Human Body Measurement Estimation with Adversarial Augmentation

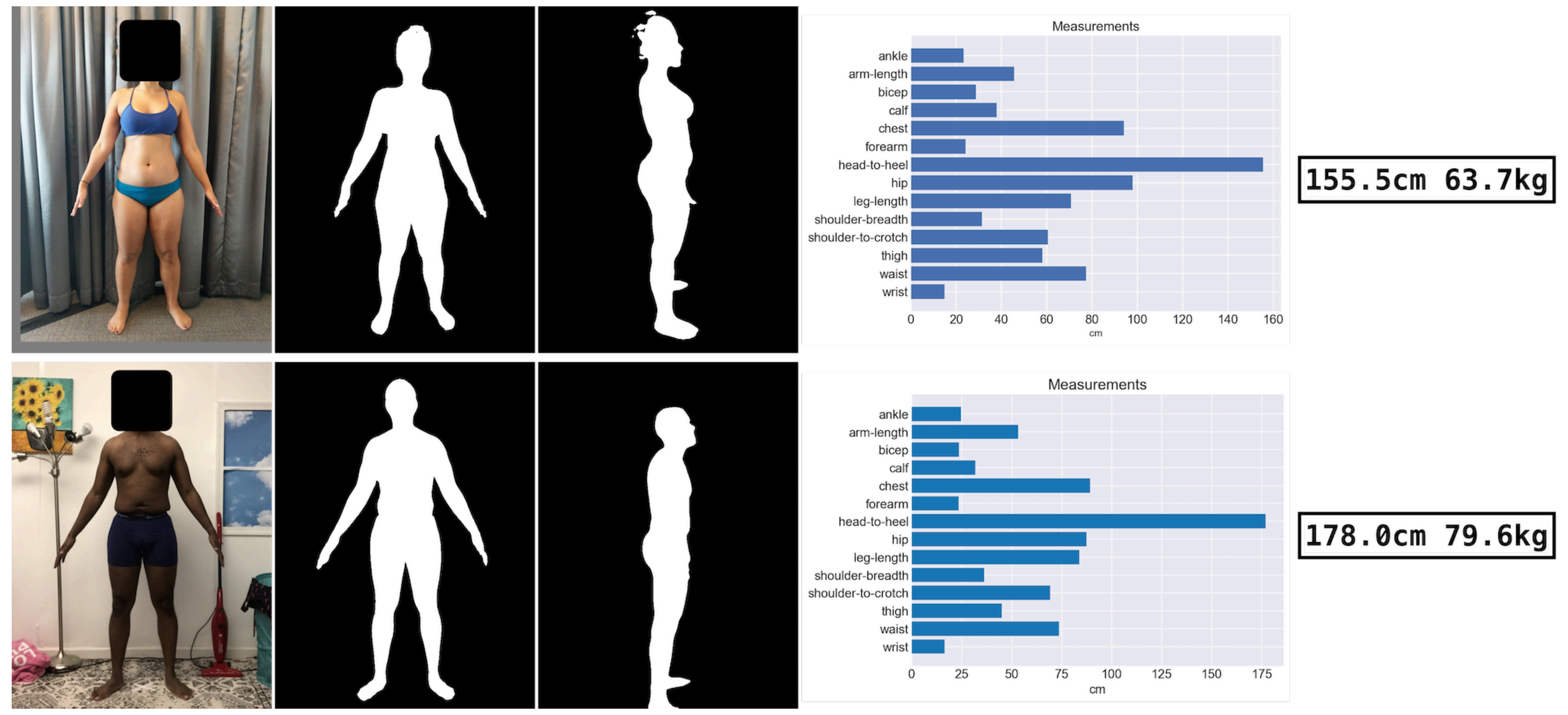
Nataniel Ruiz†*, Miriam Bellver†, Timo Bolkart†, Ambuj Arora†, Ming C. Lin†, Javier Romero‡, Raja Bala†
3DV 2022 · †Amazon · *Boston University · ‡Reality Labs Research

Problem and Approach

- Human body measurement estimation is key for several tasks including health applications such as body fat measurement or fashion applications such as made-to-measure garments.
- Train and test data is **limited** for such models. We release the **first** large public body measurement dataset using real subjects and a method to directly regress body measurements from silhouettes.
- We propose a differentiable framework for **learning how to test** such a network using a body simulator in an **adversarial manner** in order to find weaknesses, and **further improving** the model by training using the generated adversarial bodies.
- Our BodyM dataset is available at https://adversarialbodysim.github.io

BodyM Dataset

The first large public body measurement dataset.



