Estimating the age of human body shape

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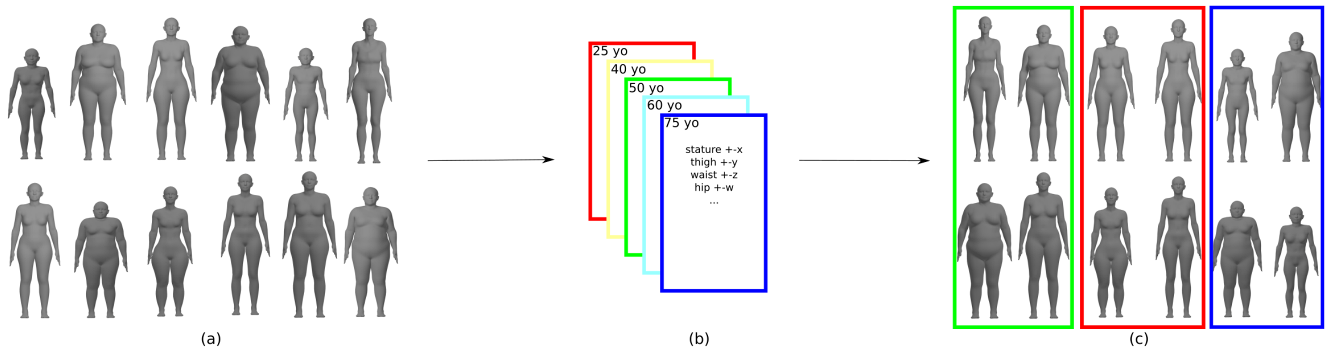

Fig. 1: a) Samples of female 3D bodies; b) Illustration of age estimator; c) Sample bodies grouped by age.

***Abstract*—Human aging estimation is an important soft biometrics topic, with several applications in human-centered multimedia communication, human identification, and aging simulation. Despite recent efforts, this task is still challenging due to the number of features required to provide a biologically accurate estimation. Assuming that our body reflects our aging process, we present a method to estimate the age of a 3D adult human body represented as a mesh. We train a Gradient Boosting Regression estimator to estimate a person's age from their anthropometric measurements. The data for this step is from a large dataset containing the anthropometric measurements plus the age of 10,000 individuals. The precision of this estimator is 87.65% for males and 86.99% for females. To validate our approach, we build a set of 10,000 3D random anthropometric valid bodies of each gender, semi-automatically deriving a set of their measurements, the same set used to train the estimator. We then input this set to the estimator, finding their corresponding ages, and checked the precision of the estimated ages against the dataset. We achieved an average accuracy of 90.76% for male bodies and 92.40% for female bodies. We believe our work could help estimate unknown ages of individuals for applications in several fields, such as forensics, simulations, and multimedia communication.**

I. Introduction

A person's age is a soft biometric information and an important one for many practical purposes: ergonomic studies, identification, and design of products, among others. There are also forensic applications where knowing the age of a victim is essential [1]. Particularly in Computer Vision, there has been substantial work estimating a person's age and other demographic traits such as race and gender from face photographs [2]. The use of 3D information is not very common for the task of estimating age. Interestingly, there has been work estimating the age of buildings [3] using 3D information. For people, Matthews and colleagues [4] used prototypes, which are 3D archetypal models representing the shape of a typical head. Martinez *et al.* used 3D skeletal data extracted from MRIs [5].

Our approach complements current age estimators for people by using readily available information: our anthropometric measurements. We present a technique to estimate the age of a 3D human adult body from anthropometric measurements computed semi-automatically from the triangle mesh representing the body. To our knowledge, this possibility has not been explored before in graphics research. We believe our technique could be applied to augment the precision of age estimation from face photographs if at least one single image of the whole person is available. This image could be the input for building the 3D body model since there are now efficient approaches for computing 3D body shapes from images like [6] and [7].

The remainder of this paper is organized as follows: firstly, we introduce the most relevant related works in Section II. Section III describes our methodology to estimate the body age. In Section IV, we present and discuss our results. Finally, in Section V, we present our conclusion and the present work's limitations.

