Distribution and Depth-Aware Transformers for 3D Human Mesh Recovery

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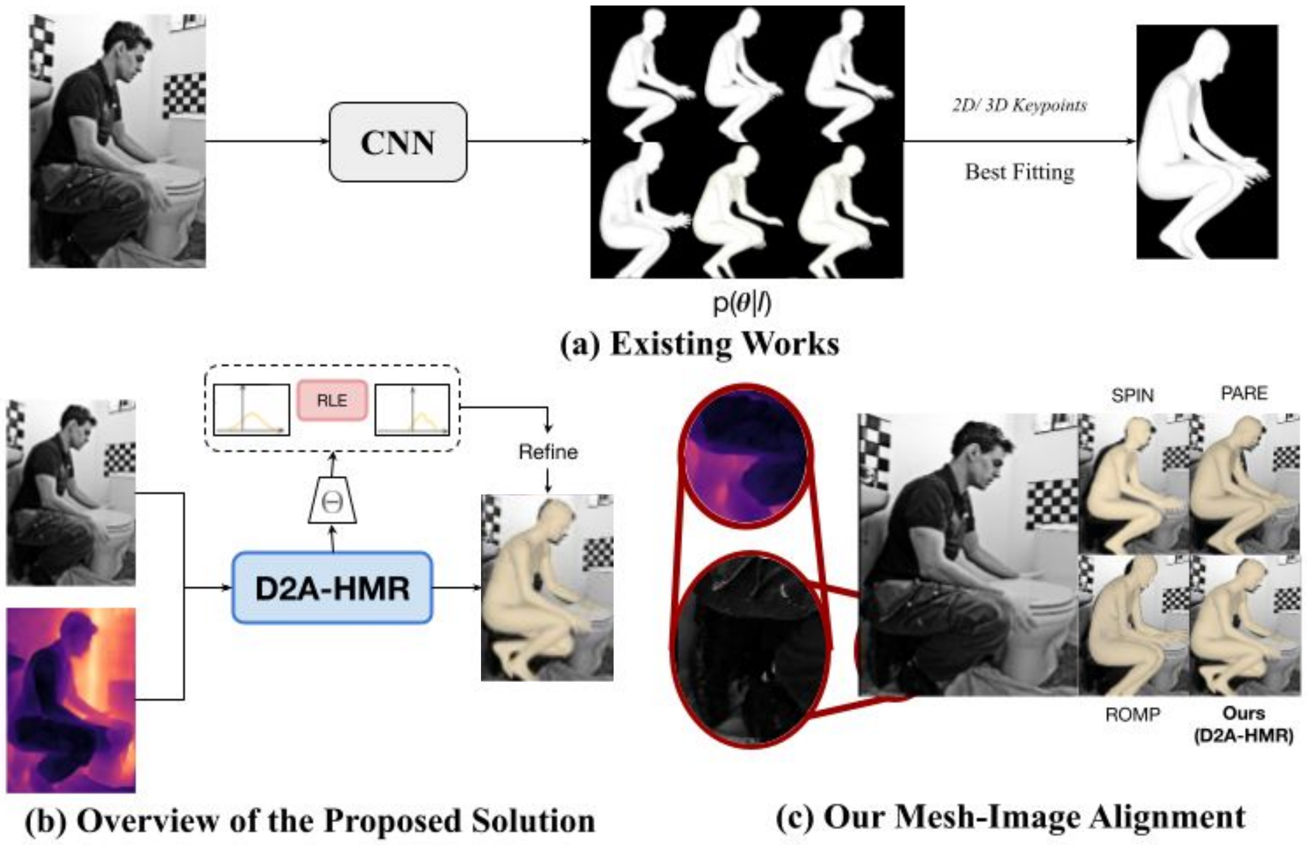
Overview

Objective:

