Comenius University in Bratislava
Faculty of Mathematics, Physics and Informatics

# Comparing Synthetic and Real Data for Anthropometric Measurements Estimation

Bachelor Thesis

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Comenius University in Bratislava
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Bachelor Thesis

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|---|---|
| Study Programme: | Computer Science |
| Field of Study: | Computer Science |
| Department: | Department of Computer Science |
| Supervisor: | Mgr. Dana Škorvánková |

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Fakulta matematiky, fyziky a informatiky

# ZADANIE ZÁVEREČNEJ PRÁCE

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| **Meno a priezvisko študenta:** | Michal Baránek |
| **Študijný program:** | aplikovaná informatika (Jednoodborové štúdium, bakalársky I. st., denná forma) |
| **Študijný odbor:** | informatika |
| **Typ záverečnej práce:** | bakalárska |
| **Jazyk záverečnej práce:** | anglický |
| **Sekundárny jazyk:** | slovenský |

**Názov:** Comparing Synthetic and Real Data for Anthropometric Measurements Estimation
*Porovnanie syntetických a reálnych dát pre účely odhadu antropometrických mier*

**Anotácia:** Odhad mier ľudského tela je úloha, ktorá priťahuje v posledných rokoch pozornosť viacerých vedeckých oblastí. Automatický a presný prístup na riešenie tohto problému je kľúčový v rôznych oblastiach počítačového videnia. Výroba odevov a šitie odevov na mieru patria medzi aplikácie, kde by presný odhad mier tela z vizuálnych dát človeka bol prínosným, nahradením tradičného manuálneho merania tela.

**Cieľ:** Cieľom tejto bakalárskej práce je naštudovať problematiku odhadu rozmerov ľudského tela, otestovať vybrané state-of-the-art metódy založené na hlbokom učení a evaluovať ich pomocou syntetických aj reálnych dát. Úlohou je týmto spôsobom analyzovať rozdiely medzi danými doménami, a vyhodnotiť výhody augmentácie reálnych dát pomocou syntetických obrazov pre účely trénovania modelu.

**Kľúčové slová:** miery tela, neurónové siete, hlboké učenie

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| **Dátum zadania:** | 25.09.2023 |
| **Dátum schválenia:** | 04.10.2023 |

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# THESIS ASSIGNMENT

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| **Name and Surname:** | Michal Baránek |
| **Study programme:** | Applied Computer Science (Single degree study, bachelor I. deg., full time form) |
| **Field of Study:** | Computer Science |
| **Type of Thesis:** | Bachelor´s thesis |
| **Language of Thesis:** | English |
| **Secondary language:** | Slovak |

**Title:** Comparing Synthetic and Real Data for Anthropometric Measurements Estimation

**Annotation:** Human body measurements estimation is a task that attracts the attention of several scientific fields in recent years. An automatic and accurate approach to this problem is crucial in various areas of the computer vision-oriented industry. Garment manufacturing and tailoring are some of the applications, where an accurate body measurements estimation from visual human data would be beneficial, replacing the traditional manual tape measuring.

**Aim:** The goal of the bachelor thesis is to study the task of body measurements estimation. The aim is to test selected state-of-the-art deep learning methods and evaluate them using both synthetic and real human body data. In this way, we aim to analyze the domain gap and explore the benefits of augmenting real data with synthetic images for training purposes.

**Keywords:** body measurements, neural networks, deep learning

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Student Supervisor

**Acknowledgments:** Tu môžete poďakovať školiteľovi, prípadne ďalším osobám, ktoré vám s prácou nejako pomohli, poradili, poskytli dáta a podobne.

# Abstrakt

Slovenský abstrakt v rozsahu 100-500 slov, jeden odstavec. Abstrakt stručne sumarizuje výsledky práce. Mal by byť pochopiteľný pre bežného informatika. Nemal by teda využívať skratky, termíny alebo označenie zavedené v práci, okrem tých, ktoré sú všeobecne známe.

**Kľúčové slová:** jedno, druhé, tretie (prípadne štvrté, piate)

# Abstract

Abstract in the English language (translation of the abstract in the Slovak language).

