Bachelor's Thesis

Body Measurement Using a 2D camera for Home Fitness

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Body Measurement Using a 2D Camera for Home Fitness

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Extended Abstract

Body Measurement Using a 2D Camera for Home Fitness

1. Problem Statement

In recent years, the home fitness industry has experienced rapid growth, driven by the increasing demand for accessible and efficient fitness solutions. As this market expands, the need for supplementary devices and systems, such as body measurement tools, has grown significantly. These systems are essential for providing personalized feedback and tracking fitness progress. However, most currently available body measurement solutions rely on 3D scanning technology, which, while effective, is often prohibitively expensive and complex. This poses a significant barrier for individuals seeking to incorporate such technologies into their personal fitness routines at home.

2. Goal of the project

The purpose of this project is to develop an affordable and user-friendly human body measurement system that utilizes 2D camera technology. By leveraging the simplicity and accessibility of 2D imaging, this research aims to overcome the cost and usability challenges associated with existing 3D-based systems. The proposed solution seeks to enable individuals to accurately measure their body dimensions in a convenient manner, supporting their fitness goals without the need for costly equipment or specialized technical expertise.

There are three primary objectives of this research. First, it aims to design a cost-effective solution that eliminates the financial barriers associated with 3D measurement technology, making it suitable for personal and home use. Second, the system will prioritize accessibility, leveraging a standard 2D camera and requiring minimal technical knowledge for operation. Third, the project focuses on delivering accurate and reliable body measurements through the development of advanced algorithms tailored to 2D imaging. Ultimately, this research seeks to produce a functional prototype of the proposed system, demonstrating its feasibility and potential to enhance the home fitness experience.

3. Proposed System

For the 2D body measurement method, this research utilizes the CNN architecture known as "Conv_BoDiEs" (Škorvánková et al., 2021). This architecture was chosen based on a comprehensive review of various body measurement methods (Bartol et al., 2021). Conv_BoDiEs takes a 2D front-facing image as input and outputs 16 anthropometric body measurements, including waist, hip, and arm circumferences.

The model was trained using two datasets. First, SMPL (Skinned Multi-Person Linear model) data (Loper et al., 2015) was used, consisting of 50,000 front-facing T-pose images generated to simulate realistic human body shapes(male and female dataset separately). Of these, 40,000 images were used for training and 10,000 for evaluation. In addition, the same architecture was trained on the BodyM dataset, which includes real images of individuals captured from the front and side views. However, BodyM consists of only around 2,000 samples, which led to significantly larger errors compared to the model trained on the synthetic SMPL dataset. Due to the limited size of the BodyM dataset and its inferior performance, the SMPL-trained model was ultimately selected for this project.

The evaluation of the model using the 10,000 test samples yielded excellent performance, achieving a Mean Absolute Error (MAE) of 5.5 mm. This demonstrates the effectiveness of the model when applied to synthetic data generated using the SMPL dataset.

For the hardware, this research reverse-engineered a product developed by Naked Labs to create a smart mirror system. The prototype integrates a 2D camera mounted alongside the mirror, which captures front-facing images of the user. The body measurement results are then visualized on a 7-inch LCD display mounted on the back of the mirror. This design offers an intuitive interface, allowing users to see their measurements directly on the mirror's integrated display.

4. Result

For real-world experiments, the setup included the smart mirror system developed in this project. A person stood in front of the mirror, with a chroma key background used to enhance human segmentation. Under these experimental conditions, the MAE rated to 2.3cm, which is significantly larger compared to the test data results. However, when analyzing the six body measurements of greatest interest to users, such as waist and hip circumferences, the MAE remained less than 2cm, and the relative error was within 3%. These results are deemed acceptable given the purpose of this project, which is not intended for highly precise medical applications but rather for general fitness and home use. MAE of 2.3cm is still considered a substantial error, and further improvements are necessary to enhance accuracy.

