Reconstructing Human Body Mesh from Point Clouds by Adversarial GP Network

ACCV 2020 Supplementary Material

Paper ID 493

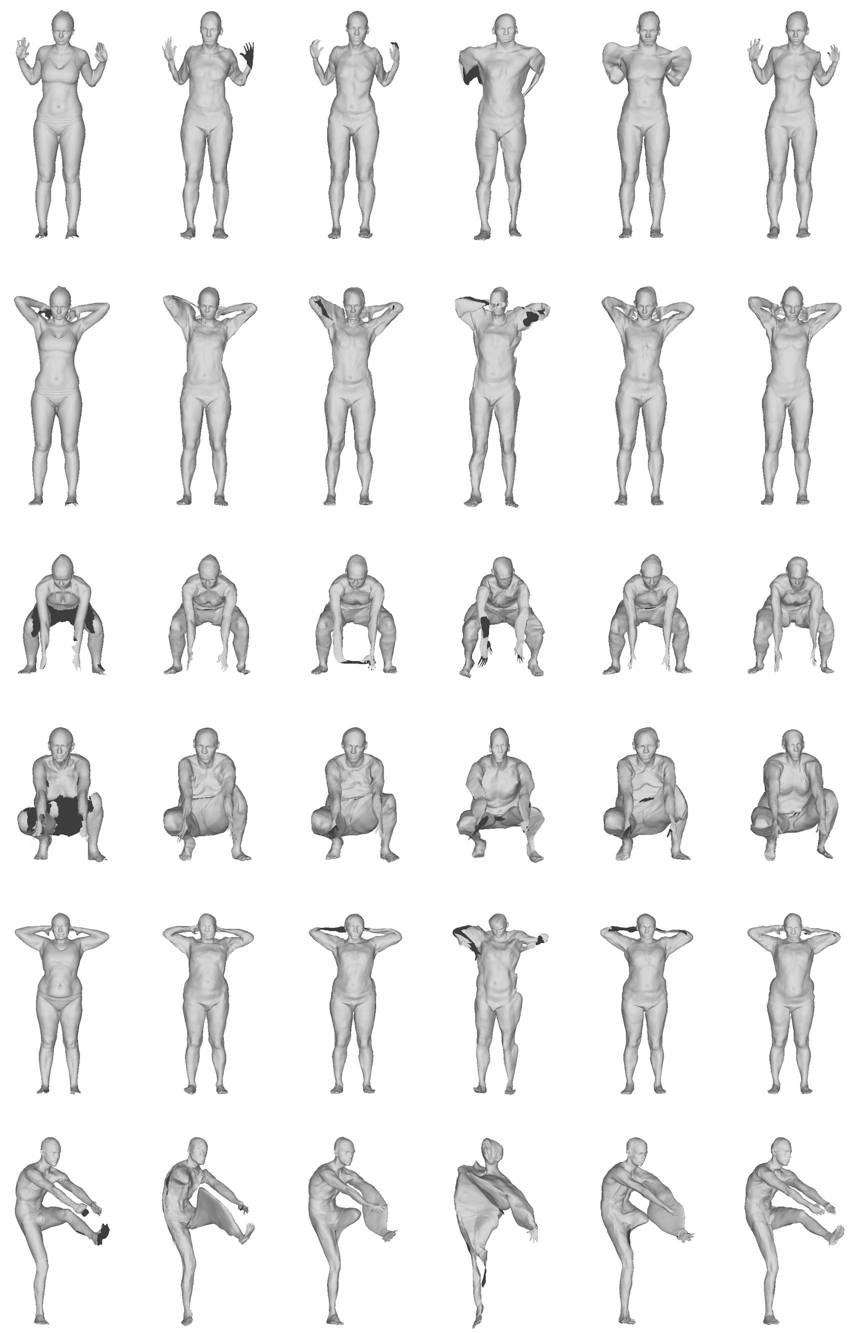
In the following, we first provide the details of the Gaussian kernels regarding the parameters γ, r and σ. We further discuss the design of our Adversarial GP network.

