitivity to data scarcity. Hence, strategically collected synthetic data may effectively supplement the real counterpart, which is often difficult to obtain.

E. Strong Supervision is Key

Due to the prohibitive cost of collecting a large amount of SMPL annotations with a real setup, it is appealing to generate synthetic data that is automatically labelled. In this section, we investigate the importance of strong supervision and discuss the reasons. We compare weak supervision signals (i.e., 2D and 3D keypoints) to strong counterparts (i.e., SMPL parameters), and find out that the latter is critical to training a high-performing model. We experiment under BT setting on 3DPW test set, Table VIII shows that strong supervision of SMPL parameters $\theta$ and $\beta$ are much more effective than weak supervision of body keypoints. Our findings are in line with SPIN [24], SPIN tests fitting 3D SMPL on 2D keypoints to produce pseudo SMPL annotations during training and finds this strategy effective. However, this conclusion still leaves the root cause of the effectiveness of 3D SMPL unanswered, as recent work suggests that 2D supervision is inherently ambiguous [64]. Note that in this work, we extend the prior study on the supervision types by adding in 3D keypoints as a better part of the weak supervision and find out that SMPL annotation is still far more effective.

More importantly, we wish to offer preliminary discussions on what makes strong supervision (SMPL parameters) more effective than weak supervision (keypoints). We argue that keypoints only provide partial guidance to body shape estimation $\beta$ (bone length only), but $\beta$ is required in joint regression from the parametric model. Moreover, ground truth SMPL parameters is directly used in the loss computation with the predicted SMPL annotations during training and finds this strategy effective. However, this conclusion still leaves the root cause of the effectiveness of 3D SMPL unanswered, as recent work suggests that 2D supervision is inherently ambiguous [64]. Note that in this work, we extend the prior study on the supervision types by adding in 3D keypoints as a better part of the weak supervision and find out that SMPL annotation is still far more effective.

More importantly, we wish to offer preliminary discussions on what makes strong supervision (SMPL parameters) more effective than weak supervision (keypoints). We argue that keypoints only provide partial guidance to body shape estimation $\beta$ (bone length only), but $\beta$ is required in joint regression from the parametric model. Moreover, ground truth SMPL parameters is directly used in the loss computation with the predicted SMPL parameters $(1)$, which initiates gradient flow that reaches the learnable SMPL parameters in the shortest possible route. On the contrary, the 3D keypoints $X_{3D}$ are obtained with joint regression $J$ of canonical keypoints with estimated body shape $\beta$, and the global rigid transformation $M$ derived from the SMPL kinematic tree $(2)$. The 2D keypoints $X_{2D}$ further require extra estimation of translation $\hat{t}$ for the transformation $T$ of the 3D keypoints, and 3D to 2D projection $K$ with assumed focal length $f$ as well as camera center $c$. The elongated route and uncertainties introduced in the process to compute the loss for

![Fig. 8. Amount of GTA-Human Data. The horizontal axis indicate the amount of GTA-Human data used as multiples of the amount of real data. HMR+ is used as the base method.](image_url)

**TABLE VII**

SYNTHETIC DATA AS A SUPPLEMENT

| Real Ratio | 100K | 200K | 300K | 400K | 500K |
|-----------|------|------|------|------|------|
| 0%        | 70.6 | 64.5 | 65.7 | 65.0 | 64.9 |
| 25%       | 62.4 | 60.9 | 58.0 | 57.6 | 57.3 |
| 50%       | 61.7 | 58.9 | 57.9 | 56.3 | 55.6 |
| 75%       | 62.4 | 58.4 | 56.8 | 55.7 | N/A  |
| 100%      | 63.8 | 62.7 | 61.7 | N/A  | N/A  |

Different data amount with different real data ratio are shown. Values are PA-MPPE (mm) on 3DPW test set. Synthetic data is sampled from $\times 4$ set during training. N/A: this ratio cannot be sustained beyond 300K data due to insufficient real data. HMR+ (BT) is used as the base method.

