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Article

Estimating Anthropometric Soft Biometrics: An Empirical Method

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Abstract: Following the success of soft biometrics over traditional biometrics, anthropometric soft biometrics are emerging as candidate features for recognition or retrieval using an image/video. Anthropometric soft biometrics uses a quantitative mode of annotation which is a relatively better method for annotation than qualitative annotations adopted by traditional biometrics. However, one of the most challenging tasks is to achieve a higher level of accuracy while estimating anthropometric soft biometrics using an image or video. The level of accuracy is usually affected by several contextual factors such as overlapping body components, an angle from the camera, and ambient conditions. Exploring and developing such a collection of anthropometric soft biometrics that are less sensitive to contextual factors and are relatively easy to estimate using an image or video is a potential research domain and it has a lot of value for improved recognition or retrieval. For this purpose, anthropometric soft biometrics, which are originally geometric measurements of the human body, can be computed with ease and higher accuracy using landmarks information from the human body. To this end, several key contributions are made in this paper; i) summarizing a range of human body pose estimation tools used to localize dozens of different multi-modality landmarks from the human body, ii) a critical evaluation of the usefulness of anthropometric soft biometrics in recognition or retrieval tasks using state of the art in the field, iii) an investigation on several benchmark human body anthropometric datasets and their usefulness for the evaluation of any anthropometric soft biometric system, and iv) finally, a novel bag of anthropometric soft biometrics containing a list of anthropometrics is presented those are practically possible to measure from an image or video. To the best of our knowledge, anthropometric soft biometrics are potential features for improved seamless recognition or retrieval in both constrained and unconstrained scenarios and they also minimize the approximation level of feature value estimation than traditional biometrics. In our opinion, anthropometric soft biometrics constitutes a practical approach for recognition using closed-circuit television (CCTV) or retrieval from the image dataset, while the bag of anthropometric soft biometrics presented contains a potential collection of biometric features which are less sensitive to contextual factors.

Keywords: Anthropometrics; soft biometrics; landmark localization; estimation

1 Introduction

Anthropometric soft biometrics is originally geometric features of the human body, and they are gaining a lot of attention from the research community due to their value for better recognition [1], as compared to qualitative soft biometrics usually known as categorical and comparative features. Anthropometrics are scientific measurements of the human body such as ratios and proportions acquired using images and they always perform better recognition or retrieval than qualitative soft biometrics. In research on soft biometrics [2], these measurements are termed as soft biometric features and by applying computer vision techniques their value is determined using human body landmark information [3], where pose estimation tools are the underlying architecture.

Several benchmark open-source pose estimation tools exist in the field and perform landmark localization as a preliminary step. These tools usually work on a single image or sequence of images to localize several landmarks on the human body, including a confidence score for each landmark. Moreover, the use of human silhouette is another important aspect supported by a few pose estimation tools and they are developed to perform pose estimation in multiple different circumstances [4]. Usually, soft biometric features are annotated using three different types of annotation methods, known as categorical, comparative, and absolute [5,6]. The application of categorial methods is limited only to short-term tracking, while comparative methods are feasible where the dataset size is small for image or feature-based retrieval. On the other hand, absolute annotation seems one of the most successful methods for soft biometric feature annotation, only if the output of anthropometric feature estimation is highly accurate on images using computer vision techniques [7]. The human body anthropometric measurements can be estimated from two common modalities of the human body such as extended facial region and body including limbs. By using full-body images or videos of the human body, anthropometric soft biometrics can be measured easily and finally, the task of recognition or retrieval can be performed successfully. For this purpose, human body landmarks are the key source to determine the values of these anthropometric soft biometrics.

To this end, Sayed et al. [8] proposed a solution for matching the body with the head and it used human body anthropometrics to acquire anthropometric soft biometrics from the full structure of the human body. In earlier studies, it was revealed that the whole human body can be divided into several golden sections and these sections are unique to everyone in the world [9]. The proposed method uses Canonical Correlation Analysis (CCA) [10] to find a correlation between the features of the head and body. A set of more than 15 features was selected from the head and body images and anthropometric soft biometrics were computed automatically using computer vision techniques. Another method [11] assumes that the human body signature can determine its shape and size while certain anatomical landmarks can be used to estimate anthropometric soft biometrics to recognize people [12]. The proposed method computes the Euclidean distance between four pairs of skeleton joints to determine the size of the human body, while the surface distance between circular body parts was used to measure the shape of the human body from an image. The proposed algorithm was a novel contribution to the field because it segments circular body parts using geometry and cylindrical fitting.

