A Rule-Based Framework for Clothing Fit Recommendation from 3D Body Reconstruction

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***Abstract*—This research presents a comprehensive framework for body size estimation that accurately derives anthropometric measurements—specifically, the circumferences of the waist and hips—from a singular image by utilizing OpenPose for joint localization and SMPLify-X for precise 3D body modeling. The proposed methodology involves projecting the generated three-dimensional model onto a horizontal plane and applying a convex hull geometric assessment to extract relevant body measurements. These derived measurements are then classified into standardized clothing size predictions (XS–XL) via a transparent rule-based classification system suitable for e-commerce sizing and virtual fitting applications. Empirical validation conducted on the Agora dataset substantiated the framework's reliability across diverse body types, demonstrating strong consistency with industry sizing standards. The method is non-intrusive and interpretable, effectively addressing practical challenges in automated human pose estimation for retail contexts. Limitations include constraints related to body posture and potential clothing interference; however, the modular design enables enhancements such as integrating chest circumference measurements and mobile deployment. This scholarly contribution thus provides a robust, accessible solution for automated, image-based clothing size recommendations.**

Keywords*—Body size estimation; SMPLify-X; OpenPose; 3D body modeling; clothing size prediction; e-commerce sizing; human pose estimation

I. Introduction

In the current digital epoch, marked by the extensive proliferation of e-commerce, the necessity for accurate and sophisticated techniques to derive human body dimensions from images has markedly escalated—especially in the ready-to-wear fashion industry, augmented reality applications, and virtual fitting features within online retail contexts. A predominant obstacle encountered by online merchants pertains to size-related product returns. Research indicates that as much as 30% of returned apparel arises from discrepancies in sizing or erroneous estimations at the time of purchase [1]. This predicament not only incurs financial and logistical detriments for enterprises but also adversely affects user experience, diminishes customer satisfaction, and erodes trust in virtual retail platforms.

In response, progressive computer vision and 3D modeling technologies have surfaced as promising instruments for addressing this quandary. These technologies facilitate the extraction of body shape, dimensions, and measurements from a solitary 2D image—a process increasingly bolstered by powerful machine learning frameworks. OpenPose, for example, proficiently extracts human joint keypoints under diverse real-world imaging scenarios, including suboptimal lighting or cluttered backgrounds [2], [3].

The identified joints can subsequently be aligned with 3D parametric models such as SMPL and SMPL-X through algorithms like SMPLify-X, which captures intricate body characteristics including hands and facial expressions [4], [5]. Models such as DensePose2SMPL and ExPose have also demonstrated high precision in fitting under various conditions, encompassing loose garments and complex poses [6], [7].

Recent research corroborates that SMPL and SMPL-X surpass conventional measurement techniques by substantially minimizing errors in body circumference estimation, particularly when side-view or fitted clothing data is accessible [8]. Furthermore, models like LayerNet and SMPLicit provide garment-aware reconstructions with semantic garment-layer processing, advancing the frontiers of practical virtual try-on functionalities [9], [10].

Nonetheless, numerous existing frameworks still encounter limitations when faced with non-standard postures, oversized attire, or occluded limbs [11], [12].

To confront these challenges, this study proposes a comprehensive, fully automated pipeline for body size estimation from a single RGB image. The methodology commences with joint detection via OpenPose, followed by 3D body modeling utilizing SMPLify-X, digital measurement calculation, and conclusive size classification employing rule-based logic. The pipeline is crafted for resilience in varied real-world scenarios and can be seamlessly integrated into virtual fitting and e-commerce platforms [13], [14].

For validation, this research employs the Agora dataset [15], which encompasses multi-pose images alongside corresponding 3D data files (obj, pkl, and openpose.json). This extensive dataset facilitates a systematic assessment of each component within the pipeline—from image acquisition to 3D modeling and final garment size categorization.

The remainder of this study is organized as follows: Section II reviews related literature. Section III details the proposed methodology. Section IV presents experimental results. Section V discusses findings and limitations, and Section VI concludes the work.

II. Literature Review

The domain of automatic estimation of human body dimensions has experienced significant advancements in recent years, primarily driven by the exponential rise of e-commerce, virtual fashion, and the increasing need for intelligent digital interfaces that accurately replicate physical human characteristics. A major component of this evolution lies in computer vision methodologies, particularly the synergistic use of OpenPose [16], SMPL [17], and its advanced variants such as SMPLify-X [5], which have enabled the precise extraction and modeling of body metrics from single RGB images.

