Evaluation of Automated Skeleton Fitting to 4D Human Body Scan Data Using Open-Source SMPL- and OSSO Models

Ann-Malin SCHMIDT [1], Ingrid PERAZA [1,2], Yordan KYOSEV[1]
[1] Chair of Development and Assembly of Textile Products, ITM, TU Dresden, Germany;
[2] Ghent University, Belgium

https://doi.org/10.15221/24.40

Abstract

4D scan data capture the body's surface in motion, enabling analysis of body deformation, skin stretching, and clothing fit, but are limited to surface-level information. Previous work used 4D scan data to develop individualized Finite Element (FE) models for digital clothing fitting, but these models lack a bone structure and require labor-intensive manual placement or costly CT scans.
An automated method for fitting a skeleton to 4D scan data has been tested and evaluated on three subjects in two different poses. This method involves converting 4D scan data into SMPL models, followed by the automatic application of a skeleton using the open-source Python module OSSO.
The fitting process of the SMPL model demonstrated high accuracy and repeatability, with mesh differences of less than 5 mm for static A-Pose configurations. Although the SMPL model simplifies body surface details, resulting in a slightly slimmer appearance, it successfully supports accurate skeleton fitting to the original 4D scan data. In dynamic poses from 4D scans, inaccuracies and low repeatability were observed for the SMPL fitting. The OSSO-based method efficiently placed bone poses across all tested poses with only minor penetrations noted in areas such as the fingers, legs, and ribs. Integrating the OSSO skeleton with 4D scan data produced a model that effectively combined accurate body surface representation with a detailed skeleton. Nonetheless, pose discrepancies between the SMPL model and the 4D scan data resulted in some intersections for the skeleton mesh, which could lead to errors in Finite Element (FE) models. Minor adjustments, such as rotating joints, improved the fit of the skeleton. Overall, while the method shows promise, further refinements in SMPL model fitting process, especially for complex poses, are needed to enhance its potential for improving the precision of individualized FE models.

Keywords: 4D scanning, SMPL, OSSO, Skeleton fitting.

1. Introduction

4D scan data capture the body's surface in motion, allowing for the analysis of body deformation, skin stretching, and clothing fit [1, 2]. However, since 4D scan data only capture the external surface, analysis methods have so far been limited to those previously described.
The study [3] was one of the first to use 4D scan data to develop individualized Finite Element (FE) models for digital clothing fitting analysis. In this approach, 4D scan data are used for model generation, calibration, and validation. Currently, these FE models lack a bone structure. While creating a human body model without a bone structure is generally quicker due to the manual placement of the skeleton, this process remains manual effort. Alternatively, individual CT scans [4, 5] are used, but this method is both manual and costly due to the limited availability of CT scans. This limitations highlight the need to automatically integrate a skeleton into 4D scan data to reduce manual setup time and enhance the accuracy of FE human body models. FE models are particularly useful for analysing pressure between clothing and the body, body deformations, and clothing fit. They are commonly applied in fields such as compression socks [5] and bras [6–8].
OSSO (Obtaining Skeletal Shape from Outside) introduces a novel approach to fitting an anatomical skeleton based on a subject's 3D body surface data. Unlike traditional heuristic, non-data-driven methods, OSSO leverages machine learning and real data from Dual-energy X-ray Absorptiometry (DXA) scans of 1,000 males and 1,000 females to accurately correlate 3D surface data with internal skeletal structures. Using this extensive dataset and employing parametric 3D body shape models, such as SMPL [9] or STAR [10], which provide standardized representations of human body shapes, OSSO trains a model to infer the underlying bones from the body's external geometry. The system then models statistical variations in skeletons, trains regressors to map body shapes to skeletal parameters, and refines these predictions to ensure physical plausibility, ultimately obtaining the skeleton's position and form within the 3D shape. Consequently, OSSO has advantages in accuracy and adaptability, creating highly precise skeletal models that enhance the realism and utility of Finite Element (FE) models in medical and biomechanical research compared to existing methods [11].

This paper applies the OSSO skeleton fitting method to 4D scan data, evaluating the accuracy and usability of automatically fitted skeletons in enhancing Finite Element models.

2. Methods

To include a skeleton into 4D scan data, the open-source OSSO human body model is used. In a first step, 4D scan data are captured from three test subjects in static and dynamic poses (Section 2.1). The OSSO-model requires a mesh structure based on the SMPL-model. Therefore, in Section 2.2 the 4D scan data are transferred to a SMPL model and then fitted to the OSSO model (Section 2.3). Two evaluations are performed in Section 2.4. One analyses the fitting accuracy of the SMPL model to the 4D scan data (Section 2.4.1). The other evaluation analyses the fitting accuracy and usability of the OSSO model in the field of clothing development (Section 2.4.2). Figure 1 presents a method overview.