In another similar proposal [13], the face was compared with the body using a total of 16 different measurements from both the face and body and eight measurements were selected from each part providing significant information for the matching task. The outcome of the proposed method well-demonstrated the fact that a limited number of features avoid duplicates and results in terms of better matching. Moreover, it was revealed from the experiments that the body has more variable features [14] than the face. On the other hand, due to the larger dimensions of the body, it is always easy to locate the body instead of the face in the images and a better identification is possible [15]. The proposed method computes metric measurements using images for successful extraction of anthropometric soft biometrics, though the method is an experimental approach yet [16]. Several reasons such as lighting conditions, image quality, and posture became reasons to reduce the level of recognition accuracy. Considering additional distinguishing features [17] from the face and body can be helpful to improve overall recognition, especially using more features from the body in the case of CCTV. The proposed method has higher significance in various application domains like Big Data analysis and Internet of Things (IoT).

In another work [18], projectile geometry was used to measure the height of an individual from a single calibrated image. The proposed method used statistical knowledge about human body anthropometry and later applied the Bayesian framework for the identification task. The proposed method was tested on both 96 frontal face images and augmented images of the same individuals for measuring human body anthropometrics. In another approach, two specific human body anthropometrics known as stature and shoulder breadth were measured using low resolution images [19]. By processing image sequences, mean estimates were acquired for both anthropometric soft biometrics. Overall, there were two main contributions made in the proposed approach; i) modelling of the human body shoulder as an ellipse to estimate shoulder breadth, and ii) defining the factor of measure of mean accuracy over a sequence of images. An initial experiment used landmark information of the human body from the Two-dimensional (2D) images and then computed the mean of both anthropometric soft biometrics by incorporating camera calibration parameters.

On the other hand, a new four-step method was proposed to estimate human body anthropometric soft biometrics from non-calibrated images of the individuals. A set of points was selected from the images to constitute a pattern of landmarks, then statistical knowledge was applied to measure the height of the human body. The proposed method was geometrical and successfully produced the anthropometric height of the human body with minimal cost. Based upon the research carried out using anthropometric soft biometrics, it is evident that they are critical features of the human body, and their absolute value is highly distinguishing during any kind of recognition task using an image or video. One of the most advantageous factors in acquiring human body anthropometrics is the availability of highly accurate landmarks localization techniques which is a preliminary step in this process.

Based upon a comprehensive literature review presented, the advantages of anthropometrics soft biometrics over qualitative soft biometrics are clearly visible during the recognition or retrieval process [20]. One of the key advantages is highly discriminating feature value which is not possible to extract while using qualitative soft biometrics. On the other hand, the biggest limitation with anthropometric soft biometrics was the non-availability of correct feature value which is now feasible by taking human body landmark information using pose estimation tools [21]. In our work, we identified landmark information as one of the key problems and exploited pose estimation tools to achieve this goal. Another associated problem was the availability of a benchmark dataset for the evaluation of any developed anthropometric soft biometric system. Finally, the proposal and development of a collection of potential anthropometrics soft biometrics was another big challenge identified in the field.

By looking at the problems identified earlier, this paper achieves the following fourfold scientific contributions in the field:

- It starts with summarizing a range of human body pose estimation tools to localize dozens of different multi-modality landmarks from the human body.
- It then showcases a critical evaluation of the usefulness of anthropometric soft biometrics in recognition or retrieval tasks using benchmarks in the field.
- It further investigates several benchmark human body anthropometric datasets and their significance during the evaluation of any anthropometric soft biometric system.
- Finally, it proposes a novel bag of anthropometric soft biometrics comprising a list of anthropometrics that are practically possible to measure from an image/video.

To the best of our knowledge, these are novel contributions in the field that summarize not only the existing capabilities of different tools but also their feasibility for anthropometric soft biometric-based recognition or retrieval using an image/video recording in constrained and unconstrained environments.

