Statistical Prediction of Body Landmark Locations on Surface Scans

Matthew P. Reed[a], Byoung-Keon Park[a], K. Han Kim[a], Monica L.H. Jones[a]

[a]*University of Michigan Transportation Research Institute, Ann Arbor, Michigan, USA*

Automatic location of body landmarks on human three-dimensional surface scan data can improve the efficiency of anthropometric studies. Previous methods have relied on local features and heuristics to identify landmarks. This paper presents a purely statistical technique based on a statistical body shape model (SBSM). An optimization technique is used to identify a vector of principal component scores that maps the SBSM to the scan data. The locations of 98 landmarks and joint centers were predicted by this method and compared to the manually extracted locations for 213 men scanned in a relaxed standing posture. The mean (across landmarks) median error was 19 mm. Considering only the torso and head, the mean median error was 14 mm. Joint location discrepancies were generally less than 25 mm, comparing favourably with outer methods for locating joint centers.

Practitioner Summary: A fast statistical method for estimating landmark and joint locations was developed based on a statistical body shape model. The method can be applied to high-quality (laser) or low-quality (Kinect) scan data to estimate landmark locations in under one second.

Keywords: body scan data, landmarks, automatic landmark prediction, body shape model

1. Introduction

Three-dimensional (3D) surface scanning with laser scanners or other devices is now a common component of methodology for anthropometry in ergonomics. However, methods for analyzing scan surface data are in need of further improvement. In general, several steps are needed to make the raw scan data available for analysis. Data processing steps fill holes and remove noise. For some applications, standard anthropometric dimensions are extracted by making virtual measurements on the scan data. A template may be fit to the data to facilitate re-posturing or animating the figure.

The identification of body landmarks can be an important step for measurement and template fitting. Such landmarks are commonly marked on the subject's body prior to scanning and manually digitized with reference to color or grayscale data mapped to the surface. Because the process of marking and digitizing landmarks is time-consuming and hence expensive, an automated methodology for accurately locating body landmarks on scan data is needed.

A variety of methods have been proposed for automatic landmark identification (e.g., Ben Azouz 2006; Han and Nam 2011; Niu et al. 2011). The local shape adjacent to the landmark can be learned from examples and used to estimate the landmark location in new scans. The visual appearance of a marker can also be identified in the image data associated with the scan. In both cases, an accurate initial guess as to the landmark location is a necessary starting point.

This paper presents a statistical method for locating body landmark locations as an outcome of a template-fitting procedure. A statistical body shape model (SBSM) created from scan data that includes landmark locations is fit to scan data instances using an optimization procedure. In this paper, the method is explored by comparing the landmarks obtained by fitting the original data used to generate the SBSM..

2. Method

The SBSM used in this work was generated using data 213 men measured as part of 3D anthropometry studies conducted by the University of Michigan Transportation Research Institute (UMTRI). Each was scanned in a relaxed standing posture, shown in Figure 1. A total of 98 surface landmarks were manually digitized in Meshlab software version 1.3.1 (meshlab.org). A template based on the Jack 8 figure was fit to each scan using a two-stage optimization process (Park and Reed 2014; Reed et al. 2014). Internal joint center locations were estimated from surface landmark locations (Reed et al. 1999). An SBSM was generated by conducting a principal component analysis on the coordinates of the resulting mesh vertices and the locations of surface landmarks and joints (Park et al. 2014).

For the current analysis, an optimization procedure was used with the SBSM to fit the same scans used to generate the SBSM. The optimization procedure finds a vector of 20 PC scores that results in the best match between the model and the scan (Park et al. 2014). The total processing time is approximately one second on a typical laptop computer. The landmark locations predicted by this method were compared to the manually digitized landmark locations. Among the landmarks were internal joint centers estimated from surface landmarks on each scan.

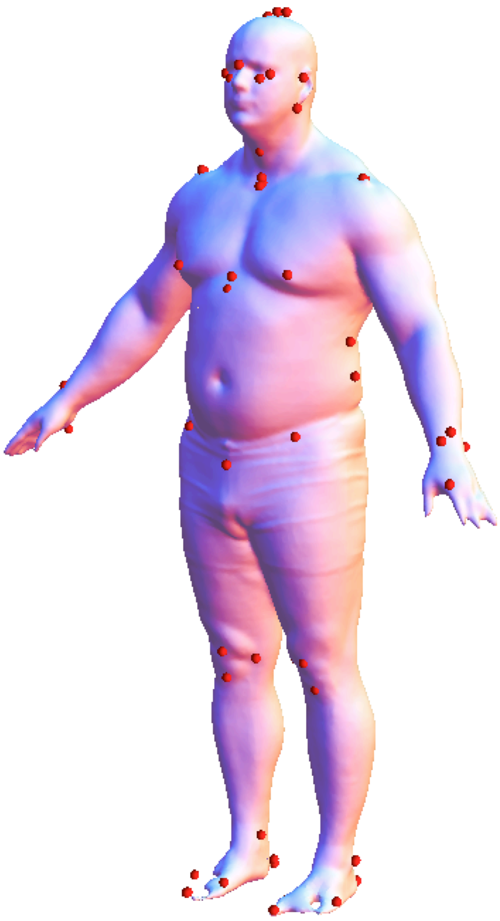

Figure 1. Example scan data showing a subset of landmarks.