	Train	Test-A	Test-B
Subjects	2,018	87	400
Silhouettes	6,134	1,684	1,160

We present the first large public body measurement dataset including more than 8,000 frontal and lateral silhouettes from more than 2,500 real subjects, paired with height, weight and 14 body measurements.

The figure above shows samples of silhouettes for a pair of subjects, including measurement bar charts with all 14 measurements and their respective height and weight.

Simulated Adversarial Training for Body Measurement Estimation

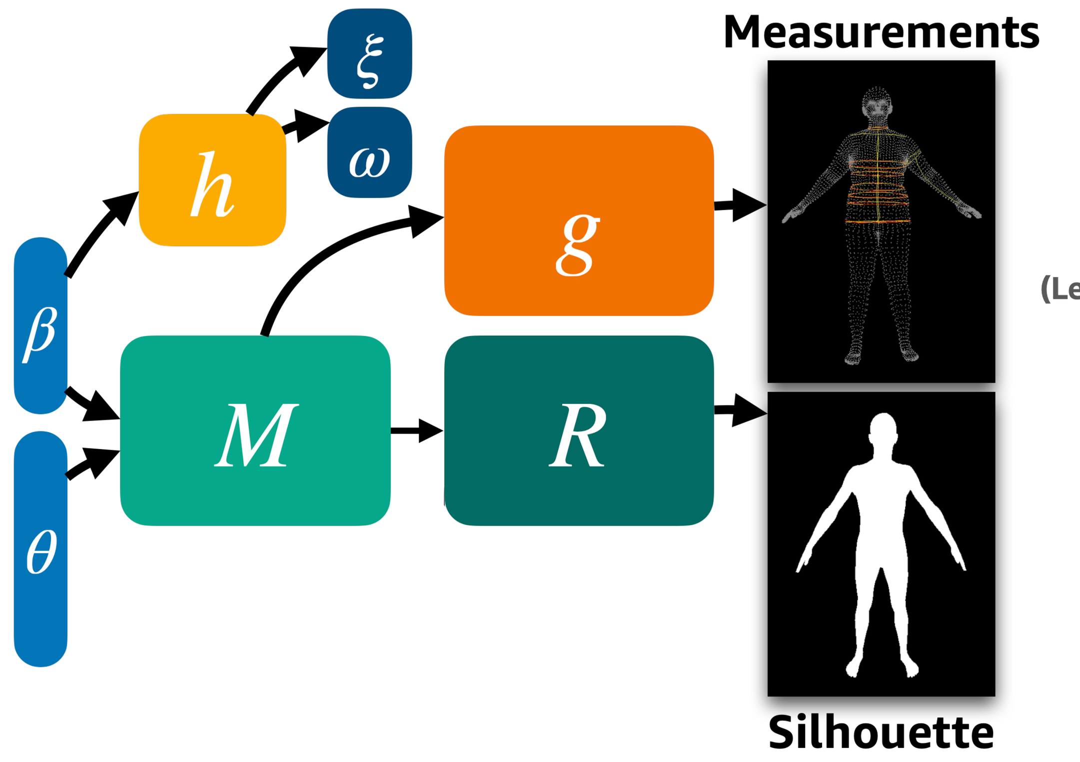


Figure I: Our differentiable simulator.