II. Related Work

Biometric recognition systems have been an object of extensive studies due to their intrinsic relevance in many areas. This field includes human identification and security models based on unique human features, such as iris analysis, fingerprint, and DNA. Although these techniques produce reliable biological evidence, sometimes it is not feasible to acquire these features. Thus, scientists proposed a new research field called soft biometrics, which uses less-obvious identification features, such as the human face [8], gait [9], eyes [10], or other body parts [11], to estimate the characteristics of an individual [2].

Among these features, most works have focused on the human face to develop age estimation models. Compared with more accurate biometrics such as iris, retina, or fingerprint, face recognition can uncover uncooperative subjects in a proficient manner [12]. According to Ali *et al.* [12], face recognition systems use data from static images [13], video data [14] and data streams [15], along with the knowledge of the context in which these data components are being actively used. In recent years, most works have focused on machine learning approaches [8], [16]–[18], mainly due to the large benchmark databases available [19]–[21].

According to Frenzel *et al.* [22], human body dimensions and shape vary between individuals in an age-dependent manner. The researchers used the LIFE database [23], containing 10,000 participants, varying from mid-age to older men and women. They find that aging results in similar reshaping of female and male bodies despite the large diversity of body types observed in the study.

While not directly related to aging, techniques to infer features from human bodies are still very prominent in the research community. These techniques can be used to several applications, such as gender classification [24], health care [25], and digital ergonomics [26]. Xiaohui *et al.* [27] proposed a novel approach to calculating human body size by extracting focal features of the body through random forest regression analysis of geodesic distances. The authors claim their method leads to robust and accurate feature extraction and size measurement for 3D human bodies in distinct postures and shapes.

The STAR work of Osman, Bolkart, and Black [28] introduces a novel 3D human body model manipulation method. It is based on principal components and joint rotations, providing an easier way to parameterize shape and movement with a pose-based correction of body shape. Their approach combines a local and global blend of shapes. Using the CAESAR [29] and SizeUSA [30] datasets, they defined an error function to optimize, training it iteratively and annealing the parameters in each interaction.

To the best of our knowledge, we are the first work to explore human age estimation using body shapes. We believe our work contributes to aging estimation for applications in which other techniques may not be accessible. Besides, it can be used as an additional technique to increase aging estimation accuracy when a human body is available.

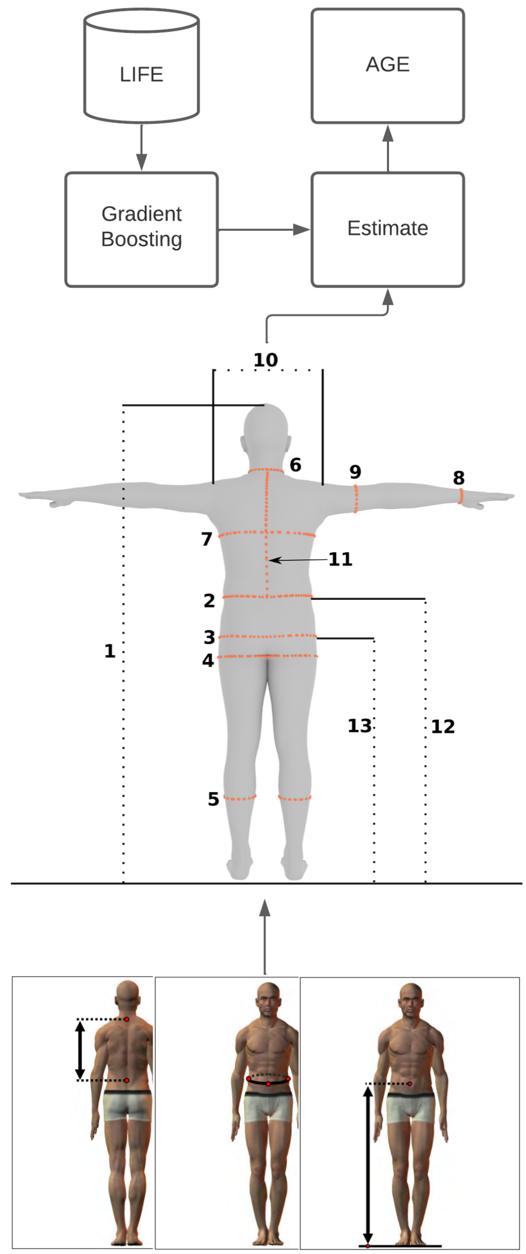

Fig. 2: Overview of our approach. Given the data in the LIFE dataset along with 13 body measurements as input, we train a regressor to estimate a human's age for 3D models. Table I contains further details regarding the measurements.