**Keywords:**

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# Introduction

Nowadays our physical bodies are not enough for us anymore. Thanks to modern technologies every day we come closer to living a new type of life. Virtual one. The beginnings were quite humble with us sharing our thoughts via text and shortly after empowering our life stories with images. Thanks to these innovations we were able to create a new type of business - online shops. Their popularity rose over the years and are now rivals to traditional ways of shopping. These new online stores however have a significant disadvantage in comparison. You cannot try the clothes on and see whether it will fit. Luckily we have already created clothing sizing system to help us choose the correct size. However to use this system one would need exact body measurements to look up correct size in the table.

Online shops however were not the only blooming business in recent years. A new prospect has appeared only just recently and it caught attention of big companies straight away. The virtual world where we could meet our friends living anywhere in the world without having to leave our home. In this world everyone would have their own avatar that would represent them. Some virtual worlds would let you become whoever or even whatever you could possibly think of while some others decided to stick with realism. Realism sounds great, but this approach requires realistic data to be able to look convincing. To create a clone of human body in the virtual world we amongst many variables would need exact body measurements to provide a believable result.

These are just two examples that require users to obtain their body measurements. While the act of measuring does not seem very problematic the measurements are prone to human error. There are no rules when it comes to measuring body parts. Usually, subjects are only guided via text or image showing them how to measure. This will never satisfy the accuracy that is required.

Thanks to progress in neural networks a new way of obtaining body measurements has emerged. With requiring only picture of body from front we can train a neural network to predict measurements of human body. This has already been proven plausible, but the accuracy lacked in some measurements. The goal of this work is to compare different .... (To make data better). The methods will vary to see how impactful they are regarding the final result.

For training we will use a synthetic dataset which will allow us to have much larger number of samples for training. For metrics we will use performance on dataset with real samples provided by BodyM dataset.

The first chapter will provide overview of the problematic, will look into traditional measuring methods, delve into obstacles this approach faces and then explain some of the mechanical works of this thesis. Second chapter will look into already existing work that is relevant to topic. In the third chapter we will define datasets. Contents of fourth chapter will focus on proposed solution and implementation. Results of our research will be located in fifth chapter while the sixth chapter will provide conclusion.

# Chapter 1

# Overview

Contents of this chapter will provide definitions and explanations to terms and methods used in following chapters. This will hopefully help to understand the topic discussed in this thesis.

## 1.1 Measuring

Measuring locations vary depending on the use and thus there is no universal guide. The professionals should be familiar with the measurements required in their field of application, but the subjects themselves are usually not as informed. This can then result into incorrect measurement.

Human body can be measured using different methods. These are usually dependent on input data and thus not every method can be used in every situation.

### 1.1.1 Hand measurement

This is the traditional method of using tape or any alike measuring device for obtaining measurements. The approach usually needs one extra person that performs the measurement on the subject. Due to measurements requiring to be taken at specific locations to provide correct information, a person without help is more prone to obtaining incorrect measurements.

### 1.1.2 Digital measuring on 3D model

Another method used for obtaining measurements is by using scanning technology. One of approaches uses devices such as photogrammetry scanners creates realistic meshes of scanned subject. The data can then be registered to SMPL [Loper et al., 2015] mesh topology. We can then use the resulting mesh for calculating the required measurements. This is also the case of [Ruiz et al., 2022], which uses these measurements as ground truth data.

#### Photogrammetry scanner

This method utilises photographs from different angles and positions to calculate and create a mesh. The device to take photos does not need any extra functionality to produce images processable into final model. However, photogrammetry scanners are being developed to provide ease of use and quality over common cameras. One of such features is a multi-camera system. Main advantage is when the subject is a living being, offering photos from multiple angles in the same instant. This prevents to faulty models due to unwilling movement of the subject.

Different approach uses 3D scanning devices. These are more expensive than equipment required for photogrammetry, but can provide precise models. The result of scan using a 3D scanner is a point cloud or a set of data points depicting shape and size of subject [Haleem et al., 2022]. This can be used directly as and input for further processing.

