Human Body Dimensions Estimation (HBDE) is a task that an intelligent agent can perform to attempt to determine human body information from images (2D) or point clouds or meshes (3D). More specifically, if we define the HBDE problem as inferring human body measurements from images, then HBDE is a difficult, inverse, multi-task regression problem that can be tackled with machine learning techniques, particularly convolutional neural networks (CNN). Despite the community’s tremendous effort to advance human shape analysis, there is a lack of systematic experiments to assess CNNs estimation of human body dimensions from images. Our contribution lies in assessing a CNN estimation performance in a series of controlled experiments. To that end, we augment our recently published neural anthropometer dataset by rendering images with different camera distance. We evaluate the network inference absolute and relative mean error between the estimated and actual HBDEs. We train and evaluate the CNN in four scenarios: (1) training with subjects of a specific gender, (2) in a specific pose, (3) sparse camera distance and (4) dense camera distance. Not only our experiments demonstrate that the network can perform the task successfully, but also reveal a number of relevant facts that contribute to better understand the task of HBDE.

Keywords: Human Body Dimensions Estimation · Human Body Measurements · Deep Learning.

1 Introduction

Human Body Dimensions Estimation (HBDE) is a task that an intelligent can perform to attempt to determine human body information from images (2D) or point clouds or meshes (3D). For instance, estimating the height and the shoulder width of a person from a picture or a 3D mesh. Being humans in the center of society, one would expect that intelligent agents should be able to perceive the shape of a person and reason about it from an anthropometric perspective, i.e., be capable of accurately estimating her human body measurements.
This problem can be characterized by specifying the intelligent agent’s perceptual input. If the HBDE problem is circumscribed to inferring human body measurements from images, then HBDE is, theoretically, a difficult, inverse, multi-task regression problem.

Practically, HBDE from images is a compelling problem, as well. HBDE plays an important role in several areas ranging from digital sizing\[28\], thought ergonomics\[6\] and computational forensics\[29\], to virtual try-on\[20\] and even fashion design and intelligent automatic door systems\[17\]. Moreover, since accurately estimating a person’s body measurements would decrease the probability that the person returns clothes acquired online, HBDE has gained attention as an important step toward a more individual-oriented clothes manufacture.

Inverse problems such as HBDE can be tackled with convolutional neural networks (CNN). However, most studies in the field of HBDE have only focused on investigating to what extent CNNs can predict body measurements. A number of factors can affect this prediction, but researchers have not treated them in depth. What is not yet clear is the impact of the person’s gender, pose, and camera distance with respect to the subject, on the estimation performance.

In this paper, we investigate these dependencies with a series of experiments. Despite the tremendous effort from researchers to attempt to better understand HBDE, there is lack of this kind of experiment in the literature. We believe that our contribution will shed light on how a CNN estimate HBDs. Upon publication, we will make our code publicly available for research purposes\[1\].

2 The Problem of Human Body Dimensions Estimation

As stated above, CNNs can be employed to approach the HBDE problem. However, supervised learning methods demand large amounts of data. Unfortunately, this kind of data is extremely difficult to collect. For the network input, several persons must be photographed with the same camera under equal lighting conditions. Further, in order to study the effect of pose, the subjects must adopt several poses; and to study the effect of camera distance, they would have to be again photographed. The supervision signal is even more challenging and costly: these same subjects must be accurately measured with identical methods to acquire their body dimensions. This is the data scarcity problem in HBDE.

A possible solution is to generate realistic 3D human meshes and calculate HBDs from these meshes. But the HBD calculation is by no means a trivial task. Properly defining HBDs suffers from two issues: inconsistency and uncertainty.

HBDs definitions differ depending on their intended purpose. To just mention one example, health studies measure waist circumference at the midpoint between the inferior margin of the last rib and the iliac crest\[7\]. However, while investigating the height of the waist for clothing pattern design,\[12\] found seven different waist definitions and \[11\] directly enunciated that not all body measurements defined by 3D scanning technologies are valid for clothing pattern. This

\[1\] Code under https://github.com/neoglez/gpcamdis_hbde
multiplicity of definitions complicates consistent conceptualization for machine learning.

Furthermore, HBDs are defined based on skeletal joins and/or body landmarks. These reference criteria are highly uncertain and depend on the person performing the measurement. A single HBD may exhibit important variability due to observer or instrument error. Also, researchers and practitioners base their analysis on HBD by presenting a figure of a thin subject with the measurements depicted by segments without further elucidation. This approach hinders the HBDs calculation reproducibility.

Formally, the HBDE problem has been defined by [13] as a deep regression problem. Given an image $I$ from a 3D human body with HBD $D$, the goal is to return a set $\hat{D}$ of estimated human body dimensions, that is

$$
\hat{D} = M(I(D)).
$$

The dataset is assumed to be drawn from a generating distribution and the deep neural network $M$ minimizes the prediction error.