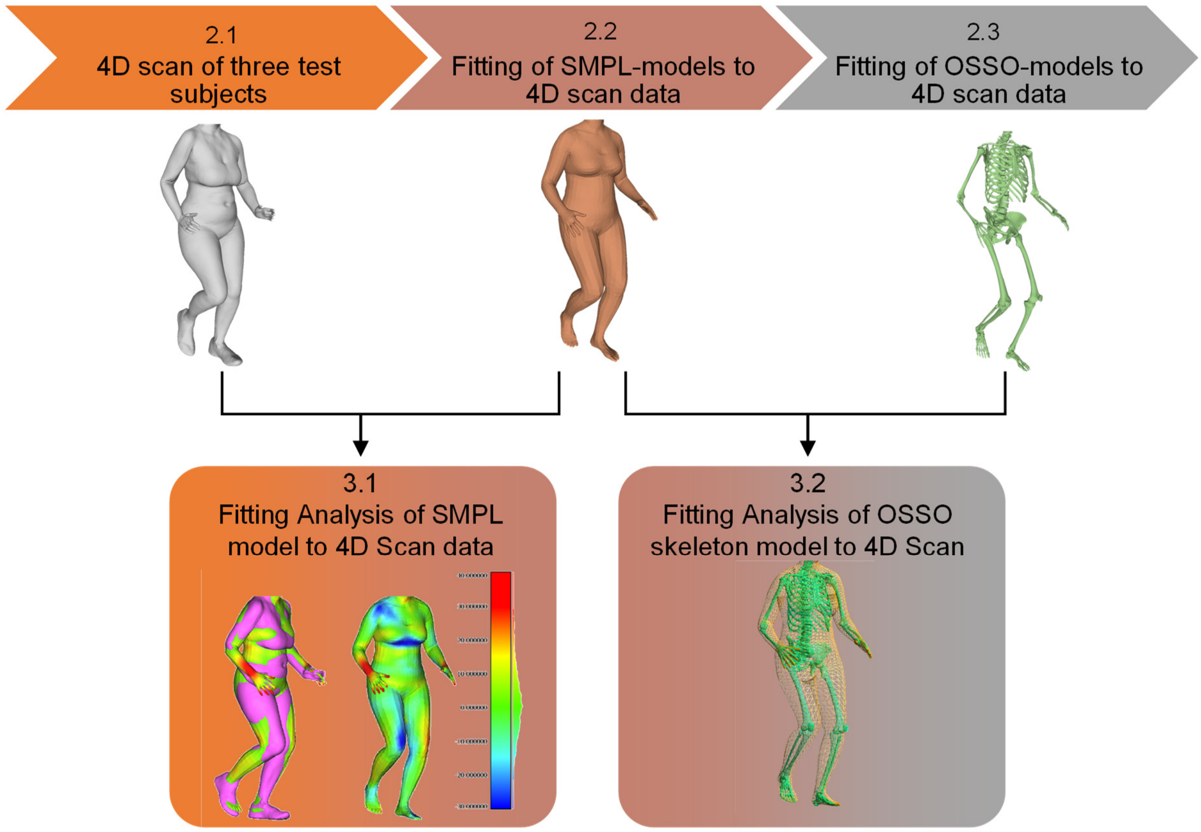

Figure 1: Method overview for the analysis of fitting accuracy of SMPL and OSSO models to 4D scan data

2.1. 4D scan of various poses and movements of three test subjects

Three test subjects are used to evaluate the fitting of SMPL and OSSO models to 4D scan data. The characteristics of the test subjects are detailed described in Table 1.

Table 1: Descriptions of the test subject

	Gender	Age years	Height cm	Weight kg	Clothing size (EU)
Test subject A	Female	63	172	80.5	L
Test subject B	Female	26	159	52	S
Test subject C	Male	32	173	84.2	M

The three test subjects are scanned using the Move4D 4D scanner developed by IBV [12]. For each subject, one static and one dynamic scan in an A-Pose is captured (Table 2). The static scan for all three test subjects is an A-Pose (Figure 2 a1-a3). The dynamic scans are captured with a frame rate of 30 frames per second (fps) for 200 frames. Test subject A performed a running movement (Figure

2 b1), test subject B a dancing movement (Figure 2 b2) and test subject C a sitting down movement (Figure 2 b3). Frame number 100 is selected from the dynamic scans for the following conversion for all three test subjects. The selected frames are processed by the internal software of Move4D by IBV into a homologous mesh (water-tight mesh) and exported as *.PLY-files.
The static scans of the three test subjects are used to compare the fitting accuracy of SMPL and OSSO model for a simple pose and between different body types and genders. The selected frame of a dynamic scan is to evaluate the fitting accuracy for complex poses. Test subject C has his fingers placed as a fist as the finger position has been required for the Move4D scanner software from 2021. Nevertheless, the influence of the finger position is additionally evaluated.