#### 3D scanner

Multiple technologies are used in 3D scanners. For example structured and laser based scanners use light to measure location of points. These devices throw blue light and cameras to record the reflection to obtain distance of point on the subject from the measuring device. While laser based devices produces lines on the subject the structured light based devices project a grid

### 1.1.3 Using point clouds

Not all scans are registered to a mesh topology. Some approaches have tried to use point cloud representation. An overview of methods used is provided by [Xu et al., 2021].

## 1.2 SMPL

SMPL [Loper et al., 2015] is short for Skinned Multi-Person Linear model. Its capabilities include generation of animated human bodies with various body shapes in specific poses. Moreover, the model is able to deform naturally. This soft-tissue motion produces results much closer to real tissue. SMPL builds on blend shapes which are represented by a vector of concatenated vertex offsets. Other than vertices the SMPL model also uses joints, which essentially create the skeleton of the model. Topology of said model does not depend on sex of resulting model.

## 1.3 Neural network

Neural network is code built on premises of how human brains work. It consists of connected nodes called neurons. Each neuron takes input variables, processes them and then sends the result to other neurons. Every connection has associated weight which determines the influence said value will have. Neurons are then organised into layers. They are usually divided into input, output and hidden layers. The function of the hidden layers is to perform the operations needed to calculate output from the input data. The process of training adjusts the weights of the connections. This automatic process of adjusting is usually based on comparing the output and correct value we provide for the network and minimising the difference. This process helps the network to find complex relationships or patterns that may not be as understandable for humans.

#### Hyperparameter

Hyperparameter is a parameter that is not learned but chosen by developer. These parameters do not change over time. These can be - choice of optimizer, learning rate, number of layers, filter size and more.

#### Loss functions [Terven et al., 2023]

The training process is guided by the loss function. They show how good or how bad the network is at predicting the output. The results then serve as a guide for the learnable parameters. Loss function measures the difference between the predicted and expected outputs. Main goal of the network then becomes to minimise the loss function. One of the commonly used losses for regression task such as this one is the mean squared error (MSE or sometimes called L2 loss). This loss function is calculated as an average of the squared difference between the predicted values and the ground truth. To define this function mathematically:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1.1}$$

In this equation $n$ is used to define number of samples, $y_i$ is the ground truth and $\hat{y}_i$ the predicted value of the $i^{th}$ sample. Being a convex function, the MSE has a unique global minimum, which helps the optimization process as the optimization methods do not get stuck in the local minima. While being a computationally simple , it is vulnerable to outliers. The issue is created by the square nature of this function. In case of existing outlier the function gets heavily influenced and may not perform as well.

### Performance metrics

After the network was trained on the training data, it has to face new, unseen data. This ability is then measured using performance metrics. They are mainly used after the network has been trained. Performance metrics are also used to compare different networks. We can use some loss functions for performance metrics. In this thesis we will use mean absolute error (MAE or L1 loss). The principle is similar to MSE, but instead of squaring the difference we will use the absolute value to always have error larger than 0, meaning 0 will be a perfect fit. Mathematical definition of the MAE is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{1.2}$$

in which $n$ is used to define number of samples, $y_i$ is the ground truth and $\hat{y}_i$ the predicted value of the $i^{th}$ sample.

### Overfitting

One of the dangers of using neural networks is the possibility of overfitting. This issue is created when a complex network is trained with insufficient data. Complexity of architecture helps the network to find and learn more complex relationships, but in a case when inadequate amount of data is used for training, the network does not find the relationships we want, but instead learns exact values to have the best results for provided images. Consequence of this issue is, that the training loss is extremely small, but the performance metrics show inadequately larger error.

Our model is mainly built on the following layers:

### Convolution layer

Most popularly used with convolutional neural networks [O'Shea and Nash, 2015] this layer plays important role in network's functionality. It is based on working with matrices called kernels. The values in kernel are learnable, which means they are adjusted over the training process to enhance performance. In this thesis we will be using these hyperparameters:

- **Depth** determines dimension of the output volume (activation maps). Influences pattern recognition as well as number of neurons.