A notable contribution in this space includes the work of Kuribaya [2], who developed a virtual try-on system capable of dynamically adapting garment sizes to match real-world anthropometrics extracted from joint keypoints. Although the model was lauded for its interactive fit visualization, it primarily prioritized graphical realism over the quantitative accuracy of body dimensions. A similar limitation was observed in the work of Yang et al [18], who proposed a GAN-based virtual try-on model that successfully preserved garment texture and pose alignment but exhibited noticeable fitting errors for users with non-standard body shapes, particularly in waist and hip regions—highlighting the trade-off between aesthetic rendering and dimensional fidelity.

Meanwhile, more metric-focused efforts have emerged. In a large-scale study by [1], a decision tree classifier trained on joint-based features from OpenPose was employed to predict military uniform sizes across 375 subjects. Cross-validation with 3D scanning and manual tape measurements demonstrated over 85% agreement, validating the approach for structured, high-stakes domains. Nonetheless, the scalability of such models to unconstrained consumer environments remains uncertain.

To address modeling accuracy for atypical body shapes, the DensePose2SMPL framework [6] introduced dense correspondence mapping from images to SMPL-based mesh representations. Their method reduced perimeter estimation error by 30% in outlier body cases, underscoring the advantages of combining surface-based mappings with statistical shape modeling.

Another critical advancement came from the DeepProfile model [19], which leveraged deep convolutional networks to predict occluded body shapes beneath garments. Their approach demonstrated superior performance under challenging visual conditions—such as loose clothing—when benchmarked against traditional silhouette-extraction methods [20]. However, its dependency on extensive labeled datasets could pose limitations in diverse real-world applications.

The generative model SMPLicit [10] advanced the state of body-clothing co-representation by embedding garment topology directly into the SMPL parameter space. This enabled realistic simulation of both tight and open garments, making it particularly suited for virtual try-on platforms and AI-driven fashion editors. Nevertheless, the model lacked direct mechanisms for deriving standardized measurements (e.g., waist, chest, hip) used in real-world size classification.

Exploring the democratization of body estimation, Sheth [21] introduced a selfie-based body measurement method using mobile phone images and mirror-based cues. Their system achieved <5% error across 11 anthropometric parameters. Such accessible methodologies—also explored by Jiang and Grauman (2020) in monocular pose-to-shape prediction—illustrate the potential for casual consumer-level body scanning, albeit with constraints related to environment and pose consistency.

From an industrial standpoint, [22] illustrated that three-dimensional geometric modeling generated from comprehensive bodily laser imaging substantially improved the precision of uniform fitting, particularly for female personnel in military environments. Expanding upon this foundation, contemporary developments within the apparel sector have underscored the incorporation of three-dimensional body scans alongside machine learning to facilitate mass customization. For instance, [23] presented a hybrid methodology that merges point cloud information from 3D scanners with clustering algorithms to categorize body types and refine garment patterning. Their methodology surpassed conventional sizing systems in terms of both fit satisfaction and production efficiency, indicating a transition towards volumetric and data-informed design within the realm of fashion e-commerce.

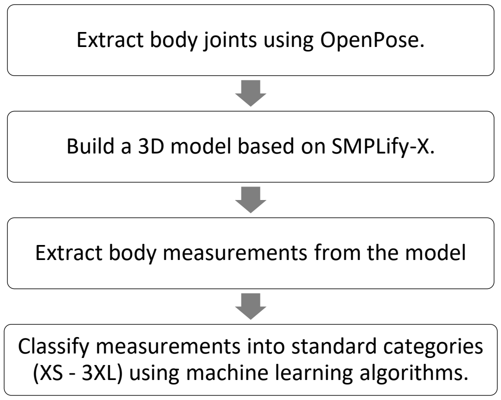
Evaluation strategies across these studies have varied—from manual anthropometry to laser scanning, structured light capture, and virtual garment draping—highlighting a lack of standardized benchmarking protocols. Efforts like the CAESAR dataset [24] and newer 3DHumanDataset initiatives [25] aim to offer such standards, though generalization to unconstrained consumer imagery remains an open research challenge.