III. Estimating age from a body mesh

In this section, we present our approach to estimate the age of a 3D body model. We first describe the datasets we used, then the methods we adopted to process the body. Next, we detail our approach to estimating the age using Gradient Boosting Regression. We illustrate the overall process in Fig. 2.

A. Datasets

We use an anthropometrical dataset and a collection of 3D human body meshes to develop this work. The dataset is from an anthropometric study named LIFE [23] by the Leipzig University in Germany. The LIFE study was a considerable effort to collect not only anthropometric measurements from 10,000 individuals but also blood pressure, age, and weight, among others. The LIFE study extracted 139 measurements automatically using the commercial solution from the Human Solutions company [31]. They used a 3D scanner, although the actual 3D body meshes are unavailable. In Fig. 3 we present the histograms of the age distributions in the dataset according to gender. More extensive sampling occurs starting after the age of 40.

The human body meshes used in the validation step is a set of random 3D body meshes generated from the STAR work

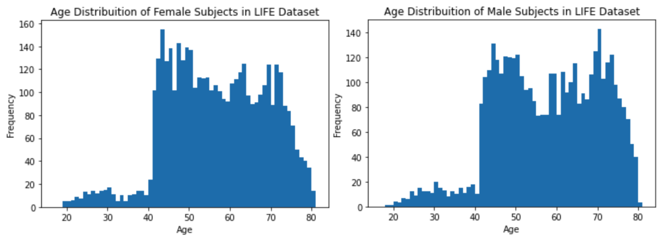

Fig. 3: Age distribution of people in the LIFE dataset.

Nº	Our Semantic	LIFE Semantic	ISO 7250
1	Stature	HEIGHT	6.1.2
2	Waist Girth	WAIST_GTH	6.4.11
3	Hip Girth	HIP_GRT	6.1.12
4	Thigh Girth	THIGH_GTH_H	6.4.13
5	Calf Girth	CALF_GTH	6.4.14
6	Neck Girth	MID_NECK_GTH	6.4.9
7	Bust Girth	BUST_CHEST_GTH	6.4.10
8	Wrist Girth	WRIST_GTH	6.4.12
9	Upper Arm Girth	UP_ARM_GTH	6.3.19
10	Biacromial Length	CR_SHOULDER	6.2.7
11	Neck to Waist Length	NECK_WAIST_C_BACK	6.2.3
12	Waist Height	WAIST_HT	6.1.6
13	Crotch Height	CROTCH_HT	6.1.7

TABLE I: Selected measures, their ISO7250 reference number and LIFE study measurements.

[28]. We generated 10000 male and 10000 female subjects in the $[-3, 3]$ interval of standard deviations of the default first ten principal components, achieving, theoretically, 99.5% of population distribution. Fig. 4 illustrates 25 female bodies from this set.

Fig. 4: Sample of random female bodies illustrating the variation in shapes and measurements invariance explained in Subsection III-B.

B. Computing anthopometric measurements

Given any 3D shape represented as a mesh, the main goal in this step is to compute the 13 measurements listed in Table I. The particular set of measurements is a subset of the 139 measurements available in the LIFE study that is also defined in the International Standard [32] on *Human body measurements for technological design*. The ISO standard provided a systematic way to guarantee reproducibility among diverse body types.