### 3 Related Work

Obviously, human body dimensions are determined by human shape. In the field of Human Shape estimation (HSE), shape has been ambiguously presented either as a parametric model acting as proxy to a 3D mesh or directly as a triangular mesh. In a community effort to be more precise, the task of shape estimation has been currently sharper defined as human mesh recovery, estimation or reconstruction. Additionally, pose estimation has been established as inferring the location of skeleton joints, albeit these not being anatomically correct. In the last five years, the body of work in these two fields has exploded. Since human mesh and pose estimation are barely indirectly related to our work, we will not discuss them here. In contrast, we focus on end-to-end adults HBDE from images, i.e., the model input are images of adult subjects and the output are human body measurements.

Undoubtedly, anthropometry has contributed most to human shape analysis. Important surveys such as CAESAR (1999)[24], ANSUR I and II (2017)[1] and NHANES(1999-2021)[2], have collected HBDs. However, they did not take images of the subjects. This makes unclear how the CNN input could be obtained. Recently, other datasets have been released for specific tasks, e.g., [23] propose a dataset with images and seven HBDs for estimation in the automotive context.

Of all these compendiums, CAESAR is probably the most convenient data in terms of realism. It contains rigorously recorded human body dimensions and 3D scans, from which realistic images could be synthesized. The project costed six million USD (see [24] executive summary). Consequently, this data is highly expensive. Alternatively, we employ a generative model derived from real humans, capable of producing thousands of 3D meshes from which we can calculate and visualize the HBDs.
Certainly, height is the HBD that has been investigated the most\cite{10, 5, 13, 21, 8, 27, 15, 29, 19}. Very early work\cite{16} investigated the effect of gender and inverted pictures when humans estimate height from images. They quantified estimation performance using Pearson’s Correlation Coefficient and established that the estimated and ground truth height where highly correlated. This fact has been confirmed recently by\cite{19}, which also concluded that humans estimate height inaccurately. Other HBDs have been explored, e.g., waist\cite{12} but, in general, they have received significantly less attention.

Strongly related to our work are studies using or generating synthetic data and calculating or manually collecting HBDs\cite{9, 10, 3, 30, 31, 32, 26}. None of these works investigated the effect of gender, pose or camera distance in the estimation performance. Here, we explore these interactions.

Recently,\cite{4} proposed a baseline for HBDE given height and weight. They claimed that linear regression estimates accurately HBDs when the inputs are height and weight. Like we, this method use ground truth derived from the SMPL model\cite{18}. Despite their input being different to ours, we will use this work for comparison.

A neural anthropometer (NeuralAnthro) was introduced by\cite{13}. The CNN was trained on grayscale synthetic images of moderate complexity, i.e., no background, limited human poses, and fix camera perspective and distance. In this work, we go further and increase the image complexity, making the input more challenging to the intelligent agent conducting HBDE.

4 Material and Methods

We now detail the dataset and CNN (model) of the supervised learning approach that governs our experiments.

4.1 Dataset

We start with the NeuralAnthro synthetic dataset. The reason to use a synthetic dataset is the cost and effort that collecting "real" data would imply. Since coherent pose variability is more difficult to find in real datasets, another important aspect is the possibility to vary the subject posture to experiment with different poses. While we did not collect our data from physical humans, we use the SMPL model, which is derived from real humans. SMPL is the most employed model in academia and industry for its realism and simplicity\cite{25}.

Input Figure\cite{1} depicts our dataset. We obtained the 3D meshes, 6000 female and male subjects in pose zero and pose one (total 12000 meshes), from the neural anthropometer dataset\cite{13}.

Using the current standard method to employ a render engine to produce the mesh corresponding images, we simulate the cinematographic technique of tracking back (sparsely and densely varying the camera distance to the mesh), as follows.
Fig. 1. Our curated dataset. We augment the NeuralAnthro dataset, containing images of female (left) and male (right) subjects in pose zero (arms stretched to the sides) and pose one (arms lowered) taken with a camera at a fix distance, by rendering photos with sparse and dense camera distances (center). Note that the subjects appear nearer or farther in the images. All instances are $200 \times 200$ pixels grayscale images displaying a single subject.

**Sparse camera distance**: back tracking by placing the camera at distances $4\,m$, $5\,m$ and $6\,m$.

**Dense camera distance**: back tracking by randomly placing the camera between distances $4, 2\,m$ and $7, 2\,m$.

In total, we synthesize 72000 pictures from the 12000 meshes. The images correspond to meshes of a specific gender and a definite pose, taken at specific camera distance with respect to the subject.

