Supplemental Materials: Learning Anchor Transformations for 3D Garment Animation

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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\textsuperscript{[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 recalcualting the anchor-vertex relationships according to the new anchor positions.

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

Meshes simplified by Quadric Error Metric (QEM)\textsuperscript{[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.

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

2. More Results

Please refer to \url{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.

Dynamic 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**