Contents

I. Introduction

1.1. Problem Statement

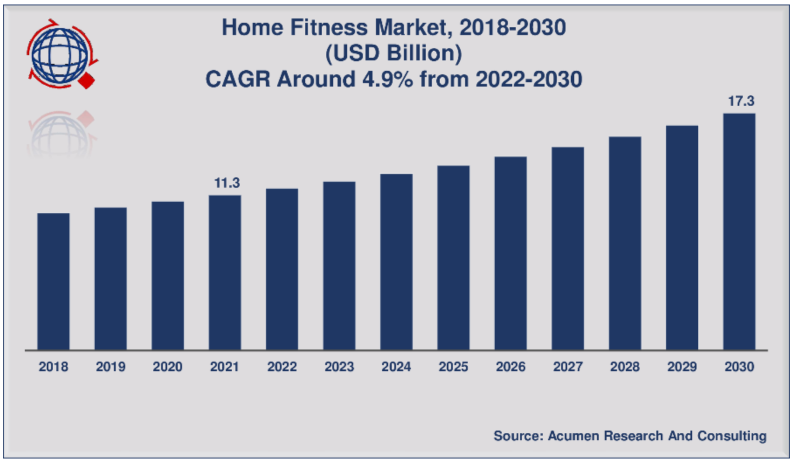

Fig 1 Global Market Size of Home Fitness

The global home fitness market has experienced substantial growth over recent years, driven by the increasing adoption of wearable devices and the lifestyle changes by the COVID-19 pandemic. These trends have sparked significant interest in fitness solutions that can be easily implemented at home. As shown in Figure 1, the home fitness market was valued at approximately \$11.3 billion in 2021 and is projected to grow steadily, reaching \$17.3 billion by 2030 with a compound annual growth rate (CAGR) of around 4.9%. This upward trend highlights the growing consumer demand for accessible, cost-effective, and efficient fitness tools.

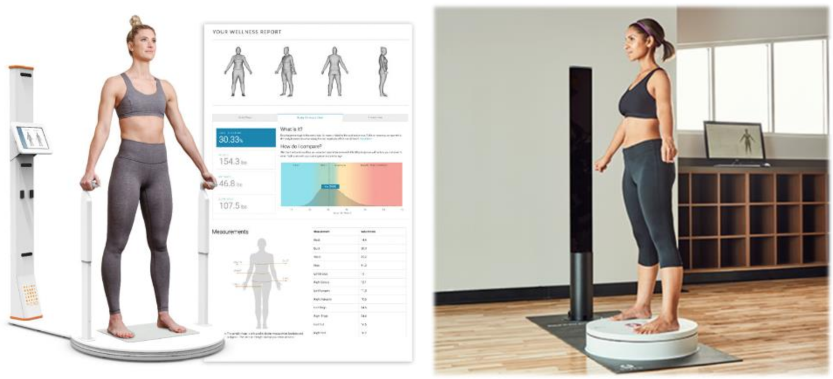

Fig 2 Existing Solutions: Left–Fit3D/Right-Styku

To meet this demand, technological advancements have enabled the development of body measurement systems, which are increasingly integrated into fitness routines to provide personalized feedback and progress tracking. However, most existing solutions like “Fit3D” or “Styku” rely on 3D cameras and advanced hardware, which are prohibitively expensive for individual home use. These barriers make such systems inaccessible for the average consumer seeking simple, affordable home fitness devices.

This project presents a device with 2D camera technology to address the challenges in home fitness applications. By replacing costly 3D systems with a more affordable 2D camera-based solution, the device ensures accurate body measurements tailored for home use. This innovation meets the demands of the expanding home fitness market by providing a cost-effective and efficient tool for tracking essential body metrics.

1.2. Goal

Fig 3 Aimed Feature of the System

The primary goal of this project is to propose a 2D camera-based body measurement system for home fitness similar with the figure 3. Regarding these conditions, four goals are stated: affordability, accuracy, user accessibility, and prototype development.

The first goal is to ensure affordability by utilizing 2D camera technology, which significantly reduces costs compared to 3D measurement systems, making it suitable for personal use. The second goal is to maintain accuracy by providing reliable and precise body measurements, focusing on key metrics such as waist, hip, and arm circumferences with minimal error rates. The third goal is to prioritize user accessibility by designing an intuitive and easy-to-use system that requires minimal technical knowledge or setup, ensuring that it can be seamlessly integrated into home fitness routines. Lastly, the fourth goal is to develop a functional prototype to validate the feasibility of the system, demonstrating its practicality and effectiveness in real-world applications.