1 Gaussian Kernels

In Figure 1 of the main paper, we show that the template is divided into 19 small patches in order to improve the reconstruction precision on each patch. And we discuss how to select the kernel according to the reconstruction error of 10 random meshes in FAUST [1] training dataset. In Table 1 we present our tuned Gaussian kernels [2].

Patch	γ	r ($\times 10^{-2}$)	σ ($\times 10^{-1}$)
left forearm	7.81	1.47	1.99
left hand	4.31	1.65	2.20
left arm	0.20	4.00	2.15
left elbow	6.31	1.39	1.99
left foot	1.98	3.88	1.99
left leg	3.15	2.64	1.99
left thigh	1.98	2.20	2.20
right forearm	5.04	1.89	1.99
right hand	7.81	1.47	1.99
right arm	0.54	3.04	2.20
right elbow	6.98	1.39	1.74
right foot	5.04	1.14	1.95
right leg	1.98	6.48	1.99
right thigh	2.15	3.86	1.99
belly	12.81	1.33	1.74
crotch	1.15	2.44	2.20
head	3.04	1.68	2.20
torso	5.31	1.80	1.95
upper torso	23.15	1.35	5.49

Table 1. Tuned Gaussian Kernels.



(a) scan (b) w/o MLP (c) w/o Adv (d) L2 (e) Dropout (f) Adv GP

Fig. 1. Quantitative results in FAUST challenge. From left to right, (a) input scan, reconstruction in high resolution of (b) Adv+GP (without MLP), (c) MLP+GP (without Adv), (d) MLP+GP+L2, (e) MLP+GP+Dropout and (f) Adversarial GP.

2 Design of Adversarial GP

In Section 3 of the main paper, we present the architecture of our Adversarial GP network. Apart from encoder and point-wise decoder, there are three parts including GP layer, MLP and adversarial training. To confirm this architecture, we prepare one model without training MLP in parallel and one model without adversarial training. Here, we consider adversarial loss as a penalty. So we also compare to two other regularisation techniques, L2-weight-decay and dropout. In Figure 1, the full model of our Adversarial GP network could correct the artifacts of the model without MLP and of the model without adversarial loss. This illustrates that our full model of Adversarial GP network improves the robustness for real scan data reconstruction. However, we sacrifice a little the fitting accuracy with adversarial learning to guarantee the physical plausibility. Adv GP deteriorates the reconstruction surface on head and back in few deformed instances in FAUST challenge, see Figure 2.

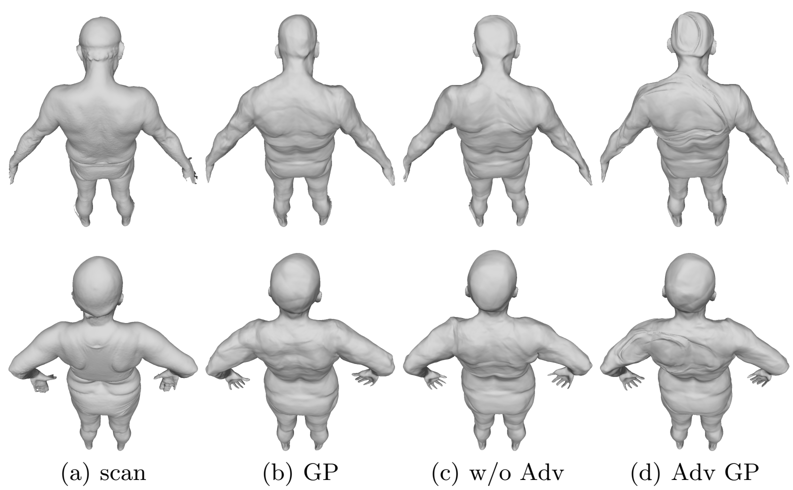


Fig. 2. Quantitative results in FAUST challenge. From left to right, (a) input scan, reconstruction in high resolution of (b) GP, (c) MLP+GP (without Adv) and (d) Adversarial GP.

References

1. Bogo, F., Romero, J., Loper, M., Black, M.J.: Faust: Dataset and evaluation for 3d mesh registration. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. (2014) 3794–3801
2. Williams, C.K., Rasmussen, C.E.: Gaussian processes for machine learning. MIT press Cambridge, MA (2006)