# Supplemental Materials: Learning Anchor Transformations for 3D Garment Animation

Fang Zhao[1], Zekun Li[1], Shaoli Huang[1*], Junwu Weng[1], Tianfei Zhou[2], Guo-Sen Xie[3], Jue Wang[1], Ying Shan[1]

[1]Tencent AI Lab [2]ETH Zurich [3]Nanjing University of Science and Technology

In the supplemental materials, we present additional details on training and inference procedures (Sec. 1) and more qualitative results and comparisons (Sec. 2).

## 1. Training and Inference

For training, we adopt the Adam optimizer [2] with an initial learning rate of 1e-3. The batch size is 8 and the number of epochs is 50. The learning rate is lowered to 1e-4 after 30 epochs. Empirically the weights $\lambda_1$, $\lambda_2$ and $\lambda_3$ of the overall objective function are set to 1, 0.01 and 100, respectively. The weight factor $\gamma$ in the transformation consistency loss is set to 0.1. The Laplacian and collision coefficients in the vertex loss are set to 0.2 and 1, respectively. At the beginning of training, we optimize the objective function without the collision term and the direction penalty term and add these two terms in the last 10 epochs while recalculating the anchor-vertex relationships according to the new anchor positions.

Fig. 1 shows the structure of the network for estimating anchor transformations and per-vertex displacements in the canonical space. For the $i$-th frame, the body pose $\theta_i$ and translation $t_i$ are concatenated and fed into the GRU layers. Anchor rotations and translations $[R_i; T_i]$ and per-vertex displacements $D_i$ are produced respectively by MLPs consisting of two fully-connected (FC) layers, where the first FC layer is followed by the PReLU activation. The anchor rotation is predicted as Euler angles by the network and then is converted to a rotation matrix. The initial state $\mathbf{h}_0$ of each GRU layer is sampled from a normal distribution with mean zero and standard deviation 0.1. At inference, the initial state is set to zero and the model can be applied to motion sequences of arbitrary length.

Meshes simplified by Quadric Error Metric (QEM) [1] are illustrated in Fig. 2, which are used as the supervision for the adaptive anchor updating. These meshes preserve intrinsic geometric structures of the surface, *e.g.*, folds and boundaries, which provide key topology information to learn representative anchors.

*Corresponding author.

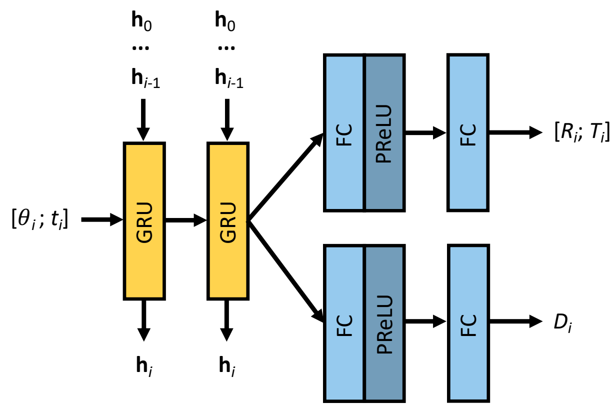


Figure 1. Structure of the network for estimating anchor rotations and translations $[R_i; T_i]$ and per-vertex displacements $D_i$ in the canonical space.

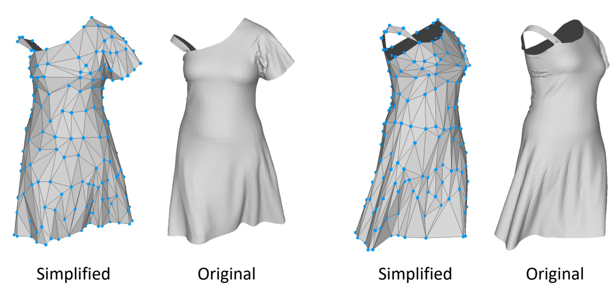


Figure 2. Visualization of simplified meshes used as the supervision for the adaptive anchor updating.

All compared models are trained using the hyper-parameters described in their papers. For TailorNet [4], we use the training code provided by its authors. VirtualBones [3] only releases the inference code, thus we re-implement the training code according to its inference code.

## 2. More Results

Please refer to https://semanticdh.github.io/AnchorDEF for examples of our AnchorDEF for dy-

Figure 3. Failure cases for some extreme poses where garment-body interpenetration may appear.

namic garment deformation in motion and qualitative comparison of our AnchorDEF with other 3D garment deformation methods [3, 4]. As shown in the demo video, given a body motion sequence which is unseen during training, our method can produce natural and realistic clothing dynamics and the garment deformation closer to the ground truth compared with other methods.

Some failure cases are shown in Fig. 3. Garment-body interpenetration may appear for some extreme poses. Preventing or reducing such garment-body interpenetration is a future research direction.

## References


[1] Michael Garland and Paul S Heckbert. Surface simplification using quadric error metrics. In *Proceedings of the 24th annual conference on Computer graphics and interactive techniques*, 1997. 1

[2] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *Proceedings of the International Conference on Learning Representations (ICLR)*, 2015. 1

[3] Xiaoyu Pan, Jiaming Mai, Xinwei Jiang, Dongxue Tang, Jingxiang Li, Tianjia Shao, Kun Zhou, Xiaogang Jin, and Dinesh Manocha. Predicting loose-fitting garment deformations using bone-driven motion networks. In *ACM SIGGRAPH Conference Proceedings*, 2022. 1, 2

[4] Chaitanya Patel, Zhouyingcheng Liao, and Gerard Pons-Moll. Tailornet: Predicting clothing in 3d as a function of human pose, shape and garment style. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020. 1, 2