II. Proposed System

2.1. Process

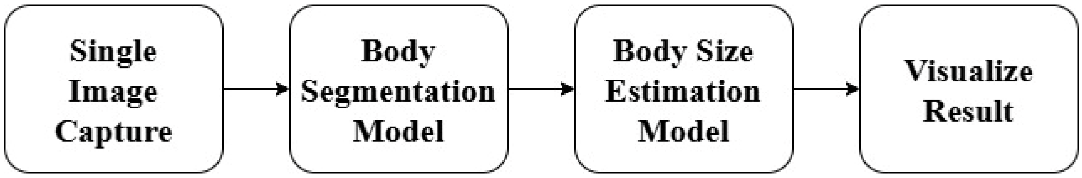

Fig 4 Overview of Proposed System

The overall process of the proposed system involves capturing a single image of the user, performing body segmentation to isolate the relevant features, estimating the body measurements based on the segmented image, and finally visualizing the results for body sizes and human features through a user-friendly graphical user interface (GUI) framework.

2.1.1. Single Image Capture

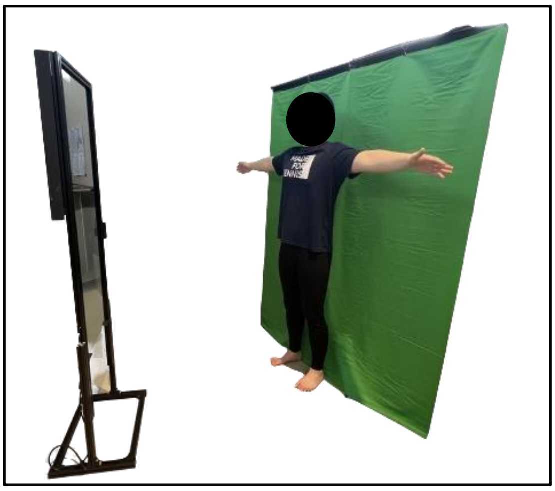

Fig 5 Capturing Single Image

The single image capture involves taking a front-facing T-pose photograph of the user. During this process, a chroma key background is placed behind the user to enhance the accuracy and performance of the subsequent body segmentation step. Additionally, the system is designed to allow users to preview the capturing image in real-time through the LCD screen integrated into the smart mirror, ensuring proper positioning and alignment before the image is processed.

2.1.2. Body Segmentation Model

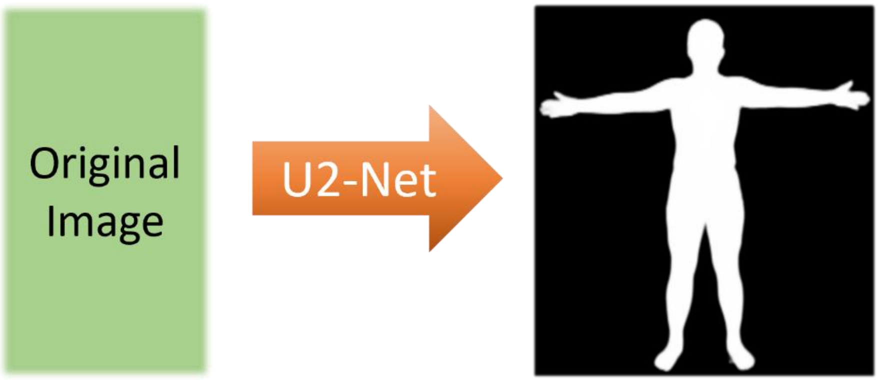

Fig 6 U2-Net Background Removal

For the body segmentation, the initial approach was to use traditional image processing techniques. However, achieving precise segmentation in areas outside the chroma key background proved to be challenging. To address this issue, a pretrained model, U2-Net, was utilized for background removal. This model demonstrated effective segmentation performance, even in parts not included in the chroma key, making it a robust solution for the task. Specific model for human segmentation is used for the process.