While antecedent methodologies have achieved notable advancements in either augmenting garment authenticity, forecasting dimensions utilizing joint-based classifiers, or reconstructing intricate three-dimensional models beneath loose apparel, a limited number of techniques furnish a completely automated, interpretable, and rule-based framework that is simultaneously scalable and independent of extensive training datasets. In contrast to generative or learning-centric frameworks that may experience challenges related to opacity or overfitting, the proposed approach presents a transparent workflow anchored in anatomical reference points and geometric evaluation (e.g., convex hulls) to ascertain waist and hip circumferences. By amalgamating OpenPose and SMPLify-X with rule-based size classification, our methodology facilitates real-world applicability within e-commerce contexts—achieving elevated accuracy without the necessity for comprehensive manual annotations or costly scanning technology. This positions it uniquely for economically viable implementation across a variety of consumer settings, distinguishing it from prior models that emphasize visual fidelity or necessitate controlled acquisition environments.

While prior research has extensively explored machine learning-based frameworks, fewer studies have provided a fully rule-based approach. Our proposed methodology uniquely integrates OpenPose and SMPLify-X to deliver practical size recommendations without extensive training data, bridging an important gap between theoretical models and industry practicality.

III. METHOD

The framework aims to provide a comprehensive, systematic solution for estimating body measurements using only a single image. The framework relies on a series of organized steps:



A. *Step 1: Joint Extraction from the Image*

OpenPose is applied to detect 25 key body joints, covering the upper limbs (shoulders, elbows, wrists), lower limbs (hips, knees, ankles), torso (neck, shoulders, chest center, hips), and head region (eyes, ears, nose).

The system uses deep neural networks capable of identifying joint positions with high accuracy, even under challenging visual conditions involving poor lighting or noisy backgrounds.

The output consists of a 2D array of (x, y) coordinates for each joint, along with a confidence score per point, enabling the exclusion or correction of joints with low reliability.

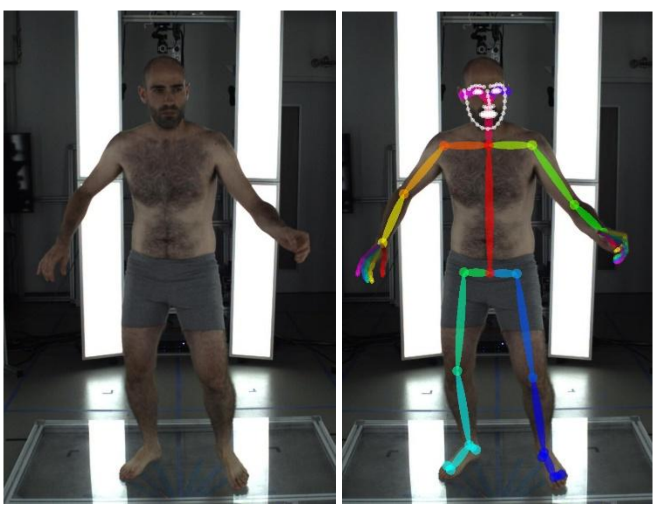


Fig. 1. Pose estimation from a single image using openpose.

B. *Step 2: 3D Body Model Generation*

The SMPLify-X algorithm is used to align a statistical 3D human model (SMPL-X) with the 2D joint keypoints extracted by OpenPose. SMPLify-X is an iterative optimization method that refines the model's shape and pose to match the detected joints.

SMPL-X is a comprehensive parametric model that accurately represents the full human body, including facial features, hand gestures, and body posture—making it ideal for virtual reality and interactive applications.

The OpenPose keypoints as shown in Fig. 1 and Fig. 2 serves as constraints for the SMPLify-X optimization, allowing it to fine-tune the model parameters (e.g., shape, pose, gender) until the 3D mesh closely fits the user's body as inferred from the image.

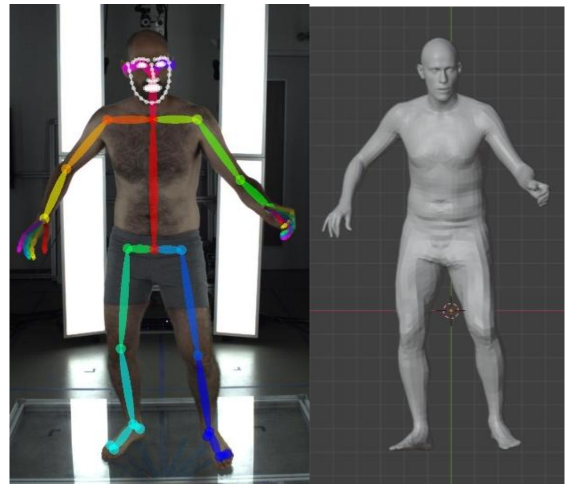


Fig. 2. From 2D pose estimation to 3D body reconstruction using SMPLIFY-X.

