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Machine Learning to Define Anthropometric Landmarks for Relevant Product Design 2D Blueprint Measures

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ABSTRACT

Functional designers use 3D body scan measurements to create 2D pattern blueprints, to develop products that size and fit bodies appropriately - to enable safety, comfort, and activity-related performance. To gather measures, surface anthropometric landmarks are critical, to enable accuracy and consistency between scans. However, many 3D scan databases do not include data with anthropometric landmarks, making bodies challenging to measure. Therefore, the purpose of this research was to develop a machine learning (ML) model for the automatic landmarking of 3D body scans from raw point clouds. A deep neural network model was developed, using the Civilian American and European Surface Anthropometry Resource (CAESAR) scan dataset (2002) for training. The model enabled 3D scans from any device that outputs in color to be used for landmark automation. Results of this work have also demonstrated that ML landmarking can enable bulk processing of 3D body scan point cloud data more efficiently compared to traditional manual landmarking methods.

Keywords: Machine learning models, Anthropometric landmarks, Functional Product Design

INTRODUCTION

The functional design of products worn on the human body is based upon a careful melding of science and art (Watkins and Dunne, 2015). Functional products can include footwear, apparel, and equipment – for users that participate in a wide variety of activities, including athletics, firefighting, military, and space operations, safety and healthcare. Fit of these products is critical, where poor fit can affect performance, comfort, and safety. To enable a good fit, specific anthropometric measures that are derived from anthropometric landmarks are needed from the body to develop accurate 2D product blueprints.

Anthropometric landmarks are anatomical locations on the surface of the body that can found on any body type, size, or shape to help derive anthropometric measures (ISO, 2017). However, a large majority of anthropometric 3D scan databases do not include relevant landmarks needed to collect measures, to draft accurate 2D blueprints for functional products. Without appropriate landmarks, product designers and developers are approximating measures, developing products that do not fit or are spending hundreds of hours re-landmarking 3D scans to their best ability to acquire appropriate measures. Therefore, purpose of this research was to develop a machine learning (ML) model for the automatic landmarking of 3D body scans from raw point clouds, to derive better body measures for the drafting of relevant 2D blueprints to improve product fit, performance, safety, and comfort.

BACKGROUND

ML gives computers the ability to recognize patterns in data and translate them to inferential knowledge without being explicitly programmed (Samuel, 1959). ML has seen widespread success in diverse domains such as medical surgery (Nguyen et al., 2020), speech recognition (Baevski et al., 2020), and self-playing agents (Silver, 2016). ML continues to show promise in applications that require automatic landmarking on the human body, where several studies have demonstrated its' capabilities for the task. Pinte, Fleury and Maurel (2021) used a ML model to localize electrode positions from Magnetic Resonance Imaging (MRI) scans by pre-training it on Ultrashort Echo time (UTE) sequences of MRI images. Hargreaves et al. (2003) performed forensic facial reconstruction on fossil bones using a generative deep learning algorithm trained on a limited amount of learning data. Grishchenko et al. (2022) created "BlazePose GHUM Holistic," a lightweight neural network pipeline for estimating 3D landmarks from monocular images. Giachetti et al. (2014) organized a point-localization contest for automatic landmarking on body scans, however, their method used hand engineered features and a small data set. In this work, we used ML to automatically identify 3D coordinates of landmarks in point cloud data from 5000 3D body scans from the 2002 Civilian American and European Surface Anthropometry Resource (CAESAR) database. This was done by training a deep neural network on the large database of scans, where useful features were extracted from the data and mapped to landmark locations that can be referenced for anthropometric measurements.

METHODOLOGY

PointNet (Qi et al., 2016) and VoxNet (Maturana and Scherer, 2015) are examples of ML methods developed for point cloud analysis. We utilized a simple convolutional neural network with smaller number of parameters making it memory efficient for learning from large point clouds. This model was a multi-layered, schematically shown in Figure 1. During training, the

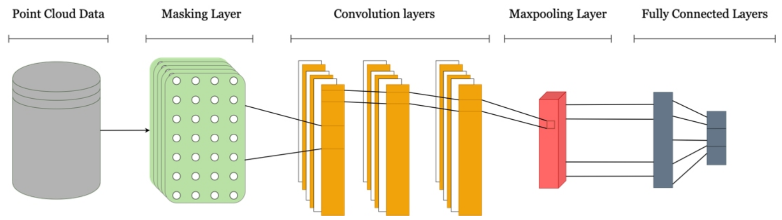

Figure 1: Model architecture.

input to the neural network was a batch of 3D body scan point clouds, where one of the pre-processing steps was to normalize the point cloud coordinates to meters, as the CAESAR data had mixed metric scales. We padded the point clouds to a uniform dimension of 200000×3 and passed the point cloud tensor through a masking layer to inform the network of the padded locations. The tensor was next passed through a stack of 1D convolution layers, where each convolution used 128 (1x1) filters. The stack of convolution was then followed by a global max-pooling layer to aggregate point features and reduce the tensor to a single dimension. The resulting tensor was followed by two fully connected (FC) layers. The first FC layer had 512 channels; the second had three channels. All hidden layers were equipped with Leaky-ReLU non-linearity. The training was done by optimizing the mean squared error (MSE) objective between predicted and ground truth landmarks using Adam at a learning rate of 1e-3. Training was done over 100 epochs and took 2-hours to reach convergence. Implementation was done with TensorFlow (Abadi et al., 2016) on a 32GB NVIDIA Tesla V100 GPU.