3. **Results**

Table 1 lists the 5th, 50th, and 95th percentiles of unsigned distance errors for a selection of landmarks and joint centers on the centerline or right side of the body (values for the left side were similar to the right side). The average median prediction error across landmarks and joints is 19 mm. The median errors were smallest in the head and face and largest on the distal extremities. The larger errors on the extremities are due to the model fitting methodology, which does not include joint articulation to account for posture differences among the scans. The average median error on the torso and head is 14 mm.

Table 1. Quantiles of distance discrepancy by landmark or **joint** (mm).

Landmark	Body Region	5th%ile	50th%ile	95th%ile
EyeCenter_Rt	Head	2.5	8.0	21.9
Glabella	Head	2.9	8.8	22.1
EyeCorner_Rt	Head	2.9	9.2	22.0
C7T1Jnt	**Torso**	**4.0**	**9.2**	**20.5**
Suprasternale	Torso	4.5	10.6	23.5
Cervicale	Torso	5.0	11.1	24.5
Tragion	Head	3.8	11.3	24.1
HeadNeck Joint	**Head**	**4.8**	**12.1**	**25.4**
Gonion_Rt	Head	4.5	13.5	30.6
SpineT04	Torso	5.7	14.2	33.2
SpineL03	Torso	5.2	14.5	31.3
KneeJoint_Rt	**Lower Extremity**	**4.3**	**14.5**	**31.1**
Substernale	Torso	5.6	15.1	30.6
BustPoint_Rt	Torso	5.8	15.1	31.4
FemoralEpiCon_Lat_Rt	Lower Extremity	5.0	15.3	31.8
Acromion_Ant_Rt	Torso	6.0	15.8	34.1
SpineT08	Torso	6.8	16.1	40.0
SpineT12	Torso	6.3	16.6	47.0
FemoralEpiCon_Med_Rt	Lower Extremity	5.9	17.1	35.8
Infrapatella_Rt	Lower Extremity	7.2	17.5	33.9
T12L1Joint	Torso	6.0	18.0	41.3
ShoulderJoint_Rt	**Torso**	**5.6**	**18.0**	**34.4**
HumeralEpiCon_Lat_Rt	Upper Extremity	6.2	18.1	34.4
Omphalion	**Torso**	**7.9**	**18.7**	**37.2**
ElbowJoint_Rt	Upper Extremity	8.4	20.3	46.4
HipJoint_Rt	**Torso**	**8.1**	**20.5**	**39.5**
AnkleJoint_Rt	**Lower Extremity**	**9.2**	**20.8**	**34.3**
Malleolus_Med_Rt	Lower Extremity	8.1	21.0	35.9
L5S1Joint	**Torso**	**7.7**	**21.3**	**42.4**
Malleolus_Lat_Rt	Lower Extremity	10.0	21.4	38.6
Wrist_Lat_Rt	Upper Extremity	6.3	22.0	49.1
Toe_Rt	Lower Extremity	12.0	23.6	42.1
Heel_Rt	Upper Extremity	9.3	23.6	38.7
WristJoint_Rt	**Upper Extremity**	**11.3**	**26.7**	**54.8**
HandMetCarp2_Med_Rt	Upper Extremity	11.0	29.4	69.3
	Min	2.5	8.0	20.5
	Mean	6.5	16.8	35.2
	Max	12.0	29.4	69.3

4. Discussion

This analysis demonstrates that surface landmark locations can be estimated reasonably well using only a global fitting technique based on an SBSM with 20 degrees of freedom. A kinematic linkage can be estimated from a single scan with joint location errors of less than 25 mm in most cases. Whether this accuracy is sufficient depends on the application. Due to the nature of the modeling methodology, the relationships between the fitted landmarks and fitted body shapes is consistent and based on the SBSM. Some of the discrepancy is due to error in the accuracy of the reference landmarks. That is, the predicted landmarks will occasionally be more accurate than the actual digitized landmarks, although we do not expect that to be common. The SBSM used in this work is not based on an articulated linkage with separate parameterization for posture and shape. A "posable" body shape model will improve the prediction of most landmarks, notably those on the distal extremities. Such a model will also allow landmark predictions for non-standardized postures.

One important concern is that the method does not provide any way to assess the accuracy of a particular prediction. For some of the landmarks, the 95th-percentile values are quite large, suggesting that for any particular scan the results for those landmarks could not be considered reliable. As noted above, a modeling methodology that accounted for pose would likely reduce errors in the extremities. Further work will be needed to determine if a small number of checks against manual measurements could be used to verify or improve performance for a particular case. For example, manual identification of a few problematic landmarks might allow the overall method to perform better.

The method will be most useful when the scan data are insufficient to perform an accurate manual landmark extraction. For example, an SBSM can be used to fit data from a Kinect sensor, producing predictions of standard anthropometric dimensions similar to those obtained when fitting data from a high-resolution laser scanner (Park et al. 2014; Reed and Park 2014). The current results suggest that reasonable landmark predictions could be obtained in these cases of low-resolution or incomplete data.

If more accurate landmark prediction is needed, the estimates produced by this method could be used to identify starting points for a local shape-based search algorithm (e.g., Han and Nam 2011). However, these algorithms work best when the landmark is associated with identifiable local shape features. Ultimately, landmarks that are not consistently located with respect to shape features will be difficult to obtain by any automated method.

The most important limitation of the current method is that the SBSM embodies a compact statistical representation of a particular population of body scans. Body shapes that are substantially different from those in the underlying dataset may not be fit well, resulting in larger errors. By using the same scans that were used to generate the SBSM, the current analysis eliminates these population differences. However, the resulting errors are likely to be smaller than would be the case with new scans. Future studies will examine the extension to other populations.

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