**Supervision Signal** While the data scarcity problem is the major challenge in HBDE, another problem is measurement inconsistency. There is no consensus regarding the correct manner to define a specific measurement, let alone several of them. The problem arises even when HBDs are automatically computed by 3D scanning technologies[20], making manually corrections unavoidable. The united method introduced by [13] with Sharmeam ($\text{Shoulder width, right and left arms length and inseam}$) and Calvis ($\text{Chest, waist and pelvis circumference plus height}$) allows us to resolve the inconsistency issue because it provides a proper method to calculate eight HBDs. Additionally, it agrees, to a large extent, with anthropometry and tailoring.

### 4.2 Neural Anthropometer

The NeuralAnthro is a small, easily deployable CNN that we use to conduct our experiments. We use the same experimental setting as in the original paper[13], i.e., we train for 20 epochs and use mini-batches of size 100. We report results based on 5-fold cross-validation. We minimize the mean squared error between the actual and the estimated HBDs using stochastic gradient descent with a momentum 0.9; the learning rate is set to 0.01.
5 Results and Discussion

For the presentation of the results we use the following abbreviations: shoulder width (SW), right arm length (RAL), left arm length (LAL), inseam (a.k.a. crotch height) (I), chest circumference (CC), waist circumference (WC), pelvis circumference (PC) and height (H). Average MAD (AMAD) and Average RPE (ARPE) are both represented by a capital A. The figures we present are interesting in several ways. Due to space restrictions we can not discuss exhaustively all their aspects. Therefore, we examine the most salient results.

|       | Female | Male |
|-------|--------|------|
| SW    | 16.67  | 18.04|
| RAL   | 20.25  | 21.48|
| LAL   | 31.84  | 33.15|
| I     | 29.73  | 29.94|
| CC    | 33.94  | 32.14|
| WC    | 39.18  | 37.94|
| PC    | 34.77  | 36.26|
| H     | 47.29  | 43.67|
| A     | 52.67  | 54.99|

|       | Female | Male |
|-------|--------|------|
| SW    | 7.37   | 3.37 |
| RAL   | 3.59   | 3.59 |
| LAL   | 3.86   | 3.86 |
| I     | 3.45   | 3.45 |
| CC    | 4.57   | 4.57 |
| WC    | 4.35   | 4.35 |
| PC    | 4.16   | 4.16 |
| H     | 5.25   | 5.25 |
| A     | 5.98   | 5.98 |

![Figure 2](image.png)

**Fig. 2.** Effect of gender on HBDE. Left: we display Mean Absolute Error (MAE) in mm; right: Relative Percentage Error (RPE).

5.1 Effect of Gender

We start our discussion by evaluating the network performance when the input are images from humans of a specific gender in pose zero or one. We define training with two gender as *unisex training* and *gender training* when the input are subjects of a specific gender. Figure 2 shows the results.

Like [8], we observe that height estimation is more accurate in unisex training, compared to gender training (RPE 1.58 unisex training reported in [13] vs. gender training 2.85 female and 2.95 male).

For the network, it is considerably more difficult to estimate female gender training SW than male gender training SW. Although female gender training SW MAE is lower than male gender training (12.63mm vs. 16.07mm), the inverse relation can be observed, when considering RPE (7.37 vs. 3.93).

Curiously, regarding the effect of gender, the CNN and humans appear to estimate height differently. Unlike [16]’s results, Fig 2 shows that the female
height estimation error (RPE 2.85) is lower than male (RPE 2.95). Perhaps it is not surprisingly, that this relation holds for inseam as well (RPE 3.86 vs. 4.35). With the exceptions of these two HBDs, the RPE of estimating other HBDs is larger for female as for male subjects.

5.2 Effect of Pose

Figure 3 presents the breakdown of the estimation error when we train the network individually with images of humans in pose zero and pose one (multi-pose training). Surprisingly, the network estimated shoulder width more poorly when the subject was in pose one as in pose zero (RPE 6.4 vs. 6.0). One would expect that estimating SW would be easier when the subject is in pose one, because the arms are lowered, and, therefore, the shoulder joints could be easier recognized.

5.3 Effect of Camera Distance

The most interesting finding was that the network is able to accurately estimate all HBDs independently of the camera distance to the person (ARPE 3.04, 3.03, 2.96, 3.57 and 3.11), when training with sparse camera distance 4 m, 5 m and 6 m and randomly chosen camera distance respectively. This fact challenges intuition, e.g., contradicts current research claiming that the network can only correctly estimate height if the evaluation is performed for a particular camera distance[4]. But this finding is in accordance to when humans estimating height as reported in preliminary work[10].

Fig. 3. Effect of pose on HBDE. Left: we display Mean Absolute Error (MAE) in mm; right: Relative Percentage Error (RPE).
Fig. 4. Effect of camera distance on HBDE. We placed the camera at distances $-4$ m, $-5$ m and $-6$ m, and randomly distances sampled from $-4.2$ m to $-7.2$ m with respect to the subject. Top: Relative Percentage Error (RPE); bottom: Mean Absolute Error (MAE) in mm.