The rest of the paper is organized in the following manner. A review of nine different pose estimation tools including landmark localization capabilities is presented in Section 2, while a discussion on benchmark datasets and techniques for the recognition constitutes Section 3. Section 4 presents a novel collection of anthropometric soft biometrics which can be measured from 2D images acquired using one or more cameras. Finally, the conclusion part provides information about the application and usefulness of anthropometric soft biometrics in several different tasks like verification, matching, or retrieval using images or videos.

2 Human Body Landmark Localization

To estimate anthropometric soft biometrics from 2D images of the human body is a complex task; though, they are highly discriminating features. To facilitate this process, the use of human body landmark localization tools is beneficial which makes the overall task easy. Several tools exist for this purpose to perform landmark localization including localization confidence score for each on 2D images. By using existing tools, we intend to summarize the capabilities of different tools in terms of various recognition or retrieval tasks using anthropometric soft biometrics. An overall objective of this evaluation is to first determine the tools with higher accuracy and the number of landmarks localized followed by portraying the significance of each tool in terms of the application domain. To this end, we explored and summarized nine different pose estimation tools which internally facilitate the localization process.

2.1 CMU-OpenPose

One of the best tools for pose estimation is OpenPose [22]. It is an open-source tool, and it provides multi-person pose estimation in real time. OpenPose offers an application programming interface (API) to detect 135 key points from the face, body, hand, and foot using an image. One of the primary goals of OpenPose is to determine the pose of individuals in an image regardless of the number of persons in an image [23]. OpenPose is highly accurate in localizing landmarks of the whole human body, and it is useful to compute anthropometrics soft biometrics from facial and body regions. A sample output of OpenPose is shown in Fig. 1.

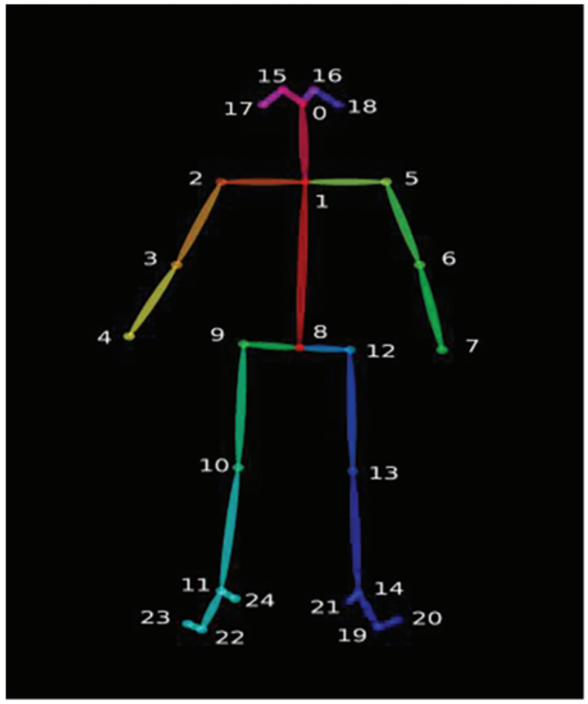

Figure 1: OpenPose output-image courtesy [22]

2.2 AlphaPose

Another prominent open-source API is AlphaPose [24] for pose estimation. AlphaPose achieved a performance of 82.1 mAP on MPII, while 75 mAP on COCO dataset. AlphaPose provides an additional pose tracker [25] to track the same person across multiple sequential frames. For anthropometric soft biometrics estimation, AlphaPose can provide 17 body landmarks along with their confidence scores. One of the best features of AlphaPose is its high accuracy in multi-camera environment. A pictorial outcome of AlphaPose is shown in Fig. 2.

Figure 2: AlphaPose output-image courtesy [24]

2.3 OpenPifPaf

OpenPifPaf [26] is another well-known pose estimation tool for 2D images. It is quite suitable for delivery robots and self-driving cars. The OpenPifPaf outperforms its competitors in low-resolution, crowded, occluded, and cluttered scenes. It also provides locations of 17 body joints in 2D images including their detection confidence. The output image of OpenPifPaf can be seen in Fig. 3, while OpenPifPaf remain a highly relevant landmark localization tool for detecting anthropometric soft biometrics in crowded places.