Table 2: Scan plan of the three test subjects

	Static 4D scan	Dynamic 4D scan
Test subject A	A-Pose	Running
Test subject B	A-Pose	Dancing
Test subject C	A-Pose	Sitting down

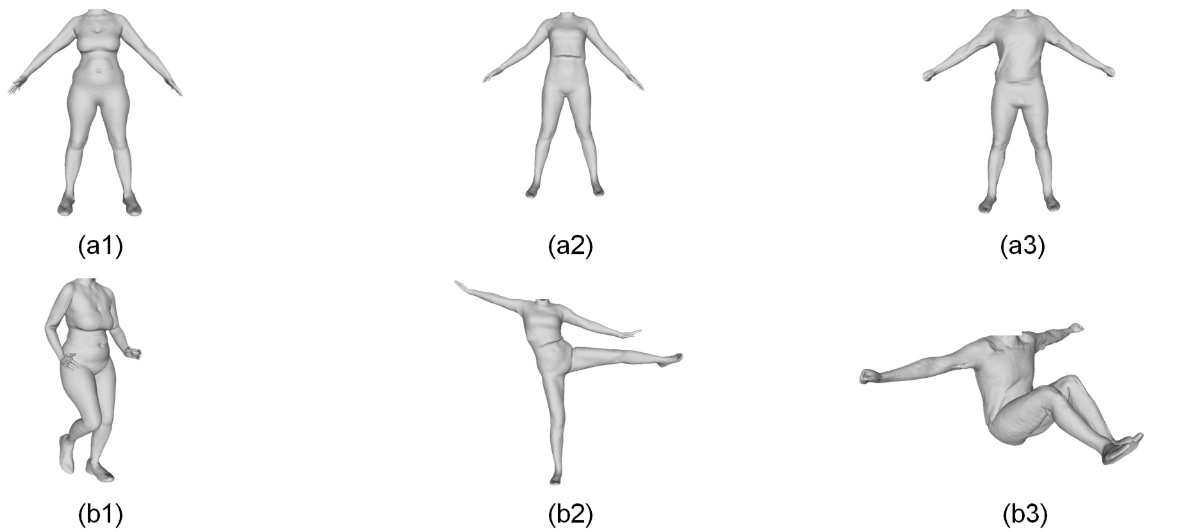

Figure 2: Selected pose of the three test subjects: test subject A in a (a1) A-Pose and (b1) Running frame, test subject B in a (a2) A-Pose and (b2) Dancing frame and test subject C in a (a3) A-Pose and (b3) Sitting frame

2.2. Fitting Analysis of SMPL model-to- 4D Scan data

The SMPL model [9] is applied to six selected 4D scan data sets. The SMPL environment is installed in Python, with Python version 3.9.18 facilitating the conversion. The `generate_batch.py` function, included in the SMPL installation package, is executed. The standard setting of the SMPL are used. For test subjects A and B, the gender parameter are set to female, and for test subject C, the appropriate gender setting was used. The resulting output was a human body mesh, exported as a *.OBJ file. Each of the six frames selected in Section 2.1 is converted five times into an SMPL model to assess the repeatability of the fitting process. CloudCompare [13] is used to visualize differences between the meshes, with color indicating the distance between them.

2.3. Fitting Analysis of OSSO skeleton-to- 4D Scan data

For the integration of a skeleton into the SMPL model, the open-source module OSSO [2] is utilized. Similar to the SMPL model, the gender parameter is set according to the subject being converted. Upon running the OSSO module, a skeleton mesh is exported in *.PLY file format.
The repeatability and accuracy of the SMPL fitting to 4D scan data were analyzed by comparing the five exported *.PLY SMPL-mesh files for each selected frame using 3D mesh comparison techniques.
In a second step, the skeleton fitting is analyzed by merging the SMPL mesh with the OSSO-generated skeleton and then merging the 4D scan data mesh with the OSSO skeleton. Intersections between the skeleton and meshes are identified and discussed.

3. Results

This section presents the outcomes in two parts. Section 3.1 evaluates the fitting of SMPL human body models to 4D scan data. Section 3.2 presents the results of fitting skeletons into 4D scan data using OSSO.

3.1. Fitting Analysis of SMPL model-to- 4D Scan data

The results of the fitting process of SMPL models to 4D scan data are illustrated in Figure 3 and Figure 6. Figure 3 displays the results of fitting the outcomes of the A-pose for all three test subjects. The simple poses were successfully fitted for all three test subjects, with a total of 15 fitting attempts yielding correct results. Notably, the hand and foot positions were accurately placed. However, differences between the SMPL model and the 4D scan data are evident in certain body details. For test subject A, the SMPL model exhibits a slimmer overall build and presents less detailed body contours (Figure 3 c1). Specifically, the thighs/hips, belly, and breast volumes are smaller in the SMPL model compared to the 4D scan data (Figure 3 a1).