Upon the successful calibration of the model, two principal output files are produced:

- obj file: This file encompasses the surface mesh representation of the three-dimensional body, detailing vertex coordinates and triangular relationships. It serves a pivotal role in visualization and rendering processes.
- pkl file: This file encapsulates the internal parameters of the model, which is especially vital for this research due to its interoperability with Python-based analytical frameworks. It comprises:
  - keypoints_3d: A matrix that delineates the three-dimensional skeletal joints in the BODY_24 format, accurately aligned with the surface mesh and utilized for the identification of anatomical landmarks such as the cervical region and the hip joints.
  - Vertices (mesh): A comprehensive three-dimensional point cloud that depicts the external dermal surface of the body, constituting the geometric foundation for the computation of circumferences through projection and convex hull analysis.
  - gender: A categorical variable that denotes the biological sex of the subject (male or female). This parameter holds significant importance, given that clothing size specifications frequently vary by gender, and precise categorization is essential for appropriate alignment with the relevant standard sizing framework.

By utilizing the pkl file, the framework gains the advantage of seamless integration with Python's data management functionalities, while simultaneously accessing the requisite anatomical and mesh data critical for accurate, automated size estimation.

C. Step 3: Standard Size Classification Using Rule-Based Tables

Accurate size determination for clothing relies primarily on three anatomical measurements: waist width, hip width and chest width, as illustrated in Fig. 3.

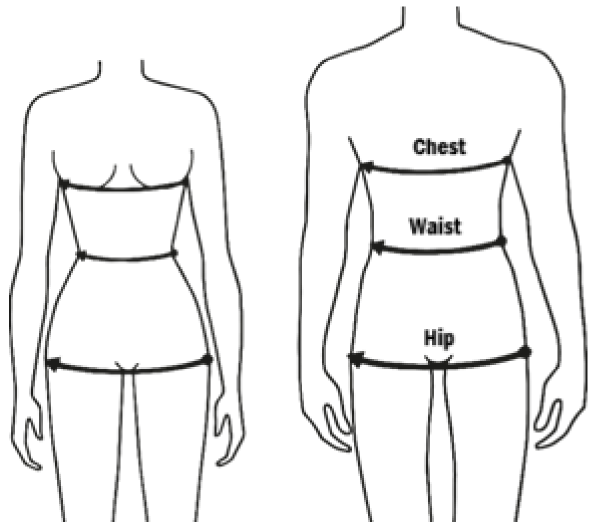


Fig. 3. The Anatomical locations of chest, waist, and hip circumferences used in garment size estimation.

- Waist width refers to the horizontal circumference of the torso at the narrowest region between the ribcage and pelvis.
- Hip width is the horizontal circumference at the widest point below the waist.
- Chest width: Measure the fullest part of your bust while wearing a bra that fits.

Rather than relying on a single point or linear measurement, the framework analyzes entire cross-sectional slices of the body to provide a more realistic representation of body shape, accounting for anatomical variations across individuals.

1) Identifying waist, hip, and chest levels. The positions of the waist and hip are inferred from skeletal joints stored in the .pkl file under the array keypoints_3d. This array contains the 3D coordinates (X, Y, Z) of 25 keypoints following the BODY25 format.

Two key points, as shown in Fig. 4, are central to this analysis:

- Mid-Hip (index 8): Represents the center of the pelvis or hip region.
- Neck (index 1): Marks the lower end of the neck and the start of the torso.

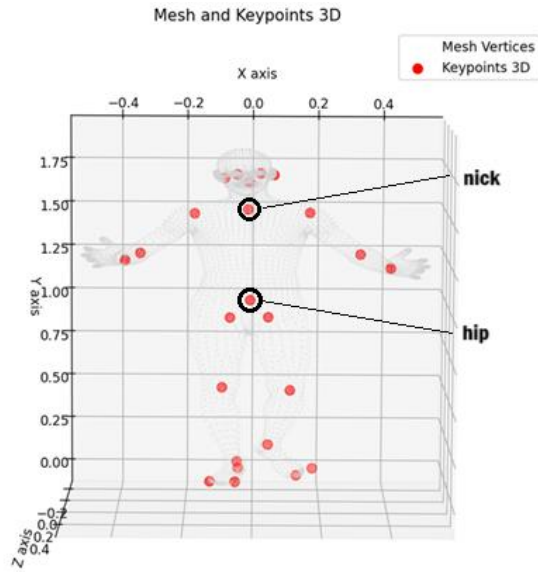


Fig. 4. Integration of 3D mesh and skeletal keypoints for anatomical reference.