Figure 3: OpenPifPaf output-image courtesy [26]

2.4 DensePose

DensePose [27] was originally developed by Facebook and it maps pixels of the human body in a 2D image to a three-dimensional (3D) surface of the human body.

The goal of DensePose is also human pose estimation and it is highly valuable for recognizing people. On the other hand, 3D surface geometry is a valuable feature for DensePose-based landmark localization and it was used to estimate anthropometric soft biometrics. A pictorial view of DensePose image to surface mapping is presented in Fig. 4.

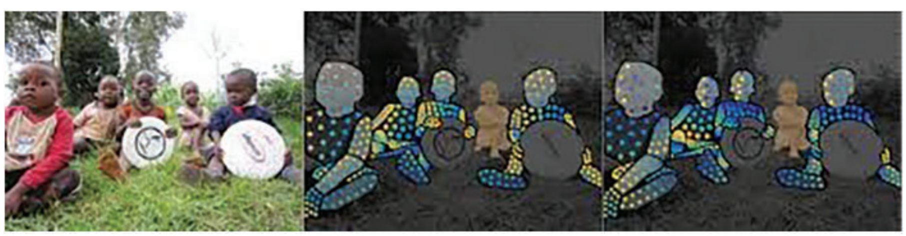

Figure 4: DensePose output-image courtesy [27]

2.5 Real-Time Multi-Person Pose Estimation

Real-Time Multi-Person pose estimation (RTMPPE) [28] is an earlier version of OpenPose. It localizes 15 landmarks of the human body including their confidence scores. It is applicable to 2D images and useful for anthropometric soft biometric estimation in videos. An outcome of Real-time Multi-Person pose estimation is presented in Fig. 5.

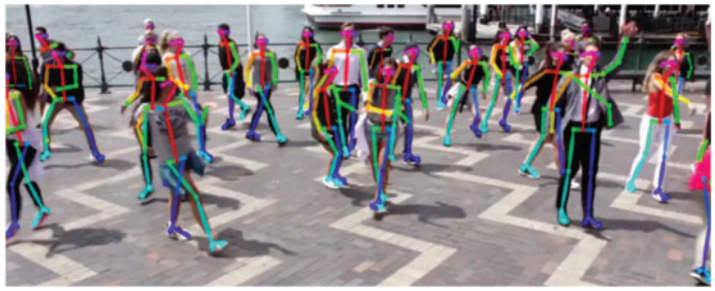

Figure 5: Real-time multi-person pose estimation output-image courtesy [28]

2.6 DeepPose

DeepPose [29] is another open-source tool to find the pose of the human body. It was originally developed by Google. Initially, it traces the joint coordinates, then using those joint locations, it determines the pose of the human body. DeepPose falls under the category of human body landmarks localization tools, and it has genuine application for anthropometric soft biometrics estimation is sports scenarios. A pictorial view of DeepPose output is shown in Fig. 6.

Figure 6: DeepPose output-image courtesy [29]

2.7 HyperFace

HyperFace [30] is a famous deep-learning framework for landmark localization, pose estimation and face detection. For recognition tasks, the human body landmark localization components of HyperFace are useful to estimate anthropometric soft biometrics. A pictorial representation of HyperFace output is shown in Fig. 7.

2.8 WrenchAI

WrenchAI [31] is a highly competitive API for human body landmark localization. It provides body, face, and hand models including models for 3D pose estimation. A pictorial outcome of WrnchAI is shown in Fig. 8. Overall, WrenchAI and OpenPose work in a similar fashion however, there exist several different parameters to distinguish both.