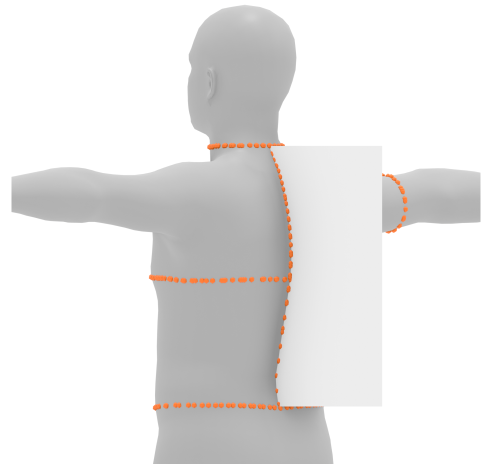

Fig. 5: Our Neck To Waist Length (11 from Table I) cutting plane defined from other 2 measures.

There are two types of measurements: linear (1,10,11,12,13 from Table I), and girth-type measurements (2,3,4,5,6,7,8,9 from Table I). We used the distance between two measures or between one measure and the floor as a reference for the linear measurements. For example, we consider the max and min vertex values to calculate the stature (measurement 1 in Table I). For the waist's height (measurement 12 in Table I), we used the distance of average vertices of the waist to the floor. The most complex measure to calculate was the neck to waist length (measurement 11 from Table I), calculated using the neck's and waist's height to define a cutting plane that follows the spine, as illustrated in the Fig. 5.

To compute the girth measurements, we calculate a set of points from the intersection of a plane with the body. From the set of points, we compute the measurement. Since we need to consistently measure all possible body shapes, we first compute the planes for average male and female bodies. We generate these average bodies with the STAR technique, using the average dimensions for all body parts. The main idea starts by using the average bodies to compute their measurement curves only once. Then, we transfer them to any body shape, assuming that they have the same topology,i.e., the same number of vertices and triangles connected the same way.

We manually defined initial cutting planes for each girth measurement for this average body and used an iterative process to find their correct positions on the body. The iterative process moves the cutting plane in steps, minimizing the mean absolute error between the current and corresponding LIFE measurements. We defined a fixed number of 500 steps to sweep the geometry for each measurement.

As the cutting planes do not match precisely with the mesh topology, we need to calculate the intersection points

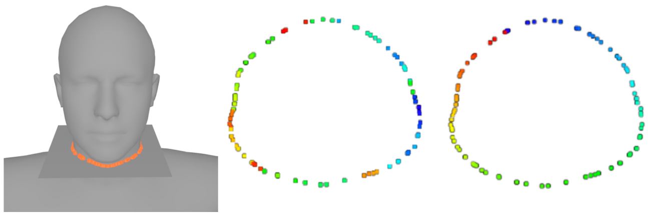

Fig. 6: Our level curve approach applied on the neck girth (measurement 6 from Table I) followed by the point-set sort. Left: the plane intersection with the mesh at the neck. The set of computed intersection points are shown unsorted in the center, followed by the sorted set on the right.

between the plane and the edges of triangles using a ray-polygon collision approach. Once we have the set of points, we can generalize for any other body shape using barycentric coordinates since all bodies share the same topology.

Another important step of this approach is sorting the intersection points since the extracted points from our curve level depend on ordering the vertices on the mesh. This sorting is an instance of the Shortest Path Problem, which we solved with a Vehicle Routing Problem algorithm. To sort q points, this algorithm has $\mathcal{O}(q^2)$ complexity. Fig. 6 illustrates the plane intersection for measurement 6 (from Table I) on the neck and the resulting curves.

The whole process takes approximately 2min per measurement. Although it is a high computational cost, this process only needs to be done once for the average body. Once it is complete, we can reuse the curve definitions for any body with the same topology. To visually validate our curve level extraction, we selected 25 bodies with large variation from the average and checked if the measurements maintained the correct positions along the different bodies. Fig. 4 presents the positive result of this experiment.

C. *Estimating age from measurements*

We use a machine learning technique to estimate age from a set of measurements defined in Table I from the LIFE dataset. We segmented the dataset randomly into $2/3$ for training and $1/3$ for testing. The selected machine learning technique was the Gradient Boosting Regressor, which presented a better distribution of the predicted data compared to other similar methods, such as Random Forest Regressor and Ada Boost Regressor, proving to be the most suitable for our tests. We used the python Gradient Boosting Regressor implementation from the scikit-learn library [33] with all default parameters, except for the random state and the number of estimators. We chose the random state at 42 for experiment repeatability. The number of estimators was chosen as 1000 experimentally. We found a good correlation between training time, obtained accuracy, and the number of non-covered ages.