**TABLE VIII**

STRONG SUPERVISION IS KEY

| Keypoints | SMPL | MPPE | 3D-MPPE |
|-----------|------|------|---------|
| -         | -    | 98.5 | 61.7    |
| ✔         | -    | 93.4 | 60.9    |
| -         | ✔    | 92.0 | 56.3    |
| ✔         | ✔    | 88.7 | 56.0    |

The first row is the HMR+ baseline without any GTA-Human data added.
Strong su-  

Training (3)  

Deeper and more powerful back-  

M  

The effectiveness  

The more data, the better because model  

3)  

(1)  

B  

to encode pose as a set of 3D coordinates of the 24 key joints, and plot the distance from the mean pose and T-pose respectively. The data density of e) and f) are in log scale.

TABLE IX  

BIG DATA BENEFITS BIG MODELS

| Backbone      | #Param | Real | +GTA-Human |
|---------------|--------|------|-----------|
| ResNet-50     | 26M    | 61.7 | 56.0 (-5.7) |
| ResNet-101    | 45M    | 60.1 | 54.5 (-5.6) |
| ResNet-152    | 60M    | 58.4 | 54.3 (-4.1) |
| DeiT-Small    | 22M    | 66.5 | 60.7 (-5.8) |
| DeiT-Base     | 86M    | 61.2 | 55.2 (-5.0) |

Real: training with only the real datasets. +GTA: blended training setting is used with GTA-Human. Values in green indicate the error reduction in PA-MPIPE (mm) with blended training.

2D keypoints (3)) hinder the effective learning.

\[
\mathcal{L}_{SMPL} = ||\theta - \hat{\theta}|| + ||\beta - \hat{\beta}||
\]

(1)

\[
\mathcal{L}_{3D} = ||\tilde{X}_{3D} - X_{3D}||
\]

(2)

\[
\mathcal{L}_{2D} = ||\tilde{X}_{2D} - X_{2D}||
\]

(3)

where

\[
\tilde{X}_{3D} = M(J(\hat{\beta}), \hat{\theta})
\]

(4)

\[
\tilde{X}_{2D} = K(T(\tilde{X}_{3D}, \hat{\mathbf{t}}), \mathbf{f}, \mathbf{c}).
\]

(5)

F. Big Data Benefits Big Models

ResNet-50 remains a common backbone choice, since HMR is first introduced for deep learning-based 3D human recovery. In this section, we extend our study of the impact of Big Data on more backbone options, including deeper CNNs such as ResNet-101 and 152 [27], as well as DeiT [30], as a representative of Vision Transformers. In Table IX, we evaluate various backbones for the HMR baseline. We highlight that including GTA-Human always improves model performance by a considerable margin, regardless of the model size or architecture. Note that using Transformers as the feature extractor for human pose and shape estimation is under-explored in recent literature; there may be some room for further improvement upon our attempts presented here. Nevertheless, the same trend holds for the two transformer variants. Interestingly, additional GTA-Human unleashes the full power of a small model (e.g., ResNet-50), enabling it to outperform a larger model (e.g., ResNet-152) trained with real data only. This suggests data still remains a critical bottleneck for accurate human pose and shape estimation.

V. Conclusion

In this work, we evaluate the effectiveness of synthetic game-playing data in enhancing human pose and shape estimation especially in the wild. To this end, we present GTA-Human, a large-scale, diverse dataset for 3D human recovery. Our experiments on GTA-Human provide five takeaways: 1) Training with diverse synthetic data (especially with outdoor scenes) achieves a significant performance boost. 2) The effectiveness is attributed to the complementary relation between real and synthetic data. 3) The more data, the better because model performance is highly sensitive to data density. 4) Strong supervision such as SMPL parameters are essential to training a high-performance model. 5) Deeper and more powerful backbones also benefit from a large amount of data. As for future works, we plan to investigate beyond 1.4 M data samples with more computation budgets to explore the boundary of training with synthetic data. Moreover, it would be interesting to study the sim2real problem for 3D parametric human recovery more in-depth with GTA-Human, or even extend the game-playing data to other human-related topics such as model-free reconstruction that are out of the scope of this work. In addition, the annotation pipeline may be upgraded to fully capture the body shape besides the bone lengths from the 3D mesh of the subjects.

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