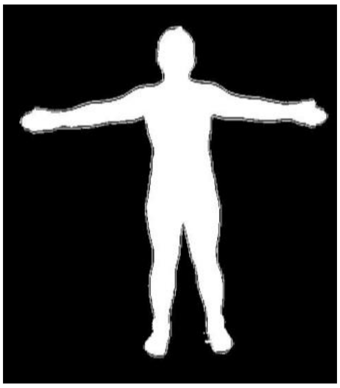

Fig 7 rembg Background Removal

Initially, the Python library "rembg" was tested for background removal. However, when the removed background was replaced with a black background using OpenCV, significant distortions were introduced, making the resulting images unsuitable for further processing. As shown in Figure 7, boundary lines were generated, which could lead to considerable errors. Switching to U2-Net effectively resolved these issues, delivering reliable and clean segmentation results.

2.1.3. Body Size Estimation Model

When exploring methods to estimate body sizes from a 2D image, several alternatives were considered before selecting a CNN-based AI model. One such method was key point extraction, which involves identifying specific anatomical landmarks on the body to calculate measurements. However, Bartol's review of body measurement methods (Bartol et al., 2021) highlighted that AI model-based estimation was the most effective approach for 2D body measurement systems. Based on this insight, the AI model approach was chosen for further evaluation.

Model

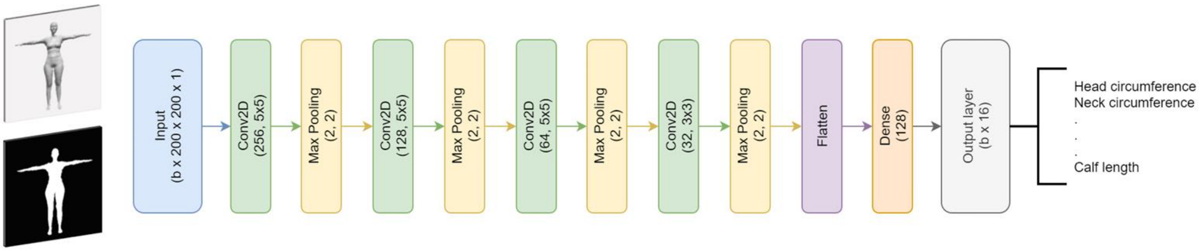

Fig 8 Architecture of Conv_BoDiEs model

Several AI models were reviewed for 2D image-based body measurement systems. Among the reviewed theses, the model "Conv_BoDiEs" (Škorvánková et al., 2021) stood out for its detailed and practical architecture, making it the most suitable choice for this project.

Figure 8 shows the architecture of the "Conv_BoDiEs". The architecture consists of four convolutional layers, each followed by max pooling, and a fully connected layer. The model takes a single image of the body as input and outputs 16 body size measurements, including waist, pelvis, and bicep circumferences.

Dataset

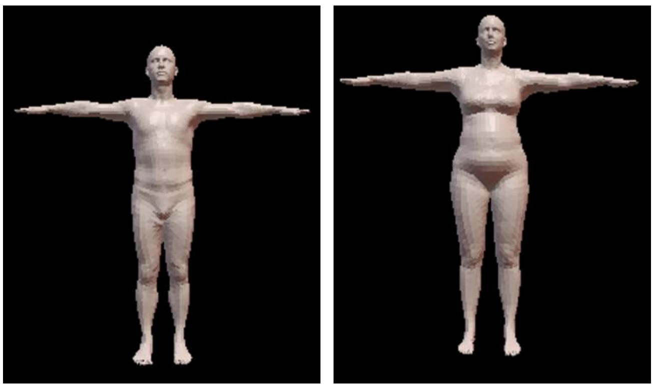

Fig 9 Training Dataset: SMPL in T pose

Acquiring real human body images along with their corresponding body size measurements is inherently challenging due to privacy concerns, limited availability, and data collection complexities. To address this limitation, this project utilized a synthetic dataset generated using SMPL (Skinned Multi-Person Linear Model), available through Skeletex (Skeletex, 2023) shown in figure 9.