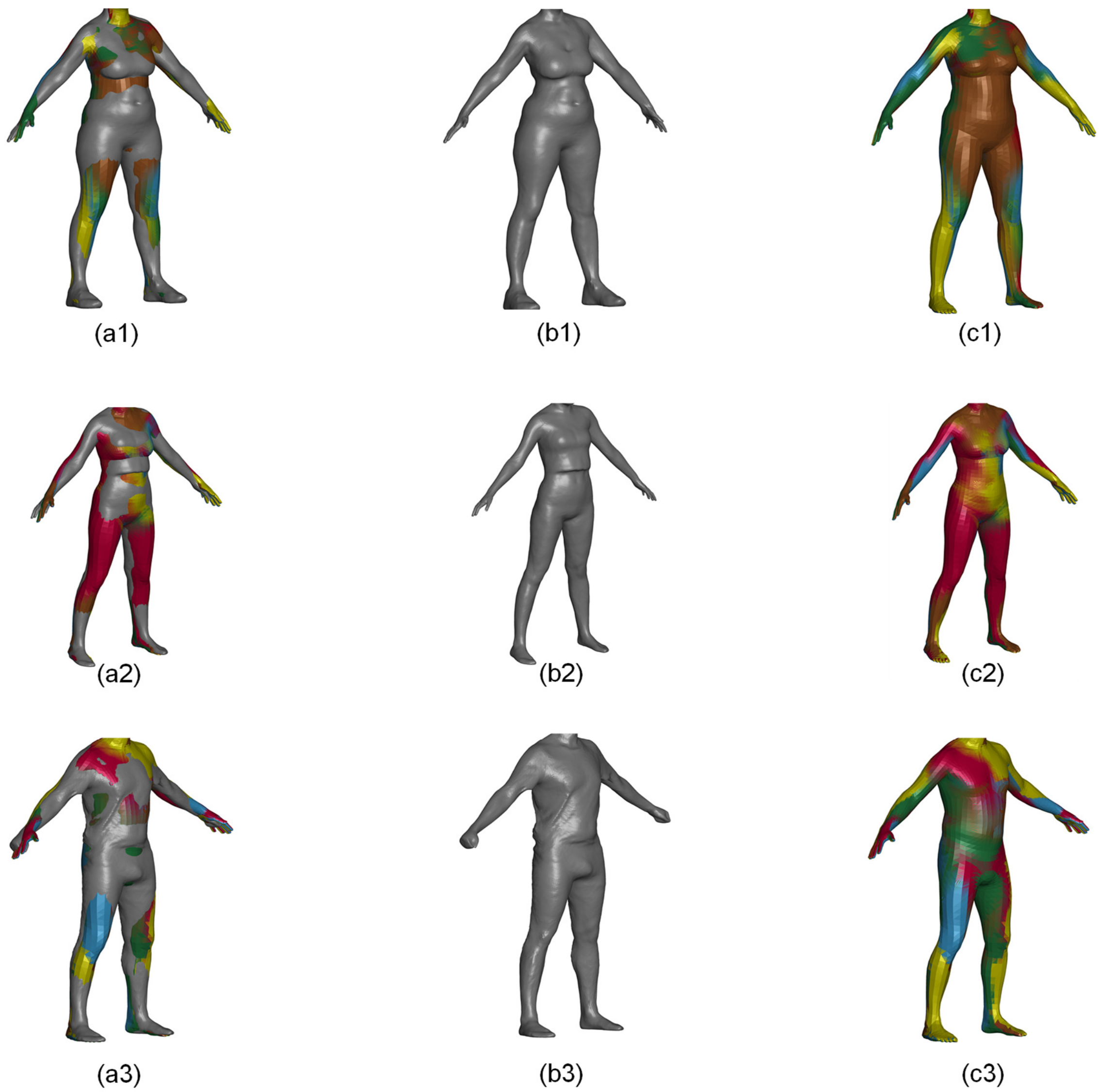

Figure 3: SMPL model fitting to 4D scan data of (a1) test subject A, (a2) test subject B and (a3) test subject C. (b) displays the 4D scan data, (c) shows the five SMPL fitting results.

Test subject B is slimmer, with less soft tissue, resulting in a better fit with the SMPL model. The volumes of the legs, belly, breast, and arms closely match the original 4D scan (Figure 3 a2).

However, a slight difference in pose fitting is noticeable. While the 4D scan shows completely straight arms and legs, the SMPL model fits them with a slight bend.
Test subject C's fist hand position could not be replicated by the SMPL model (Figure 3 a3). Similar to test subject B, the SMPL model shows more bent extremities (Figure 3 c3), and like test subject A, the SMPL model appears slimmer compared to the 4D scan.
The observed loss of detail in the SMPL model can be partially attributed to the significant difference in mesh densities. While the 4D scan mesh consists of 99059 elements, the SMPL mesh only has 13776 elements. A reduction factor of approximately seven times. Figure 4 illustrates both meshes and highlights the differences in surface detail. Notably, the samples showcased by the SMPL developers [9] exhibit remarkable detail retention, representing various body sizes, folds, and contours. Which suggests that the current implementation using standard settings may not be fully optimized.