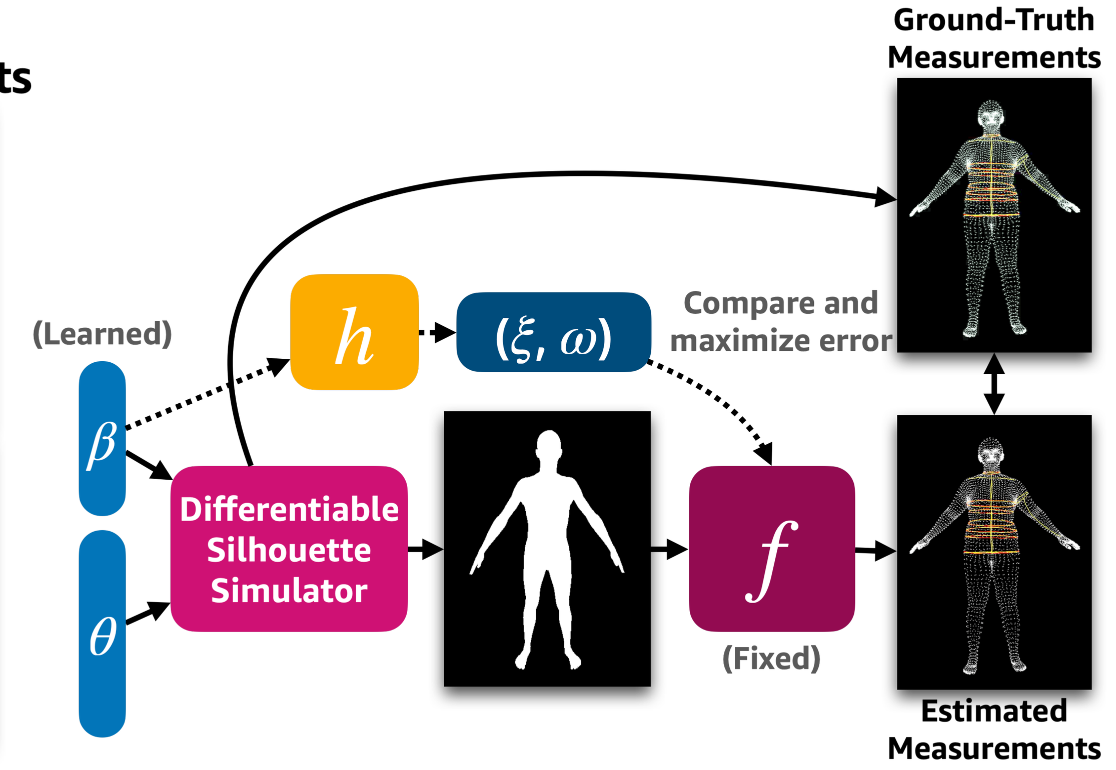
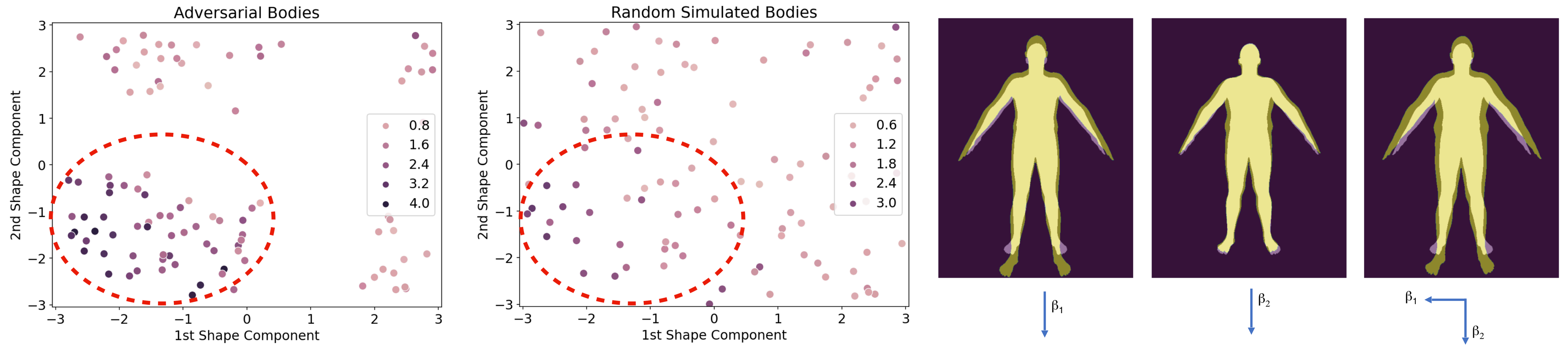


Figure II: Our full system.

Our differentiable simulator is comprised of the SMPL model M that takes in shape β and pose θ. We generate height ϵ and weight ω using a trained regressor h, generate measurements using a deterministic measuring function g operating on vertices, and we render the silhouettes using a renderer R.

In order to simulate adversarial bodies, we optimize the shape β by **maximizing** a loss between the ground-truth measurements and the measurements estimated by our model f. The resulting shape parameters give rise to an adversarial body, which are then used to train the model f.

Simulated Adversarial Testing for Interpretability



We show that adversarially simulated bodies are concentrated in certain regions of body shape space. Here we can see that adversarial bodies are concentrated in negative regions of the 1st and 2nd shape component and have higher loss than random bodies. We also observe that the negative directions of these components correspond to **taller** and **wider** bodies.