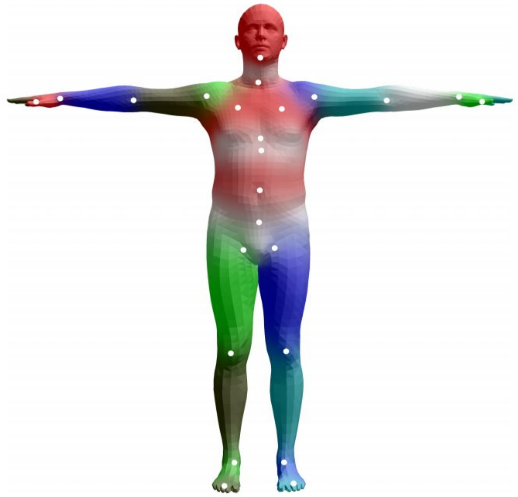
- ❖ Generalizable 3D human modeling from monocular images.
- ❖ Robust alignment in diverse conditions.

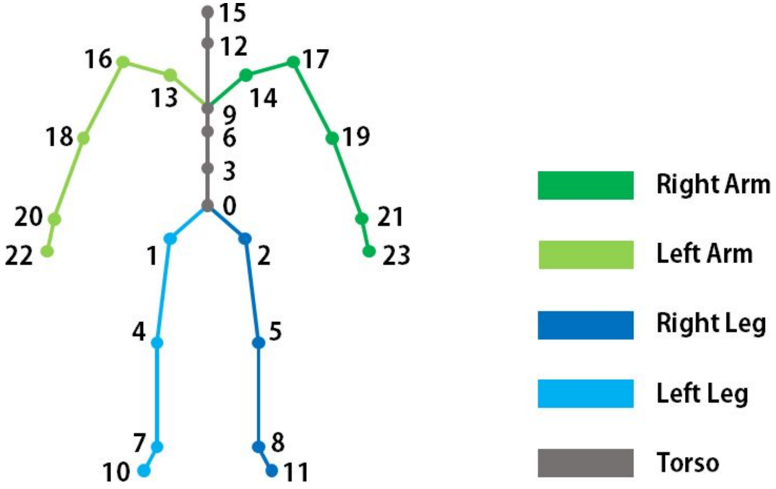
Model the depth and distribution

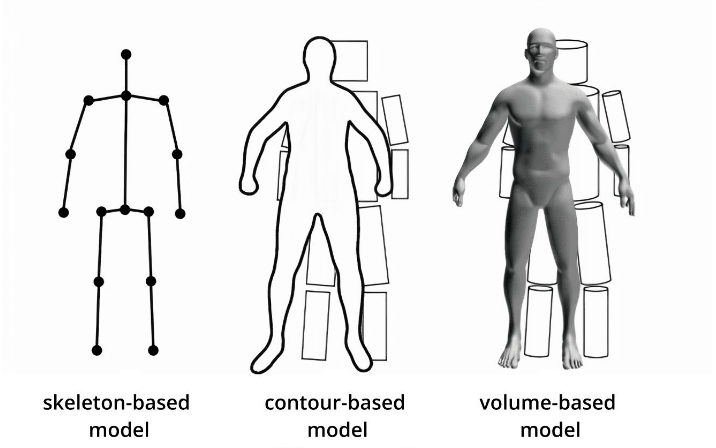


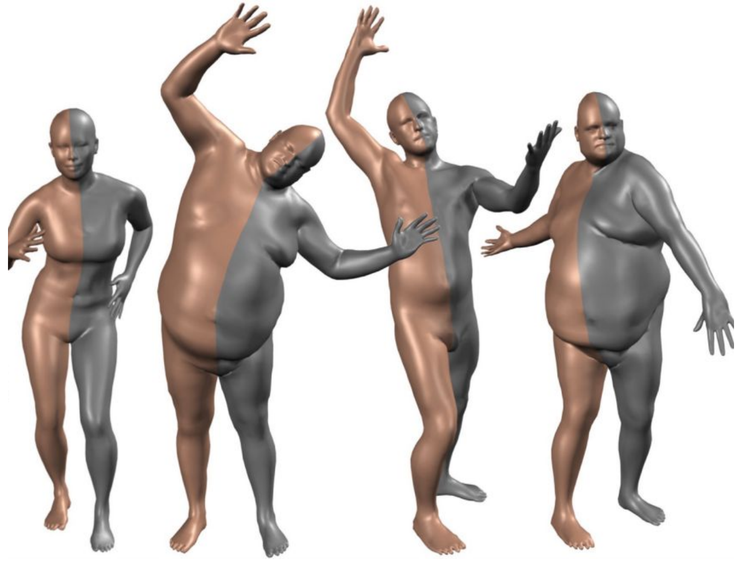
Background - SMPL

- ❖ Skinned Multi-Person Linear model [1].
- ❖ 72 joint and 10 shape parameters -> 6890 vertices.