The waist level is estimated by averaging the vertical (Y) coordinates of the Mid-Hip and Neck keypoints. This approach yields three critical horizontal slices:

- Hip slice: Taken at the same vertical level as the mid-hip joint (y_hip).
- Waist slice: Estimated to be roughly halfway between the neck and the hip, calculated as the average of their vertical coordinates $y\_waist \approx y\_hip + (y\_hip + y\_neck) * 0.4$.
- Chest slice: Located near the neck joint (y_neck), representing the lower section of the torso.

The parameter settings, such as the 40% ratio used to estimate waist position, were empirically chosen based on anatomical observations and real-world validation. Future work may refine these parameters for specific demographic groups."

This method allows for the extraction of more anatomically accurate cross-sections, improving measurement precision compared to single-point estimation methods.

a) Projection to the Horizontal Plane (X-Z): The three-dimensional coordinates utilized in each horizontal section are obtained from the surface mesh of the anatomical structure, specifically from the array of vertices that delineate the external geometric configuration of the model. These coordinates are projected onto the X-Z plane through the elimination of the vertical (Y) component. This two-dimensional projection facilitates a more straightforward analysis of the cross-sectional morphology of the body, rendering it appropriate for the estimation of circumference values via geometric methodologies.

The precision of this projection-centric methodology is predominantly ascribed to the incorporation of anatomically significant reference points—namely the Neck (index 1) and Mid-Hip (index 8)—whose vertical coordinates are retrieved from the array of key points. These joints function as dependable reference markers for the estimation of the positions of the chest, waist and hip sections, thereby ensuring uniform alignment across disparate body models.

b) Convex Hull Application: A Convex Hull algorithm is employed on the two-dimensional projected coordinates to generate the minimal closed polygon that encompasses all data points.The convex hull simplifies the body's outline at each cross-section, removing small irregularities while retaining overall shape.It effectively eliminates minor irregularities or localized noise within the mesh that do not significantly influence the overall shape.

The perimeter or area of the resultant convex hull, as shown in Fig. 5, is subsequently calculated and utilized as an approximate indicator of the waist or hip circumference, contingent upon the specific slice under examination.

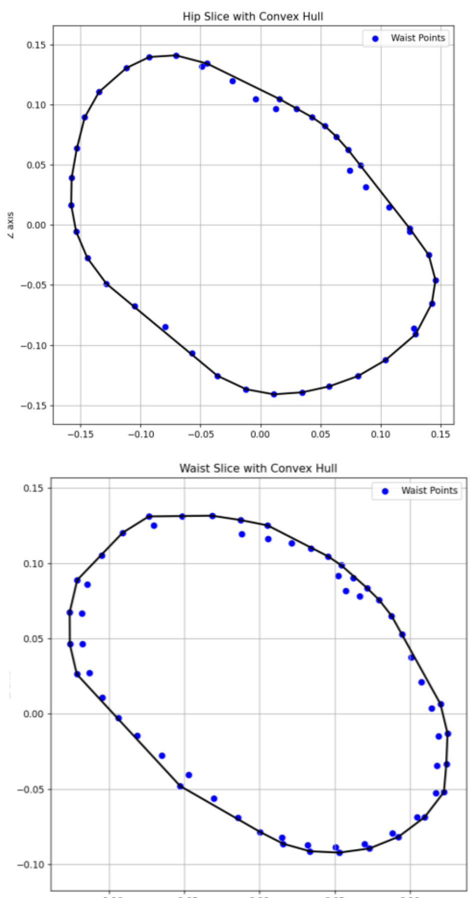


Fig. 5. Projection of waist and hip vertices onto X-Z plane.

2) Conversion to standard sizes. In the concluding phase, the extracted body measurements are compared against established standardized sizing tables (e.g., ISO or specific retailer charts) to ascertain the most suitable clothing size category, such as XS, S, M, L, XL, among others (see Table I).

This classification is executed through a rule-based methodology, wherein each measurement (e.g., chest, waist, hips) is juxtaposed with threshold ranges corresponding to each size category. The system identifies the closest matching category, optionally employing priority rules (e.g., prioritizing waist over chest for trousers). This methodology guarantees transparency, consistency, and compatibility with pre-existing sizing systems employed by manufacturers and online retailers—without necessitating the implementation of machine learning models.