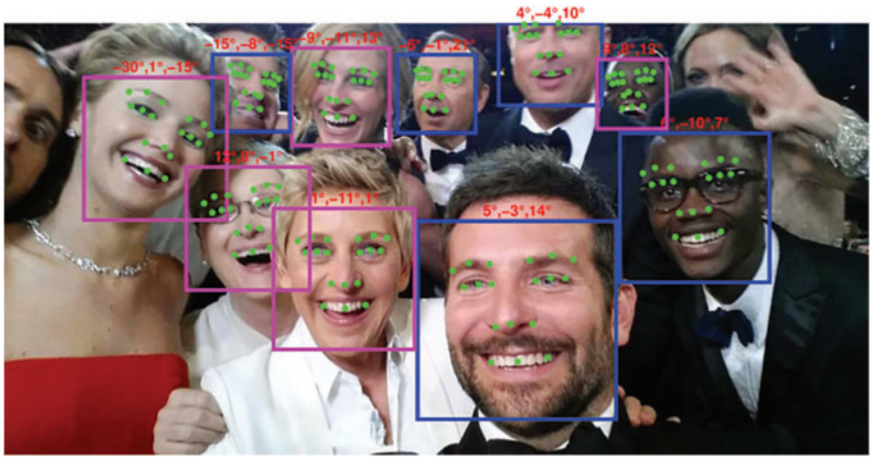

Figure 7: HyperFace output-image courtesy [30]

Figure 8: WrnchAI-image courtesy [31]

2.9 Multi-Person Pose Estimation in the Wild

Generally, it is a bit challenging task to localize human body joints and to estimate pose in an open environment; however, Multi-Person Pose Estimation in the Wild is a great API for this purpose [32]. It follows a two-step process as; i) drawing a bounding box surrounding the person and cropping a rectangular area, and ii) localizing 17 landmarks from the face and body. A workflow of Multi-person Pose Estimation in the Wild API is shown in Fig. 9.

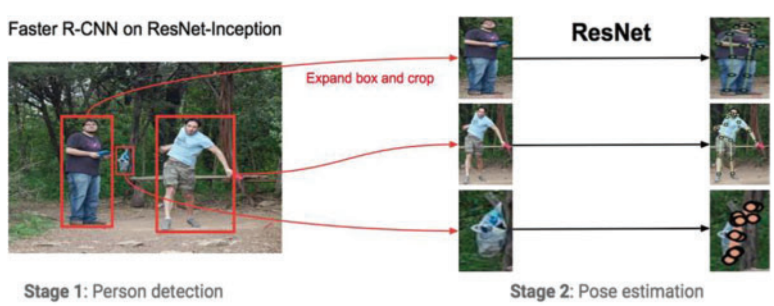

Figure 9: Multi-person pose estimation in the wild output-image courtesy [32]

Based upon an analysis presented on nine different landmark localization tools, it is evident that they are potential techniques for anthropometrics soft biometrics estimation though all of them are not practically useful nowadays.

Some of them were not further trained and validated on new and challenging datasets of images or videos while others were upgraded to new versions, like OpenPose [22] is a new version of RealTime Multi-Person Pose Estimation [28] tool. Currently, only a limited number of pose estimation tools are rich in terms of localizing the higher number of landmarks from the human body and they establish a strong basis for the selection of those tools while leaving the others. Also, they outperform other similar tools while localizing the greatest number of landmarks from the human body. Some examples of such types of tools include Open and AlphaPose [24], as a benchmark. While performing the task of pose estimation using the large number of landmarks localized from the human body, they were trained and validated on different benchmark datasets. In [15], OpenPose and AlphaPose were used to estimate anthropometric soft biometrics from the images of the human body, and that is why, we decided to compare the landmark localization capabilities of both tools using different landmarks of the human body as shown in Table 1.

Table 1: A review of landmark localization for OpenPose and AlphaPose

Modality	Keypoint/tool	AlphaPose				CMU-OpenPose
		COCO (D)	MPII (D)	COCO (F)	MPII (F)	
Face	Nose	✓	×	✓	×	✓
	LEye	✓	×	✓	×	✓
	REye	✓	×	✓	×	✓
	LEar	✓	×	✓	×	✓
	REar	✓	×	✓	×	✓
	Neck	×	✓	×	✓	✓
	Head	×	✓	×	✓	×
Body	LShoulder	✓	✓	✓	✓	✓
	RShoulder	✓	✓	✓	✓	✓
	LElbow	✓	✓	✓	✓	✓
	RElbow	✓	✓	✓	✓	✓
	LWrist	✓	✓	✓	✓	✓
	RWrist	✓	✓	✓	✓	✓
	LHip	✓	✓	✓	✓	✓
	RHip	✓	✓	✓	✓	✓
	LKnee	✓	✓	✓	✓	✓
	RKnee	✓	✓	✓	✓	✓
	LAnkle	✓	✓	✓	✓	✓
	RAnkle	✓	✓	✓	✓	✓
	Pelv	✓	✓	×	×	×
	Thrx	×	✓	×	✓	×