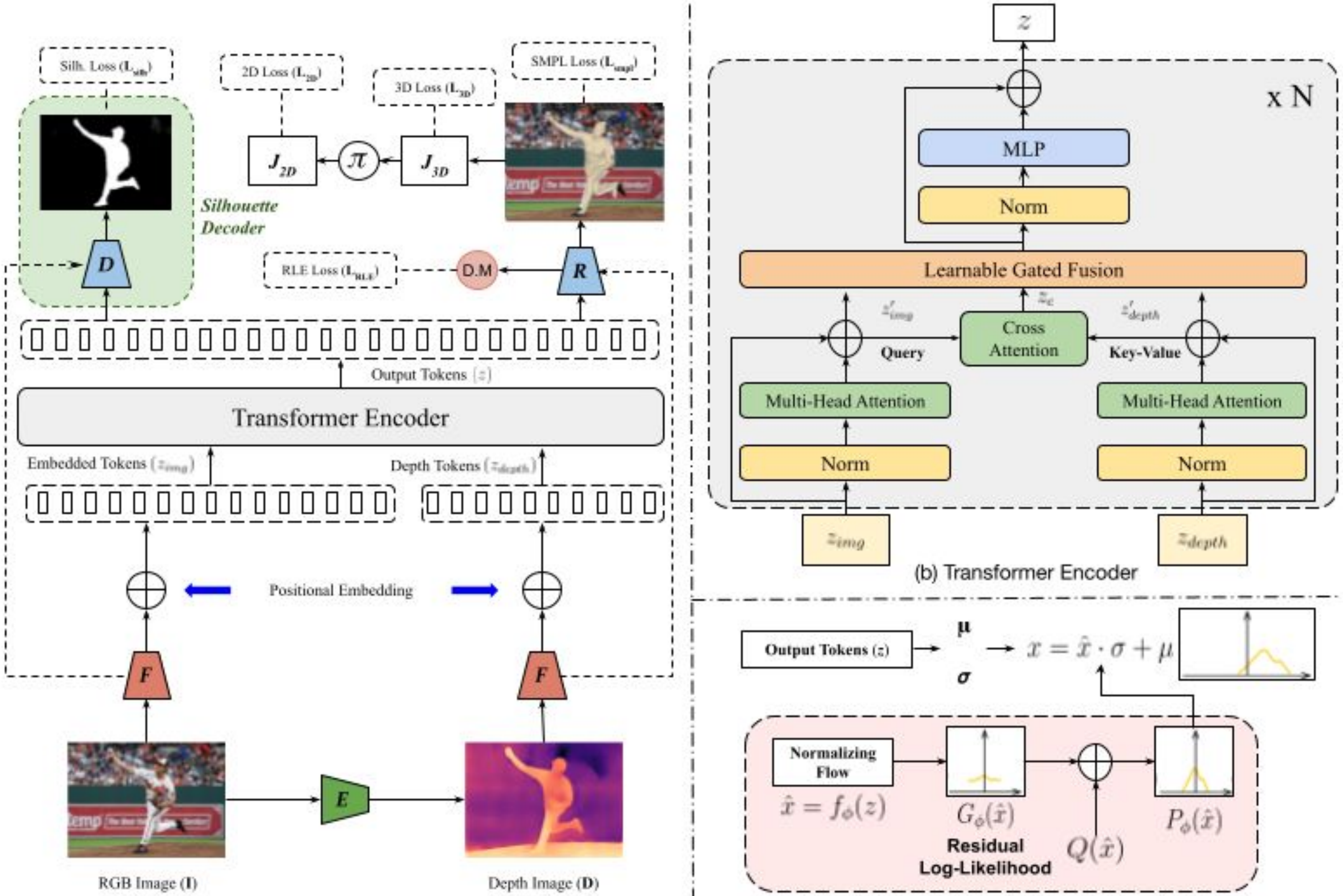






[1] Loper, Matthew and Mahmood, Naureen and Romero, Javier and Pons-Moll, Gerard and Black, Michael J. *SMPL: A Skinned Multi-Person Linear Model*. ACM Trans. Graphics (Proc. SIGGRAPH Asia), 2015

Our Work



(a) Proposed D2A-HMR framework

(b) Transformer Encoder

(c) Distribution Matching (D.M)

Objective Functions

- **Distribution Loss:**

$$\mathcal{L}_{RLE} = -\log Q(\bar{\mu}_g) - \log G_\phi(\bar{\mu}_g) - \log c + log\ \sigma$$

- **2D Pose Loss:**

$$\mathcal{L}_{2D} = |J_{2D} - J^g_{2D}|$$

- **3D Pose Loss:**