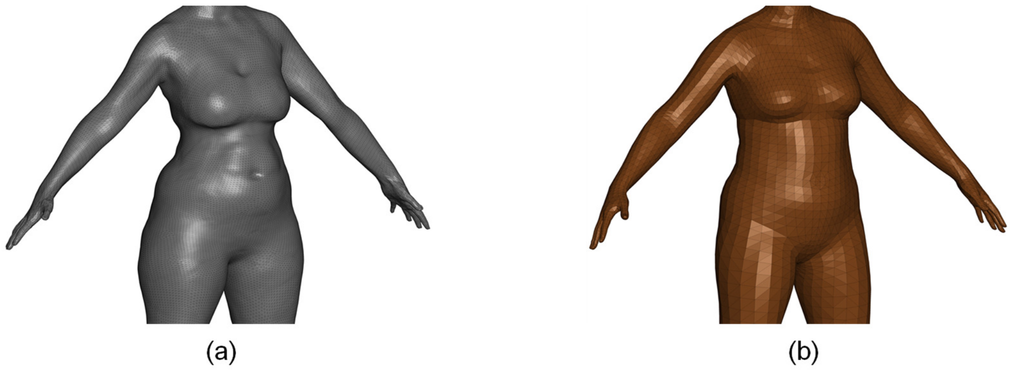

Figure 4: Comparison of the mesh density between (a) 4D scan and (b) fitted SMPL model of test subject A

The differences in body dimensions between the SMPL model and the 4D scan data were further analysed using CloudCompare. Figure 5 displays the mesh discrepancies between the two models, with color coding to indicate variations. Blue areas represent regions where the SMPL mesh is smaller, while red areas indicate where the SMPL mesh is larger compared to the 4D scan data. Notably, the blue coloration is prominent in the leg and belly areas, confirming the observation that the SMPL model tends to produce slimmer body shapes.

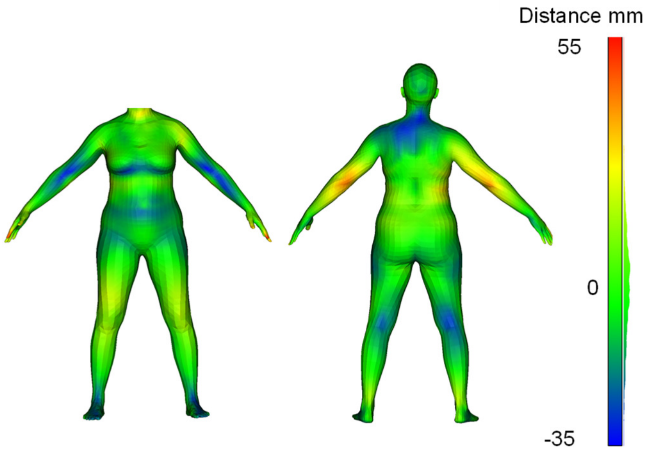

Figure 5: Comparison mesh distances between the 4D scan and fitted SMPL model of test subject A. On the SMPL body is the distance to the 4D scan mesh marked

An analysis of SMPL model fitting to more complex poses captured during a 4D scan of movement is shown in Figure 6. For the three test subjects, reliable pose fitting with the SMPL models could not be consistently achieved. For test subject A, four out of five fittings resulted in accurate pose fitting (Figure 6 d1), while one attempt led to a leg mismatch (Figure 6 c1). For test subjects B and C, none of the five fitting attempts produced a correct pose. Specifically, for test subject B, all five fittings resulted in the same incorrect pose coupled with a enlarge body structure (Figure 6 c2). For test subject C, five different incorrect poses were fitted (Figure 6 b3-d3). In the case of test subject B, the leg was misinterpreted as an arm. For test subject C, either the head (Figure 6 b3, d3) or the foot (Figure 6 c3) was incorrectly fitted to the arm.