(Continued)

Table 1 (continued)

Modality	Keypoint/tool	AlphaPose				CMU-OpenPose
		COCO (D)	MPII (D)	COCO (F)	MPII (F)	
Foot	LBigToe	×	×	×	×	✓
	LSmallToe	×	×	×	×	✓
	RBigToe	×	×	×	×	✓
	RSmallToe	×	×	×	×	✓
	LHeel	×	×	×	×	✓
	RHeel	×	×	×	×	✓
Others	Background	×	×	×	×	✓

3 Benchmark in Anthropometrics

Following successful outcomes, anthropometric soft biometrics are getting a lot of attention from the soft biometrics research community for better recognition using an image or video stream. Despite the fact, several associated factors with anthropometric soft biometrics such as the non-availability of anthropometric datasets and better techniques for estimating those using an image or a video are the biggest concerns. This paper explores and presents benchmark anthropometric datasets and anthropometric soft biometric estimation techniques in the field.

3.1 ANSUR II: A Benchmark Anthropometric Dataset

The research on human body anthropometrics is not new, it goes back to the 18th century, where the use of the Bertillon system [33] for criminal identification using human body anthropometrics was common. There are two common ways to obtain human body anthropometrics; i) manually using different measurement devices, or ii) automated estimation from an image or a video. Both methods provide human body landmarks that are straight lines or curved measurements of the human body, such as lengths, widths, area, and circumferences.

To this end, this paper remained focused on the automated estimation of human body anthropometrics from an image or a video. That is why, it was essential to look for a benchmark dataset, specifically providing anthropometric measurements of the human body measured using manual devices. In our work, we explored and discussed ANSUR II [34,35], as a benchmark dataset for evaluating any human body anthropometric estimation model as shown in Fig. 10. ANSUR II is the most common and reliable human body anthropometric dataset. It was initially developed in 2012, while released publicly in 2017. The dataset contains the anthropometric measurement of US army personnel. This dataset is a replacement of the original ANSUR I dataset and it has a large range of human body anthropometrics presented. As witnessed by the research community, ANSUR II is the most reliable source for automated anthropometric feature estimation system evaluation. Once these anthropometric features are extracted from the human body using an image or a video, the same can be used to evaluate the performance.

3.2 Anthropometric Feature Estimation

Detailed analysis of human body landmark localization tools demonstrates their significance for the recognition or verification process. With the availability of benchmark human body landmark localization tools, the development of more accurate soft biometrics applications is easy using quantitative features. This paper also reports a couple of experimental outcomes, more specifically focusing on anthropometric soft biometrics estimation from the human body. Like, [8] solves a new research problem using anthropometric soft biometrics of head-body matching. The studies on human body structure revealed that the whole human body can be divided into golden sections, and each human body has its unique anthropometrics. The proposed approach found correlation between head and body using a set of features from each modality by applying Canonical Correlation Analysis (CCA). For this purpose, there were 20 visually apparent features that were computed including 5 from the head and 15 from the body, respectively. One of the main reasons behind selecting those features was the level of accuracy associated with each feature by using computer vision models.

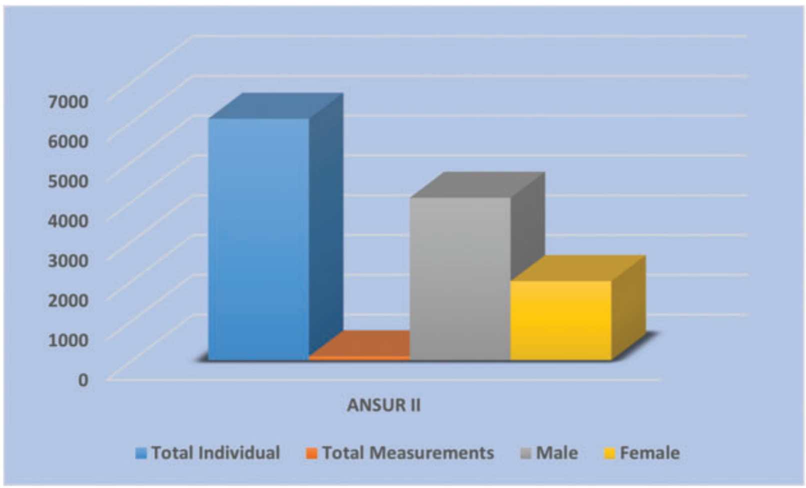

Figure 10: ANSUR II: A benchmark dataset for automated human body anthropometric system evaluation from images