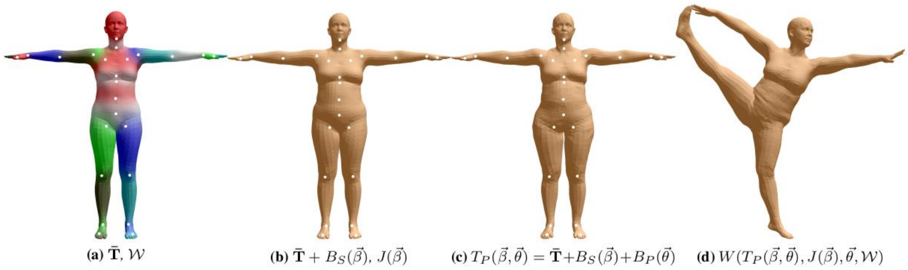

Fig 10 SMPL(Skinned Multi-Person Linear Model)

For a brief understanding of SMPL, it is a parametric 3D human body model widely used in computer vision and graphics. Like shown in figure 10, SMPL represents the human body as a deformable mesh controlled by shape parameters for body proportions and pose parameters for joint rotations, allowing the generation of realistic and versatile human shapes and movements.

For this project, a dataset of 50,000 front-facing T-pose images was obtained from SMPL-generated synthetic data. Each image was paired with its corresponding body measurements, which were systematically generated based on the measurements of the model.

To ensure that the dataset represents a diverse spectrum of human sizes, key features were extracted and analyzed to assess its reliability and coverage.

Table 1 SMPL Dataset Analysis: Mean, Standard Deviation, and Variance

Body part	Mean [mm]	SD [mm]	Variance [mm]
chest circ.	101.45	8.78	77.20
waist circ.	93.55	11.58	134.31
pelvis circ.	104.09	7.04	49.56
neck circ.	40.28	2.74	7.50
bicep circ.	30.59	3.47	12.09
thigh circ.	52.70	4.34	18.87
knee circ.	38.76	2.48	6.15
arm length	53.05	2.70	7.29
leg length	80.49	4.48	20.12
calf length	42.18	2.54	6.48
head circ.	58.64	2.31	5.36
wrist circ.	17.47	1.12	1.27
arm span	183.72	7.88	62.22
shoulders width	39.07	2.12	4.52
torso length	52.98	2.81	7.90
inner leg	74.85	4.61	21.29

As shown in the table 1, the dataset demonstrates appropriate standard deviation and variance values, indicating a wide distribution of features. The large spread standard deviation suggest that the dataset is diverse and comprehensive, making it suitable for use as training data.

Model Train

Table 2 Conv_BoDiEs Training Hyperparameters

Model	Conv_BoDiEs
Input	Single Front image Resolution: 200x200x1
Output	Size of 16 body parts
Data	50,000 SMPL model
Learning rate	4×10^{-4}
Loss function	L1loss ($L_1 = \sum_{i=1}^{n} \lvert y_i - f(x_i) \rvert$)
Activation function	Relu
Epoch	100 (early stop-10)

The hyperparameters used in this project are detailed in Table 2. Training was conducted using an NVIDIA A100 GPU. Two separate models were trained, one for males and one for females are trained.

Model Evaluation

Table 3 Test Dataset Evaluation

Body part	Test Data Error[mm]
chest circ.	9.3
waist circ.	8.8
pelvis circ.	9.2
neck circ.	5.8
bicep circ.	4.6
thigh circ.	8.4
leg length	3.7
head circ.	4.1
wrist circ.	3.0
shoulders width	3.1
⋮	⋮
MAE(total)	**5.53[mm]**

The test results were impressive, with a MAE of only 5.53mm. This outcome strongly suggests that the model architecture is effective and well-suited for potential application in real-life scenarios.