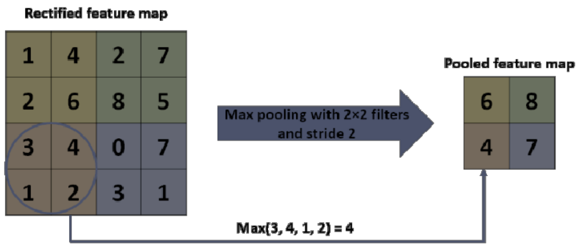


Figure 1.1: Max Pooling Example [Gholamalinezhad and Khosravi, 2020]

- **Size** determines dimensions of kernel.
- **Activation function**

The algorithm consists of sliding kernel along the input. At every position it calculates the sum of element-wise multiplication of corresponding pixels in input and kernel. The result is then inserted into the output. This process is then repeated over the whole input multiple times (depending upon number of kernels) Result of this operation captures local patterns while preserving positional relationships.

### Max Pooling layer

Max pooling is an operation of non-linear down-sampling. This means that the output image of this layer is usually smaller than the input. This helps to reduce parameters for next convolutional layer, providing faster training. This layer is defined by two hyperparameters:

- **Filter size** determines the dimensions. In case of the filter reaching out of the array, only valid values are taken into consideration.
- **Stride** determines how many columns will the filter move.

The higher these hyperparameters' values are the smaller will the output be.
This layer iterates over input field and looks at subfield with size of filter size. In this subfield it finds the largest number and writes only the largest number into the output field. After this, the filter moves by stride columns left until all columns were checked. In that case the filter moves back to first column of the input field and then moves down by the stride (refer to 1.1 as an example).
This process is repeated until whole input field is iterated.

## 1.4 Used software

**Keras [Chollet et al., 2015]**

Keras is an open-source neural network library written in Python. Thanks to its user-friendly interface and modular design is Keras one of the leading frameworks in neural network development. Its simple yet flexible architecture allows for easy prototyping and experimentation, making it an ideal choice for both beginners and experienced practitioners in the field of deep learning.

**OpenCV [Bradski, 2000]**

Open Source Computer Vision Library (OpenCV for short) is a comprehensive open-source library originally developed by Intel. It is mainly used for various tasks in fields such as computer vision or machine learning. In the time of writing this thesis, OpenCV provides over 2500 optimized algorithms. These are able to effectively perform many tasks such as face detection, object tracking, image preprocessing and many more. Providing interfaces in multiple programming languages such as Python, C++, Java and MATLAB it is very popular with community as well as recognisable and famous companies.

# Chapter 2

# Related Work

The need of knowing human measurements is always present. The methods used for obtaining have been developing and nowadays are competing with traditional measurement methods in precision. The progress has been developing also thanks to new ways of obtaining data used for these estimations. First, only numerical values were available to researchers. Available measurements were used for statistical models which were used to roughly estimate average measurements.

## 2.1 Pose estimation

## 2.2 Neural Anthropometer

An important article is the [Tejeda and Mayer, 2021] which proposes a method to tackle this task. Its Neural Anthropometer provides a valuable approach which will we use as backbone our convolutional neural network architecture. We do not need everything used in this article as we already have annotated synthetic dataset provided by [Skorvankova et al., 2021]. To keep the network as small as possible due to resource consumption and training difficulty increase with size. The proposed architecture starts with a binary image silhouette input. This is then processed by a convolutional layer. Number of channels was based on number of values on output. The output tensor is then passed through ReLU [Nair and Hinton, 2010] along with batch optimization. Subsequently, a max pooling layer is used followed by a convolutional layer. The output is then once again processed by max pooling layer with configuration same as before. The result is then flattened to a tensor which is passed to a fully connected layer and a ReLU. As the last layer a regressor is used to provide the measurements estimation.

This approach is further implemented by [Skorvankova et al., 2021]. The article delves into different data representations of human bodies and influence this

# Chapter 3

# Proposed solution

## 3.1 Problem specification

The goal of this thesis is to expand on body measurements estimation with the use of neural networks. Mainly to explore different data augmentation methods to provide better results when training is done on synthetic dataset.