IV. Results and Discussions

We performed a numerical analysis of our results in two steps to evaluate the proposed method. First, we evaluate the accuracy of the regression method in predicting the age correctly. Secondly, we evaluate the difference in measurements between bodies estimated at a certain age and the closest bodies at the same age in the LIFE dataset.

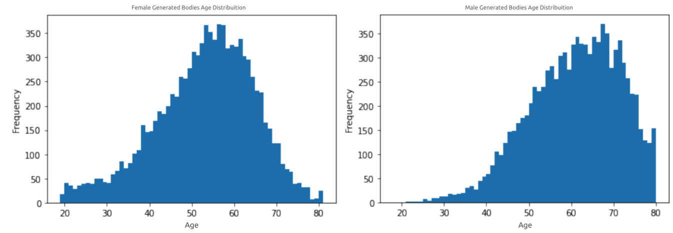

Fig. 7: Estimated age distribution for the 10000 random female and male generated bodies.

A. *Regressor Accuracy Evaluation*

We trained our Gradient Boosting Regressor separately for males and females because of the anatomic differences between genders. The accuracy obtained from the analysis is 87.65% for males and 86.99% for females. We consider the obtained values a good result, especially considering that we can observe the variation in measurements among people of the same age in the dataset. It is relevant to note that anthropometric measurements to predict age are more robust than we initially thought.

B. *Body Age Estimation Accuracy*

After extracting the measures from the set of random 3D bodies, as explained in Section III-A, we feed this data as input to our trained estimator, giving us an estimated age for each body. In Fig. 7 we present the predicted age distribution for the males and females cases. We can see that both distributions approximate the normal distribution following the distribution used for the randomly generated bodies.

Regarding the age distribution, we found three uncovered ages for the male case (18,19,20) and one uncovered age for the female case (18). We suppose this comportment is due to the normal data distribution with a finite number of subjects. We believe that these uncovered ages tend to disappear with increasing the number of subjects.

To check the shape variability among people of the same age, we randomly selected twelve female bodies: four aged 25, four aged 50, and four aged 75. In Fig. 1, we illustrate the classification process, confirming that the set of 13 measurements is a good estimator of age within the current error bounds. We also randomly selected seven random male bodies with ages estimated as 50 years old and plotted the sum of their measurements in Fig. 8. We can see that the estimator assigns the same age for distinct shaped bodies.

Finally, having the measurements for all 3D random bodies and their estimated ages, we searched the entry that minimized the measurement difference for each body with the same age in the LIFE dataset. We used min-max values from the LIFE dataset to normalize LIFE entries and body extracted

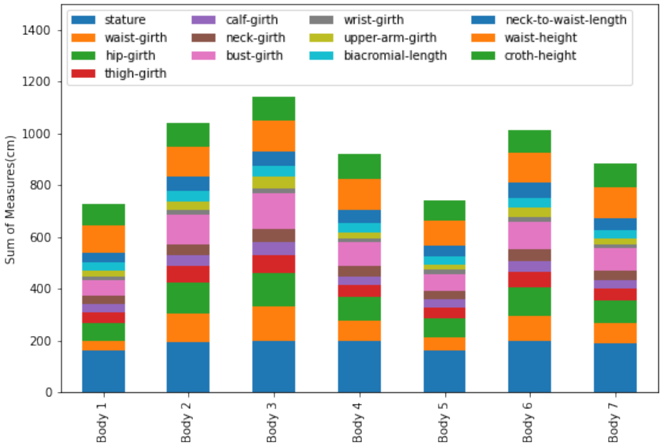

Fig. 8: Seven measurements of male bodies with the same predicted age (50 years old).

measurements to present a scale-independent metric. The mean difference from all age intervals resulted in a calculated average precision of 90.76% for male bodies and 92.40% for female bodies.