$$\mathcal{L}_{3D} = |J_{3D} - J^g_{3D}|$$

- **Overall Objective:**

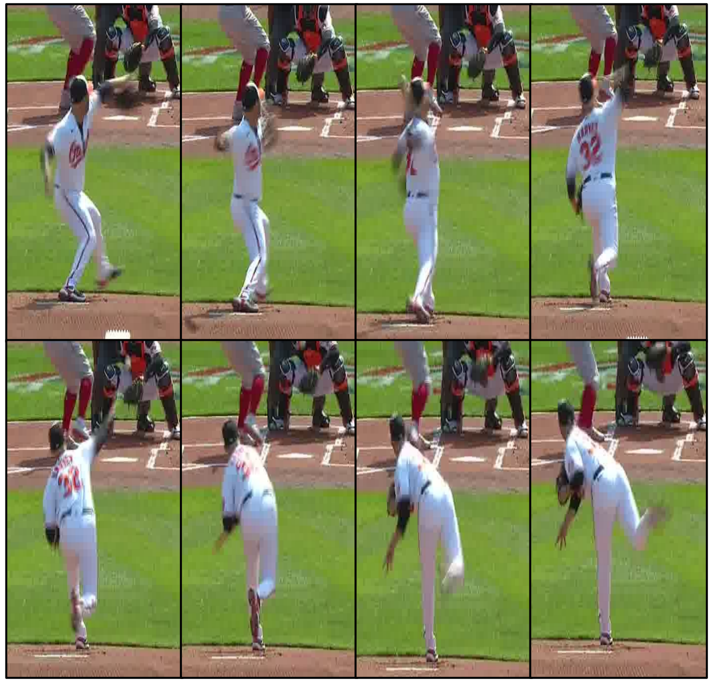
$$\mathcal{L} = \lambda_d \mathcal{L}_{RLE} + \lambda_v \mathcal{L}_v + \lambda_{3D} \mathcal{L}_{3D} + \lambda_{2D} \mathcal{L}_{2D} + \lambda_s \mathcal{L}_{silh}$$

Datasets

3D Poses in the Wild

Human3.6M

MLBPitchDB



Benchmarked Datasets

In-house Sports Dataset

Quantitative Comparison (Benchmarked Datasets)

Table I: Comparison to state-of-the-art 3D pose reconstruction approaches on 3DPW and Human3.6M datasets. **Bold**: best; <u>Underline</u>: second best.