2.1.4. Visualization

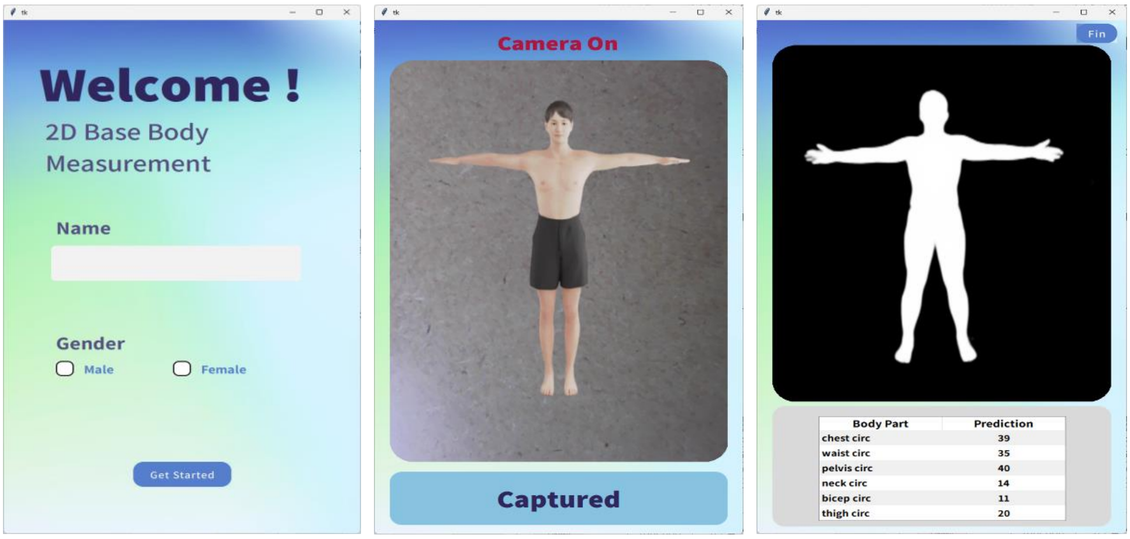

Fig 11 User GUI: Sequence of Left to Right

The primary role of the interface is to provide users with a convenient and intuitive experience. First, it prompts the user to select the appropriate model—male or female—based on their gender. Next, the interface provides instructions for the required pose and displays the real-time feed from the camera, allowing the user to see themselves live on the screen. A 5-second countdown is displayed to help the user prepare for the capture. After capturing the image, the system processes it through the segmentation and body estimation models. Finally, it displays the user's segmented image along with the calculated body measurement table below. The GUI framework "Tkinter" was used to develop the user interface for the system.

2.2. Hardware

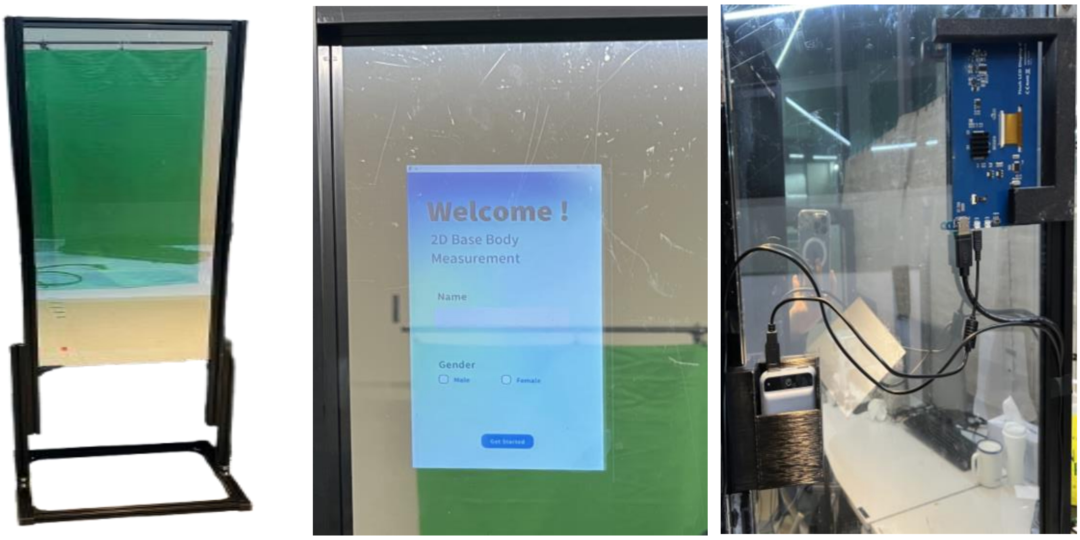

Fig 12 Hardware: 1. Overall Appearance 2. LCD Panel 3. Display Connections (left to right)

The design of the hardware was inspired by Naked Labs' 3D scanner, as shown in Figure 3. The hardware was created in the form of a full-length mirror, with an LCD panel integrated behind the mirror to display the GUI. The camera is positioned in the center-left section of the mirror for optimal image capture.