5.4 Quantitative Comparison to Related Work

Although we did not aim to present a method that outperform SOTA estimation methods, we discuss comparative quantitative results for completeness. Basically, we compare to NeuralAnthro’s original results, the best baseline results (Baseline I = 2) on ANSUR data in a recently published study on height estimation from real images by humans, and the ANSUR II allowable error.

We have been eminently cautious in comparing our results in the task of human body dimension estimation. Several reasons hinder a fair comparison and constitute a major obstacle to advance the field.

First, in the literature, Mean Absolute Error (MAE) and Mean Absolute Difference (MAD) refer to the same error quantity. Also, Relative Percentage Error (RPE) has not been consistently reported. RPE is important because human body dimensions are not in the same scale. For instance, probably 40mm MAE, say, account for a lower height estimation error (better performance) as for head circumference error (worst performance). Besides MAD and RPE, estimation performance has been reported by Mean±Std. Dev and success rate, seemingly Expert ratio. This inconsistency in reporting results complicates significantly the comparison with other research. Second, most method’s input are 3D, therefore, inadequate for comparison to 2D methods.

Third, we require that methods’ result has been reported persistently in the literature. Neither we compare to results reported online that are not longer available, nor to results that has been used for comparison but we were not able...
Table 1. Comparison to four related methods. We compare estimation performance in terms of MAD error in mm. We do not present HBDs that are not comparable (na: not applicable). Minimal errors are bold and we emphasized ANSUR II allowable error. Additionally, we enclosed in parenthesis our experiment setting that achieved best estimation results.

| Method                        | SW  | RAL | LAL | I   | CC  | WC  | PC  | H   |
|-------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Baseline (I = 2) [14]         | na  | na  | na  | na  | 29.1| 37.9| 21.6| na  |
| NeuralAnthro [13]             | 12.54| 12.98| 13.48| 12.17| 25.22| 27.53| 25.85| 27.34 |
| Our experiments               | 11.93| 13.30| 12.9 | 22.05| 25.93| 27.39| 23.28| 24.75 |
| Humans observing real images [19]| na  | na  | na  | na  | na  | na  | na  | 64.0 |
| Humans, ANSUR (Allowable error) [22] | na  | na  | na  | na  | na  | na  | na  | 6.0 |

Table 1 shows the comparison. The input to Baseline is not images (like ours) but height and weight. However, that research does establish a conceptual baseline: HBDE methods should estimate body measurements with higher accuracy compared to regression. This statement should not be categorically interpreted. Methods requiring images as input without any other information are more challenging and, therefore, might exhibit less accuracy. As it can be seen, NeuralAnthro estimates more precisely RAL, I and CC as the regression baseline, when applicable, and all of our experiment settings. This might happen because NeuralAnthro was trained and evaluated with fixed camera distance. The network probably found more difficult learning when trained with three different camera distances. Nevertheless, being SW the most difficult HBD to estimate, our experiment with one camera distance at 6m manifests the best estimation performance. Moreover, our experiment setting with randomly selected camera distances shows the best WC estimation performance.

As the authors indicate in [19], height estimation by humans exhibits poor performance. The cause is, probably, that the persons estimated the HBD from real images, which is the input with highest complexity, compare to synthetic controlled data.

Estimation error of all HBD lies over the ANSUR II allowable error, but the fact that the NeuralAnthro is a small CNN could indicate, that by incrementing the size of the network, the estimation performance could be improved as well.
6 Conclusions and Future Work

In this paper, we assessed the performance of a neural network employed to estimate human body measurements from images. To that end, we augmented our recently published dataset containing images of female and male subjects in two poses, with images of these subjects synthesized using different camera distances with respect to the subjects. We trained a CNN with two genders, two different poses and sparse and dense camera distances. After training we evaluated the network performance in terms of MAE and RPE.

The CNN estimated HBDs of male subjects more accurately than those of females. The shoulder width predictions exhibit a surprising pose dependency. The width is estimated more correctly for subjects with arms spread out to the side (compared to subjects with lowered arms, where the contours of the shoulders are more pronounced). In contrast to our expectations, network performance decreases only slightly when perceiving humans from a range of (camera) distances instead of a fixed distance; given that the person is completely visible in the image. In general, shoulder width is the most difficult HBD to estimate.

6.1 Future Work

An important question that needs to be answered is why the estimation is, in general, highly accurate (errors are reported in mm). Exploring to what extent synthetic data is representative of the real HBDs would contribute to understand this phenomenon. Increasing the level of realism of the images would probably have the strongest effect in HBDE. Also, investigating the minimum amount of data for conducting HBDs with reasonable accuracy, would help determining bounds to collect a plausible real dataset, therefore, alleviating the data scarcity problem.

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