Body Measurement Estimation Results

	Overall			Chest	Hip	Leg Length	Waist
	TP90	TP75	TP50	MAE	MAE	MAE	MAE
SPIN [34]	81.10	57.33	33.96	74.45	65.41	35.81	77.39
STRAPS [72]	103.61	75.74	45.67	82.30	63.96	48.71	108.00
Sengupta et al. [69]	68.81	47.64	28.71	53.07	47.43	42.11	53.20
Ours (Single-View, No Metadata)	**41.91**	**29.13**	**17.09**	**33.95**	**31.03**	**25.80**	**31.93**

Table I: Comparison to SotA body shape estimation methods (errors in mm)

SotA compared to off-the-shelf body reconstruction methods

We compare our method to SotA off-the-shelf body shape estimation methods such as SPIN, STRAPS and Sengupta et al. (ICCV 2021) and we find that our method outperforms them on body measurement estimation. Our method uses only one silhouette and no height and weight data for fairness.

	Ankle	Arm-L	Bicep	Calf	Chest	Forearm	H2H	Hip	Leg-L	S-B	S-to-C	Thigh	Waist	Wrist	Overall
Dibra et al. [19]	2.0	2.7	3.3	3.3	7.2	2.3	4.0	*6.0*	2.8	2.9	2.9	4.9	8.1	2.0	3.78
Smith et al. [78]	2.1	**1.7**	2.7	2.3	4.7	1.9	**2.3**	3.0	**1.5**	1.9	**1.5**	2.4	4.8	2.5	2.72
Ours	**0.8**	1.9	**1.7**	**0.8**	**4.6**	**1.3**	3.6	*1.8*	2.1	**0.9**	1.9	**1.7**	**3.8**	**0.7**	**1.97**

	Neck	Chest	Waist	Pelvis	Wrist	Bicep	Forearm	Arm	Leg	Thigh	Calf	Ankle	Height	Shoulder	Overall
Yan et al. [90]	11.8	23.0	16.5	**13.3**	4.1	11.4	7.2	**7.6**	**9.2**	17.8	8.8	**5.4**	9.0	9.2	11.0
Ours	**11.0**	**15.2**	**15.7**	17.3	**3.8**	**4.7**	**3.9**	7.7	10.0	**7.5**	**8.6**	10.0	**13.4**	**7.1**	**9.7**
Yan et al. [90]	*14.6*	21.7	17.1	14.7	5.2	9.3	8.5	**6.4**	**6.5**	**11.6**	**9.2**	**6.1**	**8.6**	7.6	10.5
Ours	**4.4**	**9.1**	**10.8**	**7.7**	**5.2**	**3.9**	**5.3**	**6.4**	10.2	13.2	9.8	12.2	20.7	**6.5**	**9.0**

Table II: Comparison to SotA body measurement estimation methods (errors in mm)

SotA compared to other body measurement estimation methods

We compare against the SotA methods for body measurement estimation and find that we outperform them overall, and over a variety of specific measurements on two different datasets.

	Overall			Chest	Hip	Waist
	TP90	TP75	TP50	MAE	MAE	MAE
Single-View (No Aug.)	19.10	13.00	7.64	19.18	11.53	16.12
Single-View (Random Aug.)	18.98	12.84	7.50	19.13	11.43	**15.76**
Single-View (Adv. Aug.)	**18.90**	**12.82**	**7.44**	**18.84**	**11.14**	15.78
Multi-View (No Aug.)	16.45	11.06	6.51	**14.40**	10.88	13.40
Multi-View (Random Aug.)	16.43	11.06	**6.48**	14.66	10.60	13.17
Multi-View (Adv. Aug.)	**16.00**	**10.00**	6.53	14.52	**10.00**	**13.00**
Multi-View (No Aug.)	26.52	17.64	10.04	24.60	19.55	21.75
Multi-View (Random Aug.)	26.13	17.35	9.90	23.09	18.87	22.44
Multi-View (Adv. Aug.)	**25.00**	**16.28**	**9.50**	**22.98**	**18.09**	**21.10**

Table III: Ablation study w.r.t. no augmentation, random aug. and adversarial aug. (errors in mm)

Simulated adversarial training improves body measurement estimation

We perform an ablation study over several setups (respectively: single-view, multi-view, and multi-view w/ 10x less real training data). We find that simulated adversarial body augmentation outperforms no augmentation and augmentation using randomly sampled simulated bodies.