## 3.2 Obstacles

One of the issues when working with human body measurements is the lack of real world data. The process of measuring is time-consuming and requires privacy measures to take place to protect subjects' personal information. This can be avoided by using synthetic datasets.
Moreover the time complexity to train a neural network can be reduced by using powerful device which is not available.

In this section, we'll explore the datasets utilized within this thesis. Our focus will be on 2D front-facing and profile human binary silhouettes. This form was chosen upon the data provided by the BodyM dataset. The subjects are positioned in an a-pose, ensuring greater consistency in the samples.

## 3.3 Datasets

### 3.3.1 SURREACT

#### Description

SURREACT [Varol et al., 2021] is a synthetic dataset built on SMPL model. The main goal of the work was to explore benefits of using synthetic data for human action recognition. The study aimed to answer whether the synthetic data could potentially improve accuracy of already existing methods. This theory was confirmed and even shown improvements over other state-of-the-art action recognition methods. This is however not as important for this thesis as we are not going to use the features that were added.

The dataset introduced by [Skorvankova et al., 2021] is an extension of the SURREACT dataset, incorporating the data generation techniques and a custom annotation method. This thesis utilizes a modified version of this dataset. The original dataset comprises 50,000 human scans, meshes, annotations, and other data of subjects in the T-Pose. In contrast, our customized version offers 79,999 frontal and 79,999 lateral images with annotations, featuring subjects in the A-Pose. They are saved in RGBA format with dimensions of 320x240 without background thus eliminating the need of segmentation. Measurements are saved in .npy file format requiring us to use NumPy [Harris et al., 2020] to read these values.

### 3.3.2 BodyM

#### Description

This public body measurement dataset [Ruiz et al., 2022] contains measurement and image data from real human subjects. The subjects were photographed in a well-lit indoor setup, resulting in the data being less prone to segmentation inaccuracies. Subjects also wore tight-fitting clothing to better reflect the measurements. After the pictures were taken, the subjects were scanned using Treedy photogrammetric scanner and fitted to the SMPL mesh. Measurements were then taken on said meshes. It also promises a wide ethnicity distribution

Table 3.1: Definition of annotated anthropometric body measurements. Note that the 3D model is expected to capture the human body in the default T-pose, with Y-axis representing the vertical axis, and Z-axis pointing towards the camera.

| Body measurement | Definition |
|---|---|
| Head circumference | circumference taken on the Y-axis at the level in the middle between the head skeleton joint and the top of the head (the intersection plane is slightly rotated along X-axis to match the natural head posture) |
| Neck circumference | circumference taken at the Y-axis level in 1/3 distance between the neck joint and the head joint (the intersection plane is slightly rotated along X-axis to match the natural posture) |
| Shoulder-to-shoulder | distance between left and right shoulder skeleton joint |
| Arm span | distance between the left and right fingertip in T-pose (the X-axis range of the model) |
| Shoulder-to-wrist | distance between the shoulder and the wrist joint (sleeve length) |
| Torso length | distance between the neck and the pelvis joint |
| Bicep circumference | circumference taken using an intersection plane which normal is perpendicular to X-axis, at the X coordinate in the middle between the shoulder and the elbow joint |
| Wrist circumference | circumference taken using an intersection plane which normal is perpendicular to X-axis, at the X coordinate of the wrist joint |
| Chest circumference | circumference taken at the Y-axis level of the maximal intersection of a model and the mesh signature within the chest region, constrained by axilla and the chest (upper spine) joint |
| Waist circumference | circumference taken at the Y-axis level of the minimal intersection of a model and the mesh signature within the waist region – around the natural waist line (mid-spine joint); the region is scaled relative to the model stature |
| Pelvis circumference | circumference taken at the Y-axis level of the maximal intersection of a model and the mesh signature within the pelvis region, constrained by the pelvis joint and hip joint |
| Leg length | distance between the pelvis and ankle joint |
| Inner leg length | distance between the crotch and the ankle joint (crotch height); while the Y coordinate being incremented, the crotch is detected in the first iteration after having a single intersection with the mesh signature, instead of two distinct intersections (the first intersection above legs) |
| Thigh circumference | circumference taken at the Y-axis level in the middle between the hip and the knee joint |
| Knee circumference | circumference taken at the Y coordinate of the knee joint |
| Calf length | distance between the knee joint and the ankle joint |