In another work, a new method was proposed [11] to compute anthropometric soft biometrics such as the size and shape of the human body, which uses specific anatomical landmarks from the human body. To measure the size of the body, the Euclidean distance was computed between four skeleton joint pairs which determine the shape of the body. For this purpose, a novel segmentation algorithm was proposed using mathematical geometry [36]. Similarly, using eight measurements from each face and body, it was investigated whether the body has enough information for identification [13]. It was observed that fewer body measurements are required for identification in comparison to the face. It was noted that the body has more variable information than the face and it has more distinguishing information for identification. Moreover, an advantage of using the body is the presence of larger dimensions which are relatively easy to find using images. Also, it avoids the effect of shape changes like facial expressions. Currently, the research is being carried out using metric measurements from images; however, noticeable success is still far away. The anthropometrics soft biometrics estimation usually depends on several factors, like ambient conditions, pose and image quality.

In one more experiment [37] where anthropometric features were considered as key soft biometrics, gender was detected using multiple anthropometric features. The experiments were carried out on NHANES and U.S. Naval datasets. To accomplish this task, several different types of measurements like diameter and girth measurement, etc., were taken and the gender was determined using a multi-layer Perceptron network. Several other diameter measurements were computed like shoulder breadth, pelvic breadth, hips breadth, chest depth, mid-expiration, wrist diameter, the sum of elbows, knee diameter, the sum of wrists, ankle diameter, the sum of knees, and the sum of ankles. In another experiment, the height of a person was estimated using a single and non-calibrated image. The model combines methods from projectile geometry and uses statistical knowledge of human anthropometry [18]. The model is designed by following Bayesian theory and it was tested on synthetic data besides original images of 96 distinct individuals. Overall, the model computes approximately ten anthropometric features including neck height, body height, and head to-chin distance. In another experiment, two common anthropometrics of the human body known as stature and shoulder breadth were estimated, as they are considered relatively easy to estimate using images [19]. To accomplish this task, a sequence of frames was used, and mean estimates were computed. There were two main contributions made in the research; i) the development of a model to estimate automatic and passive shoulder breadth measurement, and ii) the introduction of an improved model for the estimation of both anthropometrics. The proposed model first detects human body landmarks on 2D images and later estimates both anthropometric soft biometrics from the image by considering camera calibration parameters.

In another research, a four-step technique was proposed to estimate anthropometric soft biometrics and pose from a single non-calibrated image [38]. Initially, a set of image points was selected manually which forms the projection of selected landmarks using statistical information about the human body. So, the use of anthropometric features in person identification is not new, as evident from the relevant literature. By looking at the significance of anthropometric features, we decided to present a bag of potential anthropometric features that can be estimated from 2D images recorded using single or multiple cameras. This bag is unique to its kind, however, it varies as per the given scenario, though it sets a good foundation for image-based recognition.

4 Bag of Anthropometric Soft Biometrics

As mentioned earlier, human body anthropometrics emerged as a key research domain, and it achieved significant success in recognition scenarios [39]. We already discussed several research experiments with the aim of extracting or estimating anthropometric features from the images. However, they presented certain limitations and were implemented in a controlled environment. Based on the analysis, we also selected a collection of potential anthropometric features which seems possible to extract from the images [40]. Some of these features require images only from a single camera, while others require multi-camera images.