There exist numerous clothing sizing frameworks utilized globally, differing according to geographical region, brand identity, and gender classification. These frameworks encompass systems such as those employed in the United States, the United Kingdom, the European Union, and the internationally recognized ISO standards, each characterized by distinct measurement parameters and labeling protocols. In the present investigation, we have adopted a prevalent and comprehensive sizing framework that corresponds with international standards and is extensively utilized within both retail and e-commerce sectors. This approach guarantees compatibility across a wide array of applications and enhances the practical significance of the proposed conceptual model for users worldwide.

TABLE I. STANDARD WOMEN'S CLOTHING SIZE CHART (IN CM)

WOMENS SIZES (CM)						
Size	**XS**	**S**	**M**	**L**	**XL**	**XXL**
Bust (cm)	85	91	95	100	105	110
Waist (cm)	80	86	90	95	100	105
Hips (cm)	90	96.5	100	105	110	115
Front lenth (cm)	115	117	115	115	115	115

Source: https://ethnicity.in/pages/size-guide

Following common fashion industry practices, the larger of the two measurements (waist or hip) is used to determine the final clothing size. This ensures user comfort and avoids tight fitting, especially for garments like pants and skirts.

3) Code summary – core measurement extraction logic (working for waist and hip). The following Python snippet illustrates the core logic used to extract the waist and hip circumference from the 3D body mesh by projecting relevant surface vertices and applying a convex hull algorithm (Algorithm 1):

This code performs three main operations:

Algorithm 1 : Python

```
# Step 1: Define hip and waist levels directly from keypoints
y_hip = keypoints[8, 1] # Mid-Hip point (keypoint index 8)
y_neck = keypoints[1, 1] # Neck point (keypoint index 1)
y_waist = y_hip + np.abs(y_neck - y_hip) * 0.40 # Estimated waist level

# Step 2: Select surface vertices near the hip and waist levels
hip_vertices = vertices[np.abs(vertices[:, 1] - y_hip) < 0.015]
waist_vertices = vertices[np.abs(vertices[:, 1] - y_waist) < 0.015]

# Step 3: Project 3D points onto the X-Z plane for 2D contour analysis
hip_2d = hip_vertices[:, [0, 2]]
waist_2d = waist_vertices[:, [0, 2]]
```

```
    # Step 4: Compute the Convex Hull to approximate the circumference
    hip_hull = ConvexHull(hip_2d)
    waist_hull = ConvexHull(waist_2d)
```

The vertical positions (y_hip, y_waist) are derived using anatomical reference points from the keypoints_3d array, aligned using a displacement correction to compensate for origin mismatch between the vertex and joint spaces.

The waist level is estimated as a proportional offset (40%) between the hip and neck points—empirically chosen to reflect typical torso proportions.

Vertices within a narrow band (±1.5 cm in normalized units) around the estimated hip and waist levels are selected, effectively isolating the relevant cross-sections of the 3D body mesh.

The selected 3D points are projected onto the X-Z plane to obtain a 2D shape of the body cross-section.

ConvexHull() from the scipy.spatial package is used to compute the enclosing perimeter or area of the projected points—used as a proxy for waist and hip circumference.

This computational process allows for non-contact, geometry-based body measurement extraction and is robust against mesh irregularities or minor noise in the 3D data.

4) Size mapping through standardized chart. Subsequent to the calculation of waist and hip circumferences utilizing the convex hull perimeters, the derived values are juxtaposed against an established size chart in order to allocate a standardized clothing size designation. The chart, delineated in centimeters, encompasses threshold ranges for both waist and hip measurements and was formulated by averaging the discrepancies between contiguous size categories.

The executed size mapping dictionary is as follows in Table II.

TABLE II. THE EXECUTED SIZE MAPPING DICTIONARY

```
size_chart = {
"XS": {"waist": (60, 82.999), "hip": (88, 92.999)},
"S": {"waist": (83, 88.999), "hip": (93, 98.999)},
"M": {"waist": (89, 92.999), "hip": (99, 102.999)},
"L": {"waist": (93, 97.999), "hip": (103, 107.999)},
"XL": {"waist": (98, 102.999), "hip": (108, 112.999)},
"XXL": {"waist": (103, 107.999), "hip": (113, 117.999)},
 }
```

This table was developed by centering the interval disparities among proximate garment sizes in accordance with established industry benchmarks. The ultimate designated size aligns with the minimal size classification wherein both the projected waist and hip circumferences reside within the stipulated parameters. Conversely, for applications prioritizing comfort, the more expansive corresponding category may be selected to guarantee garment ease.