Table 1. Landmark body categories and landmark labels of the CAESAR database.

Category	Landmark Labels		
Head	Lt. Acromion	Lt. Gonion	Lt. Infraorbital
	Lt. Tragion	Nuchal	Rt. Acromion
	Rt. Gonion	Rt. Infraorbital	Rt. Tragion
	Sellion	Supramenton	
Torso	10th Rib Mid spine	Cervicale	Lt. 10th Rib
	Lt. Axilla, Ant	Lt. Axilla, Post.	Lt. Clavicle
	Lt. Iliocristale	Lt. Olecranon	Lt. Radiale
	Lt. Thelion/Bust point	Rt. 10th Rib	Rt. Axilla, Ant
	Rt. Axilla, Post.	Rt. Clavicle	Rt. Iliocristale
	Rt. Olecranon	Rt. Radiale	Rt. Thelion/Bust point
	Substernale	Suprasternale	
Digits	Lt. Calcaneus Post.	Lt. Dactylion	Lt. Digit II
	Lt. Lat. Malleolus	Lt. Med. Malleolus	Lt. Metacarpal-Phal. II
	Lt. Metacarpal-Phal. V	Lt. Metatarsal-Phal. I	Lt. Metatarsal-Phal. V
	Lt. Radial Styloid	Lt. Sphyrion	Lt. Ulnar Styloid
	Rt. Calcaneus Post.	Rt. Dactylion	Rt. Digit II
	Rt. Lat. Malleolus	Rt. Med. Malleolus	Rt. Metacarpal Phal. II
	Rt. Metacarpal-Phal. V	Rt. Metatarsal-Phal. I	Rt. Metatarsal-Phal. V
	Rt. Radial Styloid	Rt. Sphyrion	Rt. Ulnar Styloid
Crotch	Buttock Block	Crotch	Lt. PSIS
	Lt. Trochanterion	Rt. ASIS	Rt. PSIS
	Rt. Trochanterion	Preferred Waist	
Limbs	Lt. Femoral Lat. Epi.	Lt. Femoral Med. Epi.	Lt. Humeral Lat. Epi.
	Lt. Humeral Med. Epi.	Lt. Knee Crease	Rt. Femoral Lat. Epi.
	Rt. Femoral Med. Epi.	Rt. Humeral Lat. Epi.	Rt. Humeral Med. Epi.
	Rt. Knee Crease		

RESULTS

The CAESAR 3D body scan database is large with semantic landmark information. The database consists of scans of both sexes in three postures 1) standing (A-pose), 2) seated comfortable working (B-pose), and 3) seated coverage (B-pose). The 3D scans were stored as 3D point clouds, where each scan contained about 200K vertices per scan. We split the entire CAESAR dataset into a 7K training set and 2K samples for validation. There was a total of 100 landmarks in CAESAR, we selected 74 landmarks that have at least 10 samples in the entire dataset and trained a model for each of them.

We divided the landmarks into five mutually exclusive body categories described in Table 1. The average MSE per body category is shown in Table 2. Our model performed well on all body categories, achieving an MSE smaller than 1.83 cm, except for the crotch category which is known in the anthropometry field to be difficult to approximate. These errors were also described pictorially and specifically in Figure 2, where the size of the green sphere is proportional to the average radial deviation of the measurements made by

Table 2. Average MSE per category in the CAESAR database.

Body Category	Average MSE (cm)
Head	1.83
Torso	0.91
Digits	1.77
Crotch	2.28
Limbs	1.48