Table 2 presents a bag of potential anthropometric soft biometrics which can be extracted using a single image of an individual, however, the presence of multiple persons in a single image might be an issue [41]. This bag of human body anthropometric soft biometrics is mostly based on straight-line geometric measurements of the human body and standard methods of distance computation are applicable in such type of computer vision analysis tasks, though affected by several factors like ambient conditions [42], an angle from the camera, and occlusions. Despite the fact, distance measurement methods like Euclidean distance are genuinely helpful to extract those anthropometric measurements from the human body while considering the increasing or decreasing distance from the camera [43]. Similarly, not all the geometric measurements of the human body are straight-line measurements but circular or elliptical and this is due to the natural skeletal of the human body [44]. Like straight-line measurements, geometrical models are useful while estimating those circular or elliptical measurements of the human body. Such types of geometric measurements are genuinely useful anthropometric soft biometrics of the human body during recognition in the constrained or unconstrained scenario or feature-based retrieve from a large dataset of pedestrians [45]. In our work, we also identified several of these types of anthropometric soft biometrics of the human body as shown in Table 3, however, simultaneous images from more than one camera are required to estimate those soft biometrics from a 2D image.

Table 2: Anthropometric features measurable from 2D images

Feature	Distance	
	From	To
Acromial height	Surface	Outer end of shoulder
Acromion-radiale length	Outer end of shoulder	Elbow
Biacromial breadth	Right shoulder outer end	Left shoulder outer end
Buttock height	Surface	Buttock point
Buttock-knee length	Buttock point	Knee point
Chest height	Surface	Chest point
Hip breadth	Right buttock	Left buttock
Interpupillary breadth	Right pupil	Left pupil
Knee-height	Midpatella surface	Knee landmark
Lateral-malleolus height	Surface	Ankle
Menton-sellion length	Menton or chin	Sellion or inter pupil center
Radiale-stylion length	Radiale or elbow	Stylion or wrist
Shoulder-elbow length	Acromion landmark	Olecranon bottom landmark
Sleeve-length: spine-wrist	Midspine landmark	Olecranon
Sleeve outseam	Acromion	Stylion
Stature	Surface	Top of head
Suprasternale height	Surface	Suprasternale

Table 3: Anthropometric features measurable from 2D images or videos using multiple cameras

No.	Feature	No.	Feature
1	Heel-ankle circumference	6	Neck circumference base
2	Head circumference	7	Shoulder circumference
3	Calf circumference	8	Thigh circumference
4	Lower thigh circumference	9	Waist circumference
5	Neck circumference	10	Wrist circumference

The bag of anthropometric soft biometrics [46] presented in Tables 2 and 3, clearly demonstrates that anthropometric soft biometrics are highly significant and relevant features of the human body to improve the process of recognition or retrieval. This task can be completed using landmark information of the human body which directly supports a higher recognition rate for verification or retrieval in both constrained or unconstrained scenarios [1]. In our work, we explored and presented both types of anthropometric soft biometrics which are possible to estimate or extract using a single

2D image of an individual or a set of simultaneous images for the same individual using more than one camera. Most of this anthropometrics remain part of different research experiments in different contexts, however, they have multi-faced purposes due to being part of the human body [47]. On the other, the use of a specific anthropometric soft biometric highly depends upon its impact during that task.

5 Conclusion and Future Work

Following the discussion, this paper presents a bag of anthropometric soft biometrics, with a proposal of key approaches for anthropometric soft biometrics estimation. It is evident that anthropometrics are highly valuable features of the human body for recognition or retrieval. Human body anthropometrics are quantitative soft biometrics of the human body, and they ensure higher recognition accuracy as compared to qualitative methods like categorical or comparative. One of the key challenges in using anthropometric soft biometrics for recognition is to address the problem of accurate estimation using 2D images. That is why, this paper explores and compares nine different human body landmark localization tools and their usefulness in different recognition or retrieval scenarios. These tools are originally developed for human body pose estimation; however, they follow the process of landmark localization and are available as opensource APIs for different application domains. To estimate human body anthropometric soft biometrics, the landmark information on a 2D image using these tools is critical information to exploit and that is why this paper presented a bag of anthropometric soft biometrics which are relatively easy to estimate from 2D images or video. As a future course of action, several research challenges were identified and this paper plans to work on those. The challenges include an improve estimation accuracy for anthropometric soft biometrics using landmark localization and extending the bag of anthropometric soft biometrics further following several different real-world scenarios [1].

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