	Method	Human3.6M		3DPW		
		mPJPE ↓	PA-mPJPE ↓	mPVE ↓	mPJPE ↓	PA-mPJPE ↓
Video	HMMR [5]	-	58.1	139.3	116.5	72.6
	TCMR [33]	62.3	41.1	111.5	95.0	55.8
	VIBE [9]	65.6	41.4	99.1	93.5	56.5
Model-based	HMR [4]	88.0	56.8	-	130.0	81.3
	SPEC [34]	-	-	118.5	96.5	53.2
	SPIN [10]	62.5	41.1	116.4	96.9	59.2
	PyMAF [35]	57.7	40.5	110.1	92.8	58.9
	ROMP [36]	-	-	105.6	89.3	53.5
	HMR-EFT [37]	63.2	43.8	98.7	85.1	52.2
	PARE [11]	76.8	50.6	97.9	82.0	50.9
Model-free	ProHMR [12]	-	41.2	109.6	95.1	59.5
	I2LMeshNet [22]	55.7	41.1	-	93.2	57.7
	Pose2Mesh [7]	64.9	47.0	-	89.2	58.9
	METRO [8]	<u>54.0</u>	<u>36.7</u>	**88.2**	**77.1**	**47.9**
	D2A-HMR (Ours)	**53.8**	**36.2**	<u>88.4</u>	<u>80.5</u>	<u>48.4</u>

Qualitative Results (Benchmarked Datasets)

Comparison (In-house Sports Dataset)

Table II: Comparison of D2A-HMR on the MLBPitchDB baseball dataset [41]. **Bold**: best; Underline: second best; Double Underline: third best.

Method	Acc. ↑	mPJPE ↓
HMR [8]	65.9	61.3
SPIN [10]	84.7	32.1
ProHMR [8]	76.1	48.2
ROMP [8]	77.4	48.9
METRO [8]	81.5	37.8
PARE [11]	84.0	33.7
D2A-HMR (Ours)	**87.9**	**30.6**

Ablation Studies

Table III: Ablation study on pseudo-depth and distribution modeling for D2A-HMR evaluated on 3DPW dataset.

Depth	**Distribution**	**mPJPE** ↓	**PA-mPJPE** ↓
✓		92.7	61.8
	✓	90.0	56.9
✓	✓	**80.5**	**48.4**

Table IV: Ablation study on the impact of depth modeling for D2A-HMR evaluated on 3DPW dataset.

	mPJPE(z) ↓	**PA-mPJPE(z)** ↓
w/o depth modeling	69.1	58.3
w/ depth modeling	**65.4**	**53.6**

Table V: Ablation study on the silhouette decoder and masked modeling evaluated on 3DPW dataset.

Silhouette	**Masked Modeling**	**mPJPE** ↓	**PA-mPJPE** ↓
✓		89.5	62.2
	✓	84.7	51.4
✓	✓	**80.5**	**48.4**

Table VI: Different input representations as the backbone for D2A-HMR evaluated on 3DPW dataset.

Backbone	**mPJPE** ↓	**PA-mPJPE** ↓
ResNet50	91.1	59.9
ResNet101	89.5	55.8
HRNet-w40	85.2	52.1
HRNet-w64	**80.5**	**48.4**

Conclusion

- A novel image-based HMR model named **D2A-HMR** that adeptly models the underlying distributions and integrates pseudo-depth priors for efficient and accurate mesh recovery.

- By leveraging **residual log-likelihood** approach, we refine the model by learning the disparity between the underlying predicted and ground truth distribution.

- **Validation** of the enhanced performance through the integration of pseudo-depth and distribution-aware modules in HMR, particularly in complex human pose scenarios.

Thank you!

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