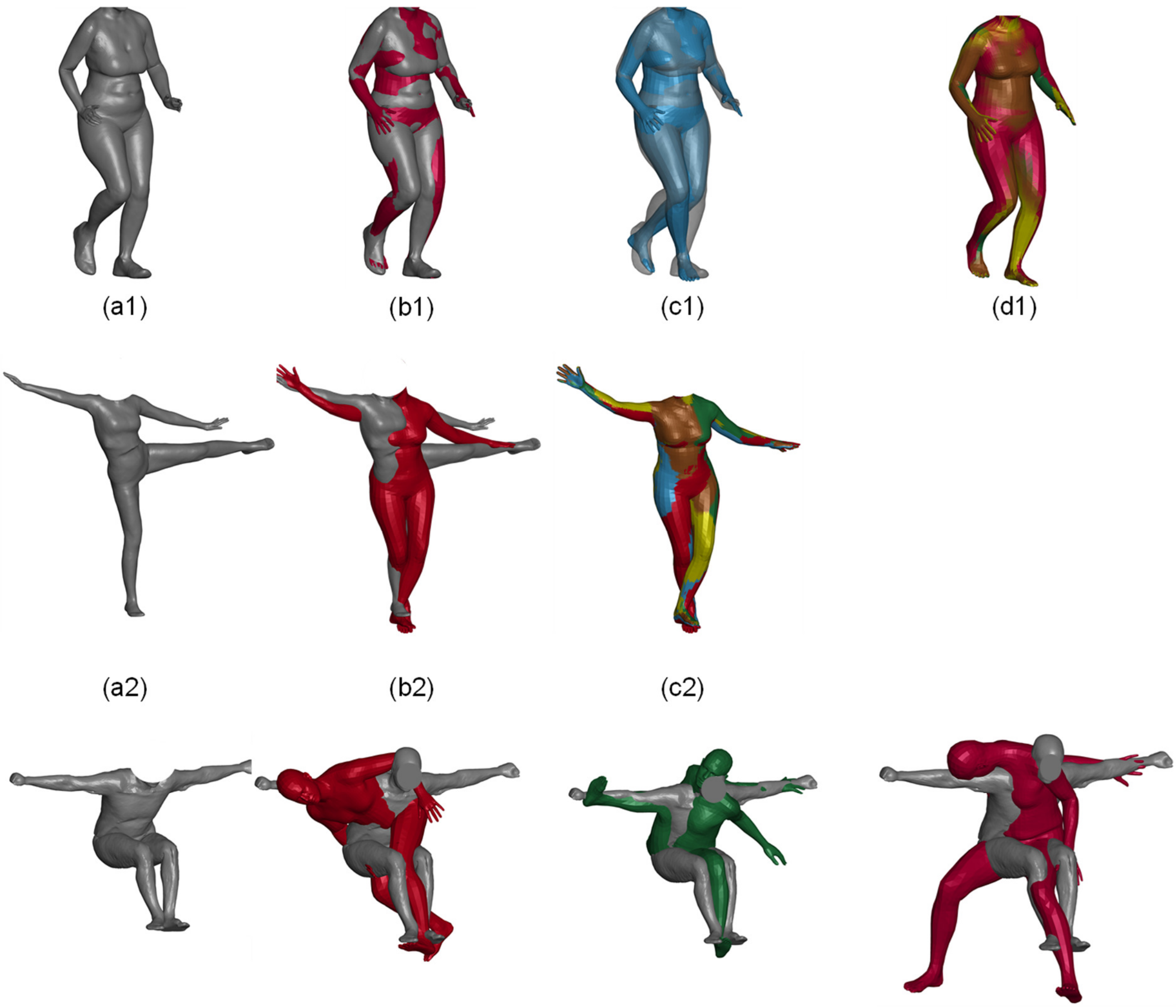

Figure 6: SMPL fitting for complex body poses of (a1) test subject A, (a2) test subject B and (a3) test subject C. (b)-(c) are the results of repeating the fitting process with the same data.

In conclusion, the following findings were observed:

- The SMPL model successfully fits simple 4D scan poses with high reliability and repeatability.
- The SMPL model fails with standard settings to accurately or consistently fit complex poses extracted from 4D scan data.
- The current SMPL conversion method reflects fewer body details compared to 4D scan data but can be potentially optimized by expanding the range of SMPL model references and fine-tuning parameters such as iteration count and convergence criteria.
- The SMPL model tends to depict the human body as slimmer than in the original 4D scan data.
- The SMPL model tends to bend the extremities more than observed in the 4D scan data.
- The SMPL model is unable to accurately model a fist.

3.2. Fitting Analysis of OSSO skeleton-to- 4D Scan data

Figure 7 presents the fitting results of the OSSO model to the SMPL human body meshes. It is evident that the skeleton meshing performs accuratly, regardless of the pose complexity. This is consistent across various scenarios, from the A-pose of test subject C (Figure 7c) to more complex poses, such as test subject A running (Figure 7 a), test subject B dancing (Figure 7b), and even the incorrectly fitted sitting pose of test subject C (Figure 7d).

However, instances of penetration between the skeleton and SMPL meshes are noticeable in all examples, particularly at the hands and feet (Figure 8). Additionally, in some cases, such as the A-pose of test subject C, the ribs penetrate the SMPL skin mesh (Figure 8).

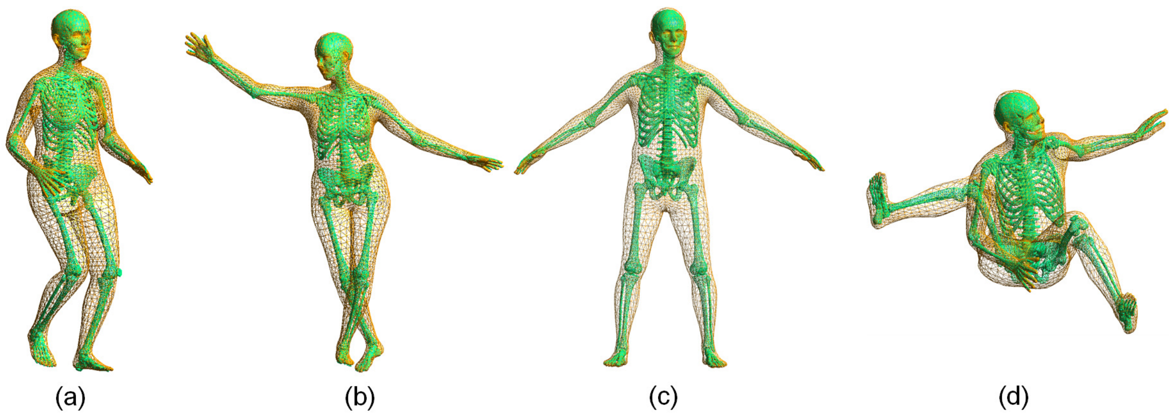

Figure 7: Fitting of the OSSO Model into SMPL models (a)Test subject A running, (b) test subject B dancing, (c) test subject C in a A-Pose, (d) test subject C sitting