#### Measurements

Information provided by BodyM dataset paper are following:

| Body measurement |
|---|
| Ankle girth |
| Arm-length |
| Bicep girth |
| Calf girth |
| Chest girth |
| Forearm girth |
| Head-to-heel length |
| hip girth |
| leg-length |
| shoulder-breadth |
| shoulder-to-crotch length |
| thigh girth |
| waist girth |
| wrist girth |

#### Issues

The paper has not provided us with any information regarding the measurement location. This requires us to believe that the measurements were taken in accordance to the norm.

# Chapter 4

# Development

## 4.1 Setting up network

## 4.2 Figuring out measurements

## 4.3 Optimalizations

### 4.3.1 Including BodyM in training

### 4.3.2 Adding height

### 4.3.3 Adding lateral image

### 4.3.4 Combinations

# Chapter 5

# Results

# Chapter 6

# Conclusion

# Bibliography


[Bradski, 2000] Bradski, G. (2000). The OpenCV Library. *Dr. Dobb's Journal of Software Tools*.

[Chollet et al., 2015] Chollet, F. et al. (2015). Keras. `https://github.com/keras-team/keras`.

[Gholamalinezhad and Khosravi, 2020] Gholamalinezhad, H. and Khosravi, H. (2020). Pooling methods in deep neural networks, a review.

[Haleem et al., 2022] Haleem, A., Javaid, M., Singh, R. P., Rab, S., Suman, R., Kumar, L., and Khan, I. H. (2022). Exploring the potential of 3d scanning in industry 4.0: An overview. *International Journal of Cognitive Computing in Engineering*, 3:161–171.

[Harris et al., 2020] Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., van Kerkwijk, M. H., Brett, M., Haldane, A., del Río, J. F., Wiebe, M., Peterson, P., Gérard-Marchant, P., Sheppard, K., Reddy, T., Weckesser, W., Abbasi, H., Gohlke, C., and Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, 585(7825):357–362.

[Loper et al., 2015] Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., and Black, M. J. (2015). SMPL: A skinned multi-person linear model. *ACM Trans. Graphics (Proc. SIGGRAPH Asia)*, 34(6):248:1–248:16.

[Nair and Hinton, 2010] Nair, V. and Hinton, G. E. (2010). Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th international conference on machine learning (ICML-10)*, pages 807–814.

[O'Shea and Nash, 2015] O'Shea, K. and Nash, R. (2015). An introduction to convolutional neural networks.

[Ruiz et al., 2022] Ruiz, N., Bellver, M., Bolkart, T., Arora, A., Lin, M. C., Romero, J., and Bala, R. (2022). Human body measurement estimation with adversarial augmentation.

[Skorvankova et al., 2021] Skorvankova, D., Riečický, A., and Madaras, M. (2021). Automatic estimation of anthropometric human body measurements.

[Tejeda and Mayer, 2021] Tejeda, Y. G. and Mayer, H. A. (2021). A neural anthropometer learning from body dimensions computed on human 3d meshes. *2021 IEEE Symposium Series on Computational Intelligence (SSCI)*, pages 1–8.

[Terven et al., 2023] Terven, J., Cordova-Esparza, D. M., Ramirez-Pedraza, A., and Chavez-Urbiola, E. A. (2023). Loss functions and metrics in deep learning.

[Varol et al., 2021] Varol, G., Laptev, I., Schmid, C., and Zisserman, A. (2021). Synthetic humans for action recognition from unseen viewpoints. In *IJCV*.

[Xu et al., 2021] Xu, T., An, D., Jia, Y., and Yue, Y. (2021). A review: Point cloud-based 3d human joints estimation. *Sensors*, 21(5).