Table 4 Hardware Specifications

Hardware Specifications	
Smart Mirror	Size: 175x54x48[cm]
LCD Panel	Screen Size: 7 inch Resolution: 600x1024
Camera	Resolution: 1090P
Battery	Capacity: 10000mAh
Glass	Size: 120x40x5[mm]

III. Result

3.1. Experiment

The experiment was conducted with 10 male participants of varying body shapes and sizes. The measurements were taken while the participants wore spandex underwear and naked top to standardize the conditions. The inclusion of female participants presented challenges for privacy issues.

3.1.1 Experiment Setting

The experiment was conducted in a $3m^2$ space. The most critical aspect of the setup was determining the optimal distance between the subject and the camera. This was essential because a 2D image lacks depth values, and this variable significantly influenced the measurement accuracy in real-world scenarios.

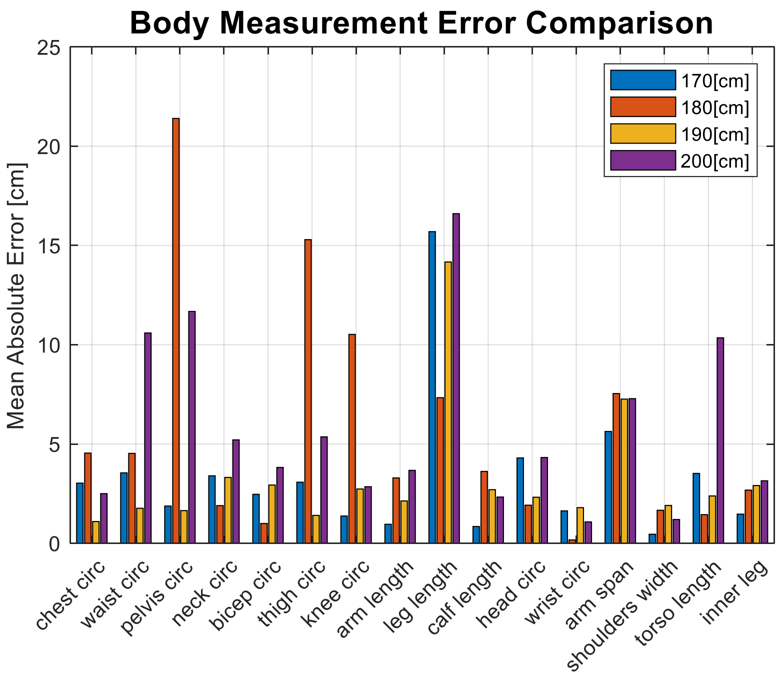

Fig 13 Body Part Errors by Distance

Table 5 Average Error by Distance

Distance [cm]	Average Error [cm]
170	3.3
180	5.5
190	3.2
200	5.7

Figure 15 and Table 4 present the errors calculated by different distance. While the average errors for distances of 170cm and 190cm appear similar, significant differences emerge for key body measurements, such as waist, chest, and pelvis circumferences. At 190cm, the error remains below 2cm for these critical measurements, whereas at 170cm, the error exceeds 2cm. This suggests that 190cm is the optimal distance for real-life implementation.

