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Shape Up! Perception based body shape variation for data-driven crowds

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***Abstract*—Representative distribution of body shapes is needed when simulating crowds in real-world situations, e.g., for city or event planning. Visual realism and plausibility are often also required for visualization purposes, while these are the top criteria for crowds in entertainment applications such as games and movie production. Therefore, achieving representative and visually plausible body-shape variation while optimizing available resources is an important goal. We present a data-driven approach to generating and selecting models with varied body shapes, based on body measurement and demographic data from the CAESAR anthropometric database. We conducted an online perceptual study to explore the relationship between body shape, distinctiveness and attractiveness for bodies close to the median height and girth. We found that the most salient body differences are in size and upper-lower body ratios, in particular with respect to shoulders, waist and hips. Based on these results, we propose strategies for body shape selection and distribution that we have validated with a lab-based perceptual study. Finally, we demonstrate our results in a data-driven crowd system with perceptually plausible and varied body shape distribution.**

I. Introduction

Simulation of crowds is needed for many applications, which tend to fall into two main categories: those that need as accurate a representation of a population as possible, and those for which visual realism and plausibility are the most important criteria. For example, for games and movies, the most important criterion is usually that the crowd is perceived to be realistic and to behave plausibly, whereas when designing a city, stadium or theme park, the planners will need to be confident that the movements, behaviors and body sizes of the agents are representative of the real humans who will actually populate the future environment. However, for many planning applications a realistic visual representation of the crowd is also important as it helps to better understand the real-world data being visualized; and often for games and movies, the more representative the virtual crowd is of a real population, the more realistic and plausible the results will be. Therefore, a data-driven approach that takes real-world demographics into account will be useful in both cases.

One of the most important factors for perceived realism of crowds is the level of variety in the 3D models used to visualize the virtual humans present. The perception of varied human appearance and motion have previously been studied in this context [1], [2], but to date, body shape variation has received less attention. However, two of the most functionally relevant and visually salient features of any crowd are the shapes and sizes of the people in it, and their relative distributions: i.e., under normal circumstances most people will have shapes close to the median of the population, and there will be decreasing numbers of more atypical bodies present. For the majority of practical applications, it is not possible to individually model each member of a crowd, so a fixed budget of 3D models is used and replicated to generate a large crowd. Therefore, strategies are needed for choosing the optimal set of characters and distributing them realistically, while minimizing the risk of perceiving visual clones.

Approaches to varying body shapes for crowd simulation have been presented, and our work is very complementary to such approaches. For example, Thalmann and Musse [3] generate models with different body types that may be distributed according to any available statistics. However, the resulting models in such systems have tended to be more stylistic representations rather than physically accurate, and the perception of body shape differences or motion variation has not been considered. In the field of psychology, body perception studies have mainly been focused on gender and attractiveness (see [4] for a recent overview) and not on the distinctiveness of different body shapes. To our knowledge, this is the first study to perceptually evaluate the effects of body shape on distinctiveness and the first to use body shapes derived from real data to explore attractiveness.

In this paper, we present a data-driven approach to creating a crowd with representative and varied body shapes. We base our model generation and distribution strategies on body measurement and demographic data from the Civilian American and European Surface Anthropometry Resource (CAESAR) anthropometric database. From preliminary studies and observation, it was obvious that the most salient body shape differences are due to the height and girth (i.e., waist circumference) of the captured actors. However, closer to the median, other types of body shape differences are increasingly salient. As there are more individuals in this group than any other, more replications of each template model will be needed. We were interested in the following question and conducted two perceptual studies to explore it: *What are the most salient factors that affect the perception of body shape distinctiveness*

Note: This work was done while all authors were at Disney Research

Fig. 1. A set of varied models created using our data-driven body shape selection and creation approach.

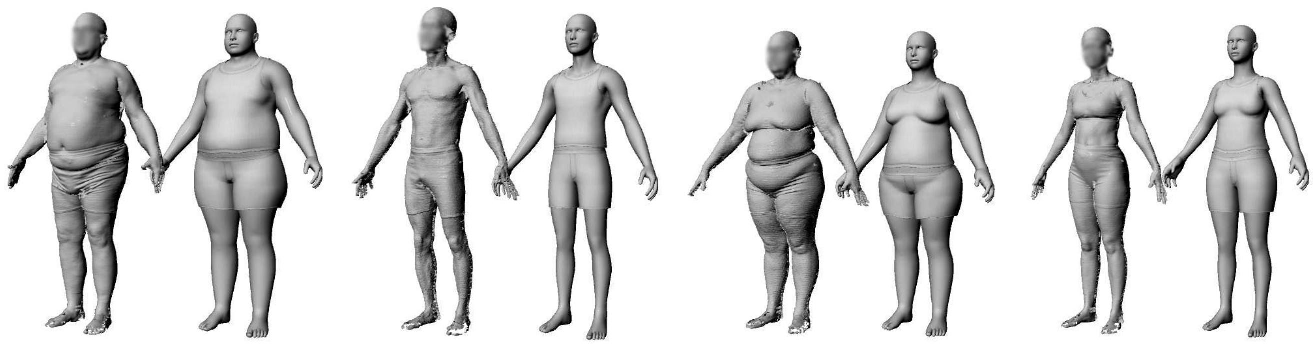

Fig. 2. Example pairs showing 3D models (right) generated from the CAESAR sample measurements (left).

for bodies close to the median height and girth?. We found that the most salient body differences are in size and upper-lower body ratios. Based on our results we strategically select of a number of models which, with clothing variation, can be used to optimize crowd variety with a limited budget of 3D models.

