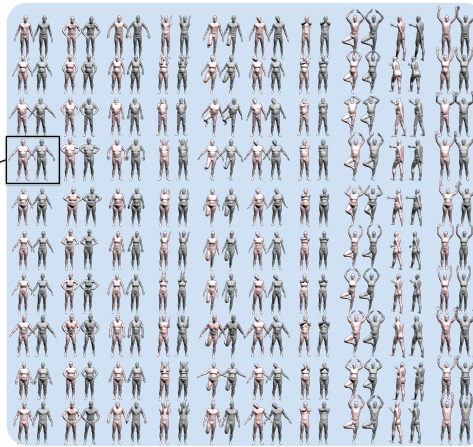
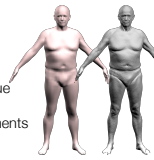


The dataset

- **300** real human body scans (10 subjects, 30 poses)
- **Ground-truth correspondences:** each scan brought into alignment with a common template using a **texture-based registration** technique
- **Training set:** 100 scans + 100 alignments
- **Test set:** 200 scans



Texture-based registration

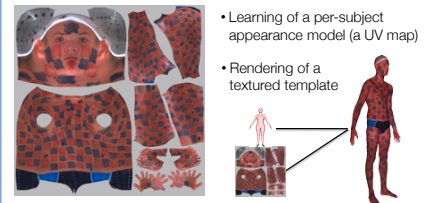
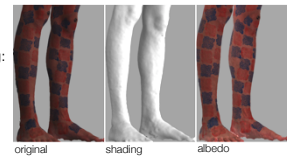
- Given a corpus of scans (S^k), we obtain a set of alignments (T^k) and learn a set of pose-dependent parameters θ by minimizing:

$$E(\{T^k\}, \theta; \{S^k\}) = \lambda_S \sum_k E_S(T^k; S^k) + \lambda_C \sum_k E_C(T^k; \theta; S^k) + \lambda_U \sum_k E_U(T^k; S^k)$$

- E_S penalizes distances between mesh surfaces in 3D space
- E_C penalizes deviations from the learned model
- E_U penalizes dissimilarity in **appearance** between scan and template

Appearance-based error term

- Image preprocessing: light estimation and albedo extraction



- Comparison between real albedo images and rendered images through a robust matching term

$$\sum_{\text{pixels } y} (RoG_{\sigma_1, \sigma_2}(A_{real})[y] - RoG_{\sigma_1, \sigma_2}(A_{rend})[y])^2$$

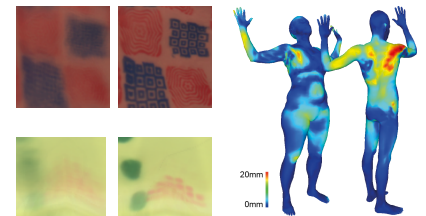
camera parameters, A_{real} , A_{rend} , RoG filtered images

- Error calculation over 22 cameras simultaneously

$$E_U(T^k; S^k) = \sum_{\text{cameras } j} \sum_{\text{pixels } y} (RoG_{\sigma_1, \sigma_2}(A_{real}^j)[y] - RoG_{\sigma_1, \sigma_2}(A_{rend}^j)[y])^2$$

Benefits

- Texture integrates the incomplete information given by 3D shape in smooth areas (e.g. stomach, torso)



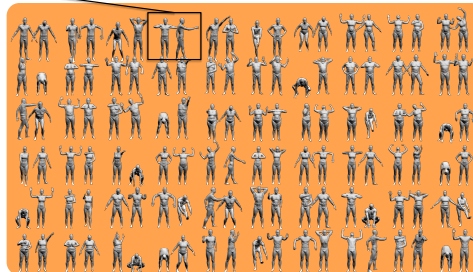
- This results in more accurate intra-subject correspondences, and therefore sharper appearance models

The benchmark

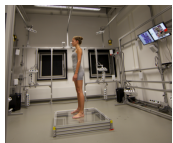
- **Intra-subject challenge:**
 - 60 scan pairs
 - dense scan-to-scan-correspondences
- **Inter-subject challenge:**
 - 40 scan pairs
 - sparse scan-to-scan correspondences



- Error metric: average and maximum Euclidean distance between ground truth and provided correspondences

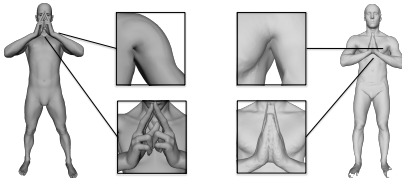


Real vs. synthetic data



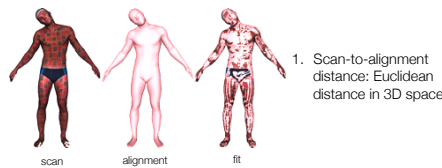
- Each scan is acquired with a high-accuracy 3D multi-stereo system, with 22 RGB cameras for texture capture

- With respect to synthetic datasets (like TOSCA [2]), FAUST scans are much more challenging:
 - realistic deformations
 - missing data
 - different topologies
 - self contacts

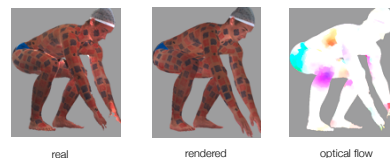


Ground-truth evaluation

- To ensure ground-truth correspondences, we evaluated our alignments in terms of geometry and color:

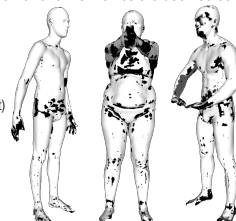


1. Scan-to-alignment distance: Euclidean distance in 3D space
2. Sliding: optical flow [3] between real and rendered (based on alignments) images



- Scan vertices with too high error for one the metrics are deemed as misaligned (shown in black)

- Main causes of misaligned vertices:
 - missing data (hands, feet)
 - skin stretching
 - clothing



Painted bodies

- Establishing ground-truth correspondences between real scans is difficult

- To achieve accurate registration, we painted the subjects with high-frequency textures



- Intra-subject dense correspondences: high-frequency texture pattern applied with stamps on the subjects' skin



- Inter-subject sparse correspondences: 17 textured markers on specific body points where bones are palpable



References

- [1] F. Bogo, J. Romero, M. Loper, M.J. Black, FAUST: Dataset and evaluation for 3D mesh registration. *CVPR* 2014.
- [2] A. Bronstein, M. Bronstein, R. Kimmel, Numerical geometry of non-rigid shapes. *Springer*, 2008.
- [3] D. Sun, S. Roth, M.J. Black, A quantitative analysis of current practices in optical flow estimation and the principles behind them. *IJCV*, 106(2):115-137, 2014.