3.1.2 Result & Analysis

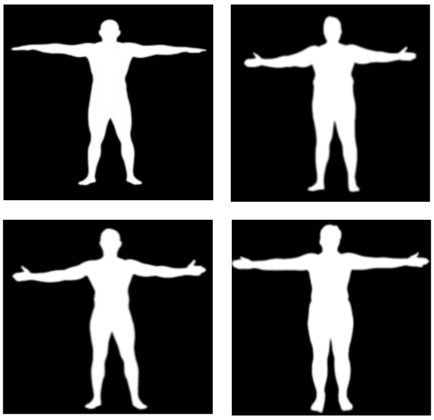

Fig 14 Sample of Test Participants

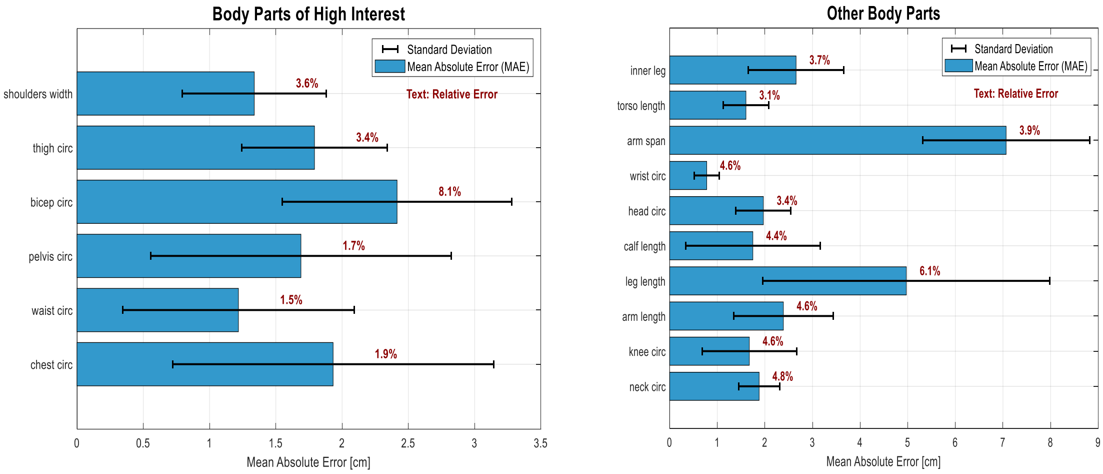

Fig 15 Result of the Experiment (Left: Body Parts of High Interest, Right: Other Parts)

Figure 16 shows some of the segmented image of the participants. As stated different body shapes and sizes of participants participated the experiment. The results demonstrate a similar trend in the analysis of distance errors, with an overall MAE of 2.3 cm. However, for the body parts of high interest (except for the biceps), the error is less than 2 cm. Notably, the errors for shoulder width and chest circumference are particularly low, remaining under 1.5 cm.

The primary reason for the higher error observed in the actual experiment compared to the test dataset evaluation lies in the differences in input data. During training and evaluation, SMPL data, consisting of synthetic 3D human models, provided controlled and idealized input with consistent scale, accurate poses, and clean geometry. In contrast, the experiment used real participant data, which introduced challenges such as variations in scale, pose inaccuracies, body shape irregularities, and noise or artifacts from imaging. Real participants might not have perfectly replicated the standardized poses used during training, and surface artifacts caused by clothing or minor movements further contributed to the discrepancies.

IV. Conclusion

This project proposed and developed a 2D camera-based body measurement system as a cost-effective and accessible alternative to existing 3D measurement technologies for home fitness applications. By combining a CNN-based body size estimation model trained on synthetic SMPL datasets with a U2-Net segmentation approach, the system successfully demonstrated its potential to provide body measurements. Experiments with real participants showed an overall MAE of 2.3 cm, with key metrics such as chest and shoulder width achieving errors below 1.5 cm, validating the system's effectiveness in real-world scenarios.

However, the project identified several challenges, particularly in adapting models trained on synthetic data to real-world conditions. Issues such as variations in scale, pose inaccuracies, and input quality highlighted areas for further refinement, including preprocessing techniques, data collection, and model generalization.

Future improvements to this system could include utilizing model such as smplify to visualize the measurements in 3D, providing users with a more comprehensive and interactive representation of their body metrics. Additionally, refining the hardware design to improve accuracy and usability would enhance the system's practical application. Finally, further optimization of the estimation model and training process, such as using larger and more diverse datasets could significantly improve measurement accuracy.

In summary, this project demonstrates the feasibility of a 2D-based body measurement system tailored for home fitness, offering a strong foundation for future developments in affordable and user-friendly fitness technologies.

Reference

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Appendix

Acknowledgment

I would like to express my deepest gratitude to Prof. Young-Keun Kim for his invaluable guidance and unwavering support throughout this project. His mentorship and advice have been instrumental in ensuring the smooth progress and successful completion of this project.

Project Software Environment

- CUDA 11.8
- Pytorch 2.1.2
- Python 3.8.20
- OpenCV-python 4.10.0.84

Further Information of Software

Link for GitHub: Body Measurement Project

SMPL Dataset: Dataset