This methodical mapping strategy provides a lucid and comprehensible alternative to opaque machine learning classifiers and retains congruence with widely recognized retail sizing frameworks.

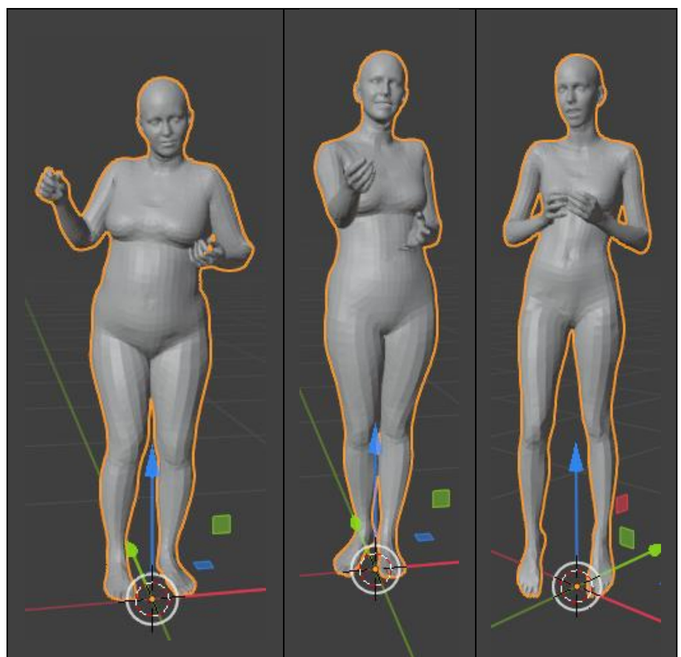
IV. Results Summary

A. Case Study: Evaluation on Agora Dataset Using (Waist , Hip)

In order to illustrate the practical implementation and credibility of the proposed framework, a collection of authentic three-dimensional body models was curated from the Agora dataset, which offers intricate anthropometric meshes that represent a variety of female body types (see Fig. 6).

The Agora dataset was chosen due to its high-quality anthropometric models and comprehensive skeletal keypoints, enabling precise evaluation across diverse body shapes and realistic scenarios.

In order to assess the practical applicability of the proposed framework, a variety of three-dimensional body models sourced from the Agora dataset were subjected to processing through the entirety of the established pipeline. Among these instances, three representative cases—Cindy, Fiona, and Alixon—have been selected to exemplify the diversity in body morphology and the corresponding assignment of clothing sizes. The larger collection of evaluated models demonstrated analogous results, thereby suggesting a uniform operational consistency of the system across varying anatomical configurations.



Name = Cindy	Name = Fiona	Name = Alixon
Hip = 1.124 m	Hip = 0.992 m	Hip = 0.892 m
Waist = 0.942 m	Waist = 0.825 m	Waist = 0.723 m
Rec = XL	Rec = M	Rec =XS

Fig. 6. Estimated waist and hip circumferences for three subjects (Alixon, Fiona, Cindy) and the corresponding predicted clothing sizes.

B. Analysis

In the case of Cindy, both her waist (94.2 cm) and hip (112.4 cm) dimensions distinctly align with the XL category as delineated by the specified size chart.

Fiona presents intermediate measurements—waist at 82.5 cm and hip at 99.2 cm—rendering her qualifying for the M category.

Alixon, possessing a waist measurement of 72.3 cm and a hip measurement of 89.2 cm, comfortably fits within the XS category.

The cross-sectional contours of each model were subjected to analysis via convex hulls within the X-Z plane. The findings indicate a robust correlation between the visually perceived body type and the size predicted by the proposed methodology, thereby affirming its efficacy within a practical context.

These findings underscore the framework's proficiency in accommodating various body proportions and autonomously delivering realistic size recommendations utilizing solely a singular three-dimensional mesh and joint keypoints as input.

V. Discussion

The findings derived from the Agora dataset underscore the practical viability and precision of the proposed image-based body measurement framework. By implementing a coherent and modular pipeline—encompassing joint extraction, three-dimensional body modeling, geometric perimeter analysis, and rule-based classification—the system adeptly estimated standardized clothing sizes across a diverse array of body shapes.

A. Strengths

Robustness Across Body Variants: The framework proficiently differentiated between various anatomical types (e.g., Cindy vs. Alixon), encapsulating both volumetric and proportional variances. Mesh-based modeling approaches like DensePose2SMPL have shown improved shape estimation performance, particularly in subjects with outlier body types [26].