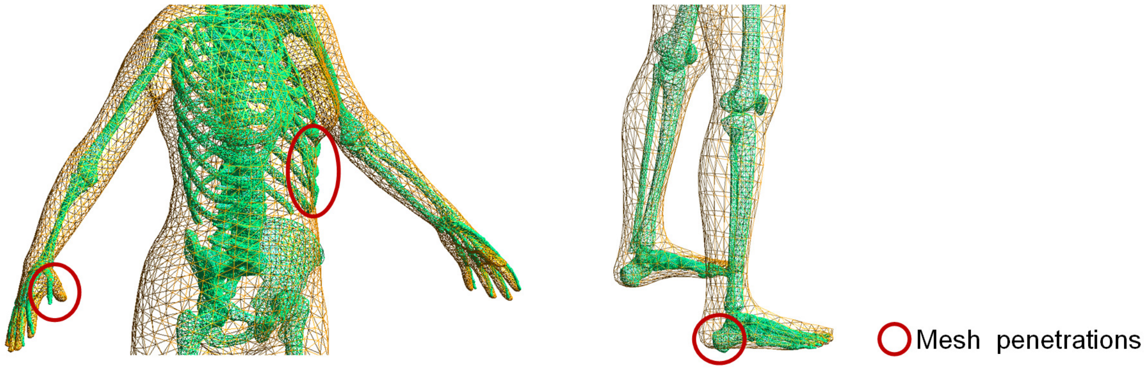

Figure 8: Mesh penetrations between SMPL and OSSO mesh

Due to the loss of detail in the SMPL mesh, the generated skeleton is transferred to the original 4D scan data. The results for the A-pose of test subjects A through C are presented in Figure 9. Overall, the fitting is accurate, and the ability to automatically place a realistic skeleton within the 4D scan data is a significant achievement.

However, the instances of skeleton penetration have increased. As discussed in Section 3.1 the SMPL model tends to fit with more bent extremities, and the OSSO skeleton follows this curvature. Consequently, the elbows and knees intersect with the surface of the 4D scan data. Additionally, the ribs protrude outside the 4D scan surface. Given the proximity of the ribs to the skin, achieving a perfect fit remains challenging.

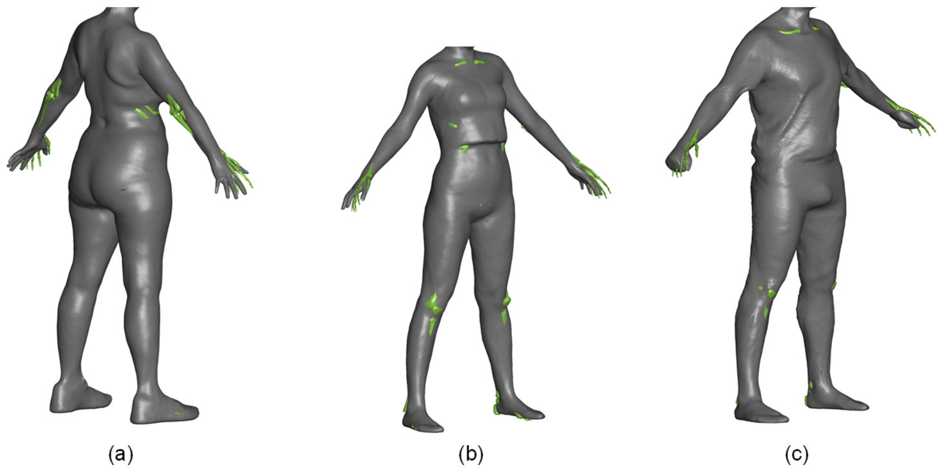

Figure 9: Combining the 4D scan data with the OSSO-skeleton (a) for test subject A, (b) for test subject B and (c) for test subject C

4. Conclusion and Discussion

An automated method for fitting a skeleton to 4D scan data was developed and tested on three subjects in two different poses. The 4D scan data was first converted into SMPL models, followed by the automatic implementation of a skeleton using the open-source Python module OSSO. This conversion to SMPL models ensures the correct number of faces and vertices necessary for OSSO's compatibility.

