

TL,DR

We introduce **Gen4D**, an automated pipeline for synthesizing diverse, realistic 4D human animations, and use it to build **SportPAL**, a large-scale synthetic sports dataset for human-centric vision tasks.

MOTIVATION

Collecting diverse, high-quality human motion data in real-world sports is costly and logistically difficult. While **synthetic datasets** offer a promising alternative, most rely on **fixed 3D assets, and repetitive animations**, resulting in limited diversity across appearance, motion, and viewpoint; ultimately restricting generalization to in-the-wild settings.

PROBLEM STATEMENT

Can we fully automate the synthesis of lifelike human animation from raw motion to scene synthesis without any manual 3D modeling?

KEY CONTRIBUTIONS

- ❖ **Gen4D**: A fully automated pipeline for synthesizing life-like human avatars with realistic animations.
- ❖ **SportPAL**: A large-scale, richly annotated synthetic dataset spanning baseball, ice hockey, and soccer, designed for human-centric vision tasks.

PROMPT MODELING

- ❖ Uses text templates to guide avatar generation via diffusion models.
- ❖ Captures diversity in appearance attributes like ethnicity, body type, age, hair, and clothing.
- ❖ Attributes are combined programmatically to avoid repetition and ensure balanced sampling.
- ❖ Enables generation of highly varied and realistic human avatars without manual asset design.

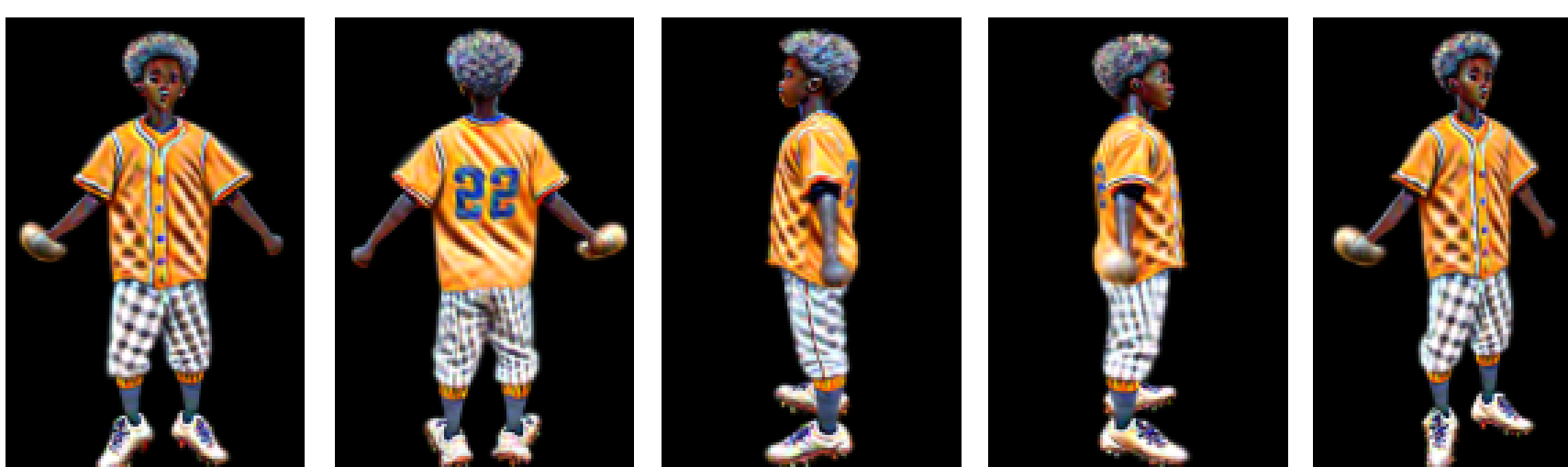
Attributes:

Ethnicity:	American	Asian	African	Indian	Mexican	African
Body Shape:	Slim	Athletic	Muscular	Fat	Slim	Slim
Age:	Teenager	Mid-aged	Old	Teenager	Teenager	Teenager
Cloth Color:	Black	Red	White	Yellow	Teal	Yellow
Cloth Pattern:	Solid	Stripes	Checks	Floral	Dots	Checks
Hair Color:	Black	Brown	Red	Grey	Bronze	Grey
Hair Type:	Straight	Curly	Wavy	Kinky	Curly	Curly
Hair Length:	Short	Medium	Long	Medium	Medium	Medium

Prompt Template:

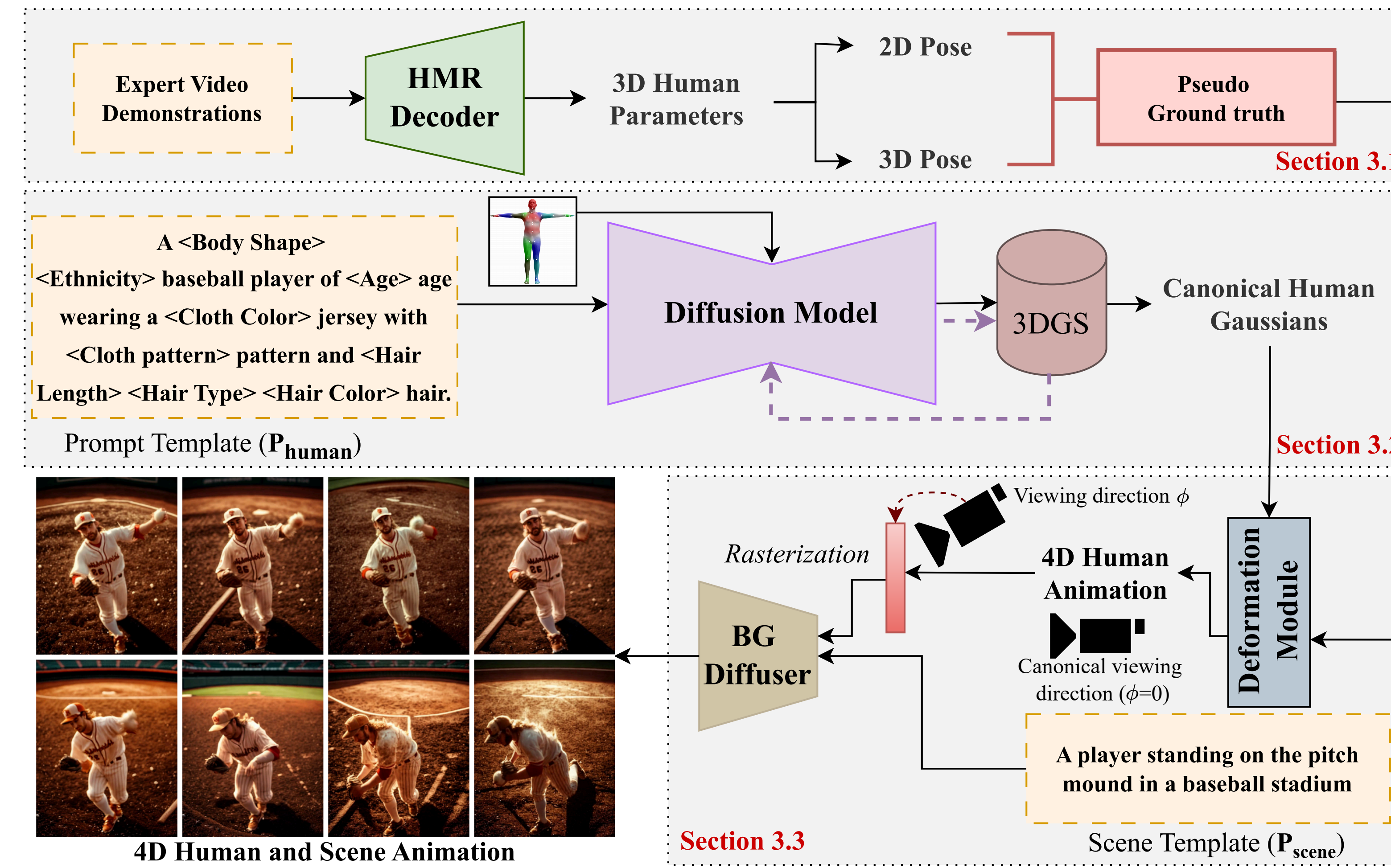
A <Body Shape> <Ethnicity> baseball player of <Age> age wearing a <Cloth Color> jersey with <Cloth pattern> pattern and <Hair Length> <Hair Type> <Hair Color> hair.

Generated Avatar:



THE PROPOSED METHOD: GEN4D

1. **Motion Extraction**: obtain motion representation from internet videos.
2. **Canonical Human Gaussians**: generates diverse human avatars via text-guided diffusion and Gaussian splatting in canonical space.
3. **Scene Composition**: Animate avatars with motion, render from multiple viewpoints, and synthesize human-aware backgrounds using diffusion-based scene generation.



QUALITATIVE RESULTS



(a) Examples of 3D canonical avatar representations; (b) Final rasterized synthetic frames with avatar animation and pose-aware backgrounds; (c) Qualitative visualizations of pose estimation results trained on SportPAL using TokenPose [1].

SPORTPAL

- ❖ Includes 583K+ synthetic frames across baseball, ice hockey, and soccer.
- ❖ Rich annotations: 2D/3D poses, SMPLX parameters, bounding boxes, and action labels.
- ❖ Built from 50 unique subjects with varied ethnicity, body types, clothing, and viewpoints.

SportPAL dataset split

Sport	Split	#Subjects	#Clips	#Frames
Baseball	Train	15	1,000	253,869
	Valid	15	304	80,810
	Test	5	300	71,875
Icehockey	Train	10	195	75,468
	Valid	10	50	18,867
	Test	5	12	7,487
Soccer	Train	10	116	57,110
	Valid	10	30	14,277
	Test	5	5	3,639
Total	-	50	2,012	583,403

QUANTITATIVE RESULTS

Impact of fine-tuning with cross-domain sports

Sport	Method	AP ⁵ ↑	AP ¹⁰ ↑	AP ¹⁵ ↑
Icehockey	w/o finetuning	62.75	96.92	99.91
	w/ finetuning	63.47 (+0.72)	98.10 (+1.18)	99.98 (+0.07)
Soccer	w/o finetuning	67.28	92.56	98.51
	w/ finetuning	71.46 (+4.18)	94.68 (+2.12)	99.13 (+0.62)

ACKNOWLEDGEMENT



REFERENCES

- [1] Yanjie Li, Shoukui Zhang, Zhicheng Wang, and et al. Tokenpose: Learning keypoint tokens for human pose estimation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 11313–11322, 2021.