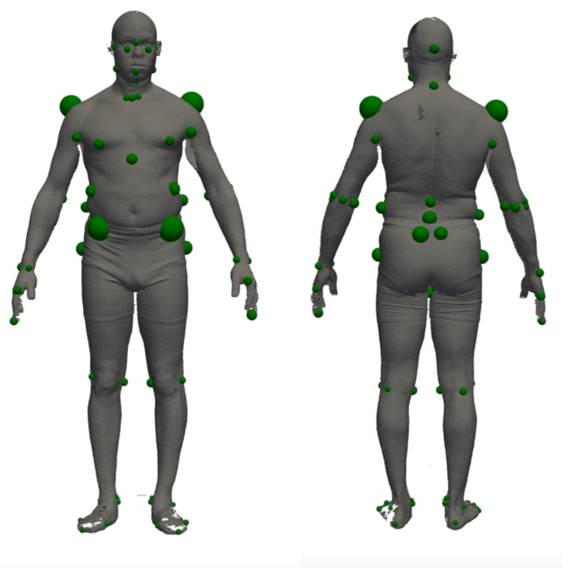

Figure 2: Predicted model landmark locations on an example 3D scan from the CAESAR database. The larger spheres depict larger prediction errors.

the model from the true landmark. Using our model, the largest errors were evident for the left and right acromion and left and right iliocristale. These landmarks are also known in the anthropometric field to be challenging to identify by humans.

CONCLUSION

Through this research we used ML to automatically identify 3D coordinates of anthropometric landmarks in point cloud data from a large database of 3D body scans (in color). In future work, ML models will be used to take anthropometric measurements, and to train new landmarks - ones different from the CAESAR dataset to enable custom measurement capabilities related to human performance and functional product creation. For example, in this study we were able to train the 10^{th} rib mid-spine landmark with as few as 25 scans, suggesting that smaller 3D scan databases with different landmarks could be used for training. This research also demonstrated that known tedious anthropometric measurement procedures could be expedited to develop more relevant 2D blueprints, to enable the efficient commercialization of functional products that fit better - to improve performance, comfort, and safety.

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REFERENCES

Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G. S., Davis, A., Dean, J., Devin, M., and Ghemawat, S. (2016). "TensorFlow: A system for large-scale machine learning." 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16), pp. 265-283.

Baevski, A., Zhou, Y., Mohamed, A., and Auli, M. (2020). "wav2vec 2.0: A framework for self-supervised learning of speech representations." *Advances in neural information processing systems*, *33*, pp. 12449-12460.

Giachetti, A., Mazzi, E., Piscitelli, F., Aono, M., Hamza, A. B., Bonis, T., Claes, P., Godil, A., Li, C., Ovsjanikov, M., and Patraucean, V. (2014). "SHREC'14 Track: Automatic location of landmarks used in manual anthropometry." In *Eurographics Workshop on 3D Object Retrieval,* pp. 93–100.

Grishchenko, I., Bazarevsky, V., Zanfir, A., Bazavan, E. G., Zanfir, M., Yee, R., Raveendran, K., Zhdanovich, M., Grundmann, M., and Sminchisescu, C. (2022). "BlazePose GHUM holistic: Real-time 3D human landmarks and pose estimation." *arXiv preprint arXiv:2206.11678*.

Hargreaves, M., Ting, D., Bajan, S., Bhavnagri, K., Bassed, R., and Chang, X. (2003). "A generative deep learning approach for forensic facial reconstruction." In *2021 Digital Image Computing: Techniques and Applications (DICTA),* pp. 1–7 IEEE.

ISO. (2008). "7250-1: Basic human body measurements for technological design - Part 1: Body measurement definitions and landmarks." *International Organization for Standardization, Geneva, Switzerland*.

Maturana, D. and Scherer, S. (2015). "Voxnet: A 3D convolutional neural network for real-time object recognition." In *2015 IEEE/RSJ International conference on Intelligent Robots and Systems (IROS)*, pp. 922–928, IEEE.

Nguyen, N., Priola, S.M., Ramjist, J., Guha, D., Dobashi, Y., Lee, K., Lu, M., Androutsos, D., and Yang, V.X. (2020). Machine vision augmented reality for pedicle screw insertion during spine surgery. Journal of Clinical Neuroscience, 72, pp. 350–356.

Pinte, C. Fleury, M., and Maurel, P. (2021). "Deep learning-based localization of EEG electrodes within MRI acquisitions." *Frontiers in Neurology*, *12*, p.644278.

Qi, C., Su H., Mo K., and Guibas L. (2017). "Pointnet: Deep learning on point sets for 3D classification and segmentation." In *Proceedings of the IEEE conference on computer vision and pattern recognition*. pp. 652–660.

Robinette, K. M., Blackwell, S., Daanen, H., Boehmer, M., and Fleming, S. (2002). "Civilian American and European Surface Anthropometry Resource (CAESAR), final report." Volume 1, summary. Sytronics Inc Dayton, OH.

Samuel, A. L. (1959). "Some studies in machine learning using the game of checkers," *IBM Journal of Research and Development* 44:1.2, pp. 210–229.

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., and Dieleman, S. (2016). "Mastering the game of go with deep neural networks and tree search." *Nature*, *529*(7587), pp. 484–489.

Watkins, S. M. and Dunne, L. (2015). "Functional clothing design: From sportswear to spacesuits." Bloomsbury Publishing USA.