Alignment with Industry Standards: Size predictions (e.g., XS, M, XL) corresponded favorably with anticipations derived from body measurements, affirming the legitimacy of convex hull-based perimeter estimation. Previous studies applying 3D scanning in apparel industries highlighted the effectiveness of geometric-based measurements for standardized size matching [27].

Contactless and Scalable: Functioning on a singular image without necessitating specialized equipment, the methodology is well-positioned for practical implementation within e-commerce and virtual try-on systems. Research on mobile- and web-based 3D scanning platforms confirms growing consumer demand for low-barrier body modeling solutions [28].

B. Potential Applications

In virtual shopping platforms, this technology allows for realistic virtual try-on experiences where garments are simulated directly onto a user's 3D model. Projects like SIZER have demonstrated the practicality of linking clothing fit with volumetric body data to personalize the shopping journey [29]. More importantly, by linking the extracted body measurements directly to sizing charts provided by online clothing retailers, the system enables users to select the most accurate size before making a purchase. This pre-selection step significantly reduces the risk of sizing mismatches, thereby lowering return rates and associated logistical costs [30].

The ability to preview fit and style interactively empowers users to make confident decisions, while retailers benefit from fewer returns and improved customer satisfaction. This seamless integration between virtual fitting and e-commerce platforms bridges the gap between user expectation and product delivery [28].

Beyond virtual worlds, the framework paves the way for intelligent mobile applications that can, from a single image, provide users with real-time recommendations not only for size but also for clothing styles that best suit their body shapes. Such applications could incorporate AI-driven styling advice based on user preferences, fashion trends, and body geometry—delivering a personalized and seamless shopping experience that merges practicality with convenience [31].

C. Limitations

Fixed Anatomical Ratios: Waist-level estimation based on a fixed ratio (e.g., 40% between neck and hip) may not generalize across different ethnicities, age groups, or postures, potentially leading to inaccuracies in landmark placement. Research highlights that human anatomical diversity undermines the reliability of fixed-ratio methods in body reconstruction [32].

Chest Measurement Challenges: Accurate chest measurement is hindered by the pose limitations of many 3D body models, which often lack favorable positions such as the Y-pose. This results in arm–torso intersections that distort the contour, especially around the upper torso. Prior work has demonstrated that dressed-human silhouettes limit measurement precision when key anatomical landmarks are occluded or misaligned [33].

Pose and Environment Dependence: The system was tested on controlled, static 3D models, which may not reflect performance in real-world scenarios. Variations in lighting, background, and body pose can adversely impact the accuracy of joint detection and mesh reconstruction. This dependency is consistent with findings that stress the sensitivity of monocular 3D body estimation to environmental conditions and pose inconsistencies [34].

Clothing Interference: Although models like SMPLify-X can recover approximate body shapes under loose garments, excessive layering or oversized clothing still causes significant contour deviation. Studies confirm that loose-fitting clothes often degrade estimation accuracy, especially in peripheral regions such as the hips and chest, suggesting tight-fitting garments are optimal for body capture [31].

D. Future Directions

Future advancements could concentrate on adapting pose-aware corrections for chest measurement through pose normalization or generative completion methodologies, implementing the model in mobile applications with real-time guidance on pose and clothing preparation, and augmenting the framework with deep-learning-based modules to enhance anatomical landmark detection under conditions of occlusion or partial visibility.

VI. Conclusion

This study presented and validated a comprehensive, image-based framework for estimating human body measurements, specifically waist and hip circumferences, using a single image processed by OpenPose, SMPLify-X, and convex hull geometric analysis. These measurements were systematically mapped to standard clothing sizes through a clear and scalable rule-based classification, enabling practical, non-intrusive size recommendations.

Experimental evaluations using three-dimensional body models from the Agora dataset confirmed the method's effectiveness in accurately identifying body variations and recommending appropriate clothing sizes (XS–XL). Results showed strong alignment with established industry standards, highlighting the robustness, cost-efficiency, and interpretability of the proposed framework. Consequently, this research contributes meaningfully towards practical applications in e-commerce, virtual fitting solutions, and body-shape analytics.

However, limitations of the study include reliance on fixed anatomical ratios that might not generalize across different ethnicities, age groups, or body postures, as well as potential inaccuracies due to clothing interference or complex poses. Future work could address these limitations by refining landmark detection, improving pose normalization, and adapting the framework for mobile and real-world scenarios.

Overall, this research significantly advances the accessibility and practical implementation of image-based body size estimation, facilitating personalized garment fitting in a contactless, efficient, and user-friendly manner.

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