V. Conclusions

We have presented an approach to estimating the age of an adult human from its 3D body shape representation. We first trained an estimator using data from 10000 individuals with information on age and body measurements. To validate this estimator, we estimated the ages of 10000 random male and 10000 random female bodies and found average precision of 90.76% for male and 92.40% for female bodies. Since building 3D shapes from a single image is now feasible [6] [7], we believe our technique may be well suited for applications where estimating someone's age is critical, such as forensic and security applications. Another possible application of our semi-automatic measurements extraction is in fashion and clothes design, enabling faster clothes customization.

Our study's main limitation is that our 3D bodies and anthropometric data come from different sources. While our anthropometric data comes from a study only concerned with age features, our 3D bodies come from a random generator that does not give us any information besides the body mesh. Thus, we are unable to compare our results with the ground truth.

In future work, we intend to add more measurements, but at the cost of finding matching correspondences in both sets. Another alternative is to use a dataset combining 3D bodies, measurements, and ages.

References

[1] C. Cattaneo, Z. Obertová, M. Ratnayake, L. Marasciuolo, J. Tutkuviene, P. Poppa, D. Gibelli, P. Gabriel, and S. Ritz-Timme, "Can facial proportions taken from images be of use for ageing in cases of suspected child pornography? a pilot study," *International journal of legal medicine*, vol. 126, no. 1, pp. 139–144, 2012.

[2] P. Punyani, R. Gupta, and A. Kumar, "Neural networks for facial age estimation: a survey on recent advances," *Artificial Intelligence Review*, vol. 53, no. 5, pp. 3299–3347, 2020.

[3] F. Biljecki and M. Sindram, "Estimating building age with 3d gis," in *Proceedings of the 12th International 3D GeoInfo Conference 2017*, ser. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. IV-4/W5, University of Melbourne. Melbourne, Australia: ISPRS, 2017, pp. 17–24.

[4] H. Matthews *et al.*, "Estimating age and synthesising growth in children and adolescents using 3d facial prototypes," *Forensic Science International*, vol. 286, pp. 61–69, 2018.

[5] N. P. Martínez Vera *et al.*, "Forensic age estimation by morphometric analysis of the manubrium from 3d mr images," *Forensic Science International*, vol. 277, pp. 21–29, 2017.

[6] S. Yan and J.-K. Kämäräinen, "Learning anthropometry from rendered humans," *arXiv preprint arXiv:2101.02515*, 2021.

[7] G. Pavlakos, V. Choutas, N. Ghorbani, T. Bolkart, A. A. A. Osman, D. Tzionas, and M. J. Black, "Expressive body capture: 3D hands, face, and body from a single image," in *Proceedings IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2019, pp. 10 975–10 985.

[8] K. Ko, H. Gwak, N. Thoummala, H. Kwon, and S. Kim, "Squeezeface: Integrative face recognition methods with lidar sensors," *Journal of Sensors*, vol. 2021, 2021.

[9] P. Punyani, R. Gupta, and A. Kumar, "Human age-estimation system based on double-level feature fusion of face and gait images," *International Journal of Image and Data Fusion*, vol. 9, no. 3, pp. 222–236, 2018.

[10] Z. Wang, C. Li, H. Shao, and J. Sun, "Eye recognition with mixed convolutional and residual network (micore-net)," *IEEE Access*, vol. 6, pp. 17 905–17 912, 2018.

[11] L. Cao, M. Dikmen, Y. Fu, and T. S. Huang, "Gender recognition from body," in *Proceedings of the 16th ACM international conference on Multimedia*, 2008, pp. 725–728.

[12] W. Ali, W. Tian, S. U. Din, D. Iradukunda, and A. A. Khan, "Classical and modern face recognition approaches: a complete review," *Multimedia Tools and Applications*, vol. 80, no. 3, pp. 4825–4880, 2021.

[13] G. Poon, K. C. Kwan, and W.-M. Pang, "Occlusion-robust bimanual gesture recognition by fusing multi-views," *Multimedia Tools and Applications*, vol. 78, no. 16, pp. 23 469–23 488, 2019.

[14] Y. Wong, S. Chen, S. Mau, C. Sanderson, and B. C. Lovell, "Patch-based probabilistic image quality assessment for face selection and improved video-based face recognition," in *CVPR 2011 WORKSHOPS*. IEEE, 2011, pp. 74–81.