Fitting the SMPL model to subjects in an A-Pose demonstrated high accuracy and repeatability, with mesh differences of less than 5 mm across five iterations. While the 4D scan model exhibits higher surface detail, particularly in areas with soft tissue such as the abdomen and legs, the SMPL model tends to flatten the body surface, creating a slightly slimmer appearance (Figure 4). Despite this simplification, OSSO fitting remains effective, as the skeleton can be accurately applied to the original 4D scan data. A notable issue arises with the SMPL model's tendency to produce more bent extremities, complicating the subsequent OSSO fitting and leading to potential intersections between bones and the body surface. When applied to complex poses from dynamic 4D scans, the SMPL model fitting displayed inaccuracies and low repeatability, limiting its utility.

Despite these challenges, the OSSO-based skeleton fitting process was efficient, with bone poses correctly placed across all tested scenarios, and only minor penetrations observed in areas such as the fingers, legs, and ribs.

Integrating the OSSO skeleton with the 4D scan data produced a model combining accurate body surface representation with a detailed skeleton. However, due to pose discrepancies between the SMPL model and the 4D scan data, intersections between the skeleton and body surface were observed, which could introduce errors when the data are transferred in Finite Element (FE) Models. Minor adjustments, such as rotating the elbows and knees, allowed for better fitting of the skeleton to the 4D scan data.

In conclusion, the proposed method for skeleton fitting in 4D scan data shows promising results but requires improvements in the conversion process to SMPL, particularly for complex poses and all body types. As SMPL models evolve, it is expected a reduction in pose fitting errors, enhancing the method's potential for improving the accuracy of individualized FE models.

Acknowledgement

The authors acknowledge the financial support by the Federal Ministry of Education and Research of Germany in the programme of “Souverän. Digital. Vernetzt.”. Joint project 6G-life, project identification number: 16KISK001K

References

[1] Y. Kyosev, V. Tomanová, and A.-M. Schmidt, "Method for Automatic Analysis of the Clothing Related Body Dimension Changes During Motion Using High-Speed (4D) Body Scanning," in *Proceedings of 3DBODY.TECH 2022 - 13th International Conference and Exhibition on 3D Body Scanning and Processing Technologies, Lugano, Switzerland, 25-26 October 2022*, Lugano, Switzerland, Oct. 2022 - Oct. 2022.

[2] A.-M. Schmidt, R. Schmidt, G. S. I. Gonzalez, and Y. Kyosev, "Automated Investigation of the Breast - Bra Interaction Using 4D Scan Data and Oscillation Analysis," in *Lecture Notes in Networks and Systems, Advances in Digital Human Modeling*, S. Scataglini, G. Harih, W. Saeys, and S. Truijen, Eds., Cham: Springer Nature Switzerland, 2023, pp. 52–61.

[3] A.-M. Schmidt and Y. Kyosev, "Finite element modelling of textile-soft material interaction using 3D/4D scan data," in *14th European LS-DYNA Conference 2023, Bade-Baden, Germany*.

[4] L. Dubuis, S. Avril, J. Debayle, and P. Badel, "Identification of the material parameters of soft tissues in the compressed leg," *Computer methods in biomechanics and biomedical engineering*, vol. 15, no. 1, pp. 3–11, 2012.

[5] E. Ghorbani, H. Hasani, R. J. Nedoushan, and N. Jamshidi, "Finite element modeling of the compression garments structural effect on the pressure applied to leg," *Fibers Polym*, vol. 21, pp. 636–645, 2020.

[6] A. Bel-Brunon, L. Bouten, J Cornolo, and F Morestin, "Numerical modeling of bra wear during running,"

[7] Y. Cai, W. Yu, and L. Chen, "Finite element modeling of bra fitting," in *Advances in Women's Intimate Apparel Technology*: Elsevier, 2016, pp. 147–168.

[8] S. Liu, G. Sun, H. Zuo, X. Chen, S. Shang, and H. Hu, "Predicting the effect of bra pad specifications on breast deformation during jumping using a finite element method," *IJCST*, vol. 35, no. 5, pp. 779–798, 2023, doi: 10.1108/IJCST-02-2023-0009.

[9] M. Loper, N. Mahmood, J. Romero, G. Pons-Moll, and M. J. Black, "SMPL: A Skinned Multi-Person Linear Model," *ACM Trans. Graph.*, vol. 34, no. 6, pp. 1–16, 2015, doi: 10.1145/2816795.2818013.

[10] A. A. A. Osman, T. Bolkart, and M. J. Black, "Star: Sparse trained articulated human body regressor," in *Computer Vision-ECCV 2020: 16th European Conference, Glasgow, UK, August 23-28, 2020, Proceedings, Part VI 16*, 2020, pp. 598–613.

[11] Marilyn Keller, Silvia Zuffi, Michael J. Black, and Sergi Pujades, "OSSO: Obtaining Skeletal Shape From Outside,"

[12] J. Zorraquino, "Move4D User Guide V1.5v003," Instituto de Biomecánica (IBV).

[13] *CloudCompare.* Accessed: 30.22.2023. [Online]. Available: https://www.cloudcompare.org/