[15] D. Ouyang, Y. Zhang, and J. Shao, "Video-based person re-identification via spatio-temporal attentional and two-stream fusion convolutional networks," *Pattern Recognition Letters*, vol. 117, pp. 153–160, 2019.

[16] B.-C. Chen, C.-S. Chen, and W. H. Hsu, "Cross-age reference coding for age-invariant face recognition and retrieval," in *European conference on computer vision*. Springer, 2014, pp. 768–783.

[17] Y. Wen, Z. Li, and Y. Qiao, "Latent factor guided convolutional neural networks for age-invariant face recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 4893–4901.

[18] R. Goel, I. Mehmood, and H. Ugail, "A study of deep learning-based face recognition models for sibling identification," *Sensors*, vol. 21, no. 15, p. 5068, 2021.

[19] Y. Guo, L. Zhang, Y. Hu, X. He, and J. Gao, "Ms-celeb-1m: A dataset and benchmark for large-scale face recognition," in *European conference on computer vision*. Springer, 2016, pp. 87–102.

[20] K. Panetta, Q. Wan, S. Agaian, S. Rajeev, S. Kamath, R. Rajendran, S. P. Rao, A. Kaszowska, H. A. Taylor, A. Samani *et al.*, "A comprehensive database for benchmarking imaging systems," *IEEE transactions on pattern analysis and machine intelligence*, vol. 42, no. 3, pp. 509–520, 2018.

[21] T. Karras, S. Laine, and T. Aila, "A style-based generator architecture for generative adversarial networks," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2019, pp. 4401–4410.

[22] A. Frenzel, H. Binder, N. Walter, K. Wirkner, M. Loeffler, and H. Loeffler-Wirth, "The aging human body shape," *NPJ aging and mechanisms of disease*, vol. 6, no. 1, pp. 1–15, 2020.

[23] M. Loeffler, C. Engel, P. Ahnert, D. Alfermann, K. Arelin, R. Baber, F. Beutner, H. Binder, E. Brähler, R. Burkhardt *et al.*, "The life-adult-study: objectives and design of a population-based cohort study with 10,000 deeply phenotyped adults in germany," *BMC public health*, vol. 15, no. 1, pp. 1–14, 2015.

[24] P. Barra, C. Bisogni, M. Nappi, D. Freire-Obregón, and M. Castrillon-Santana, "Gender classification on 2d human skeleton," in *2019 3rd International Conference on Bio-engineering for Smart Technologies (BioSMART)*. IEEE, 2019, pp. 1–4.

[25] J. W. de Souza, G. B. Holanda, R. F. Ivo, S. S. Alves, S. P. da Silva, V. X. Nunes, L. L. Loureiro, C. Dias-Silva, and P. P. Rebouças Filho, "Predicting body measures from 2d images using convolutional neural networks," in *2020 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2020, pp. 1–6.

[26] A. Saint, K. Cherenkova, G. Gusev, D. Aouada, B. Ottersten *et al.*, "Bodyfitr: robust automatic 3d human body fitting," in *2019 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2019, pp. 484–488.

[27] T. Xiaohui, P. Xiaoyu, L. Liwen, and X. Qing, "Automatic human body feature extraction and personal size measurement," *Journal of Visual Languages & Computing*, vol. 47, pp. 9–18, 2018.

[28] A. A. A. Osman, T. Bolkart, and M. J. Black, "STAR: A sparse trained articulated human body regressor," in *European Conference on Computer Vision (ECCV)*, 2020, pp. 598–613. [Online]. Available: https://star.is.tue.mpg.de

[29] K. Robinette, H. Daanen, and E. Paquet, "The caesar project: a 3-d surface anthropometry survey," in *Second International Conference on 3-D Digital Imaging and Modeling (Cat. No.PR00062)*, 1999, pp. 380–386.

[30] "Sizeusa," tc2.com/size-usa.html.

[31] "Human solutions," human-solutions.com.

[32] ISO Central Secretary, "Basic human body measurements for technological design — Part 1: Body measurement definitions and landmarks," International Organization for Standardization, Geneva, CH, Standard, Aug. 2017.

[33] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.