II. Related Work

McDonnell et al. [1], [5] have studied the effects of different types of appearance and motion variation on the perceptibility of visual clones in crowds, while Pražák et al. [2] demonstrated how only three different human motions replicated evenly through a crowd. Hoyet et al. [6] evaluated the distinctiveness and attractiveness of different types of human motion and found that average motions were the least distinctive and most attractive, consistent with findings in face perception [7]. Johnson and Tassinary [8], [9] studied the effects of both shape and motion on the perception of sex, gender, and attractiveness. Using mainly stylized silhouettes of human body shapes with varying waist to hip ratios, from exaggerated hourglass to tubular, they found that both shape (especially waist to hip ratio for women, and and motion information contributed to participants judgments of attractiveness. In particular, the waist-to-hip ratio (WHR) and hip sway are important for sex categorization and female attractiveness, while shoulders and their sway are most salient in men. Wellerdiek et.al. [10] recently explored how body shapes and postures affect perceived strength and power of male characters. See [4] for a thorough overview of recent research in body perception. apart from sex categorization, we are not aware of any studies where the distinctiveness of different body shapes has been explored.

Realistic body shape generation usually starts from real data, e.g. body scans [11] and measurements [12]. To generate a variety of body shapes, a body shape manifold or statistic model is typically learned from shape data [13]–[19]. Many assume a low dimensional manifold and dimensionality reduction techniques such as Principle Component Analysis (PCA) have been used to learn such representations. Once the manifold is learned, controlled body generation can be achieved by specifying part of the parameters and inferring the remainder. The parameter specification can be either done through sampling or user input [17], [20]. We use a commercial system (Daz3D) to generate our crowd characters, but our results would be applicable to models generated by any of these methods. With respect to crowd generation, our work is complementary to that of Thalmann and Musse [3], who generate models with different somatotypes (endomorph, mesomorph and ectomorph) which vary based mainly on the distribution of body fat, muscle and WHR. Then, these body types may be distributed according to any available statistics. Our model selection strategies and perceptual results could be used to improve the realism and representativeness of such a system.

III. Model selection and creation

To generate a set of 3D virtual human models for our data-driven crowd system, we need to select a representative sample of real body shape measurements and then create a realistic visual representation for each. Using a set of templates to be repeated throughout the crowd is efficient in terms of both

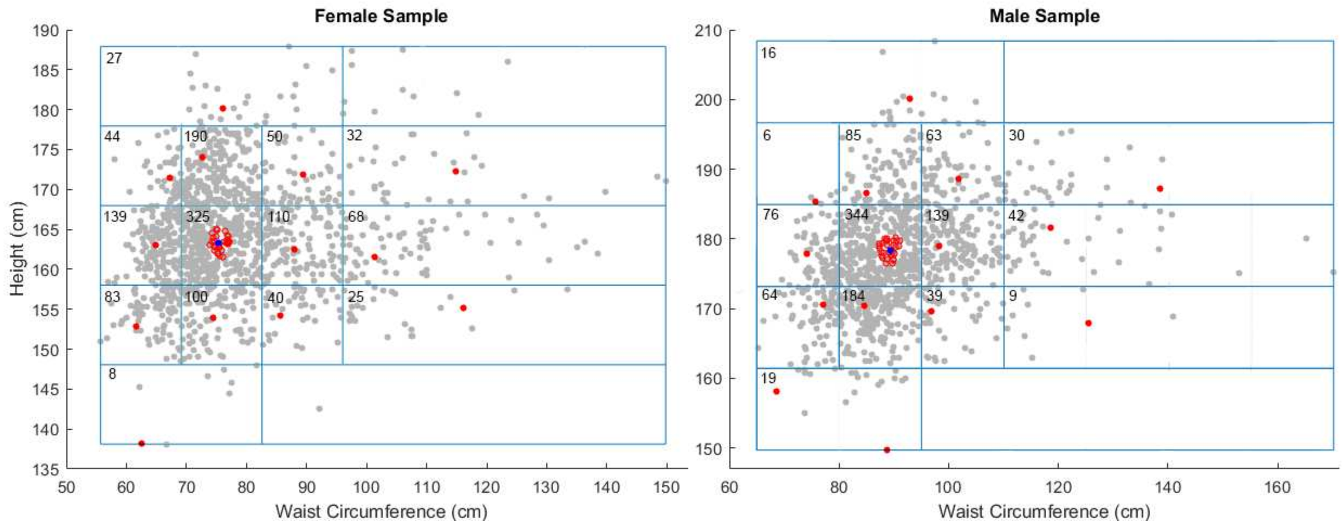

Fig. 3. The CAESAR database distribution of body heights and girths, with red dots showing the samples we picked to generate our template models; the red cluster in the median group shows the samples used to generate our experimental stimuli. The total number of samples within each quadrant is shown at its top left corner.

artist time and computational resources, as hardware instancing can be used to replicate selected models.

We use body measurement data sourced from the CAESAR project. The CAESAR data is based on stratified sampling of age, ethnicity and gender [21]. It contains demographic data, 3D range scan and measurements for 2391 US residents (52.9% female, 47.1% male, aged 18-65, with varied ethnicity). Height and girth (waist circumference) are used to pick reference samples, as we observe that these are by far the most salient features that differentiate people from each other, especially the more they deviate from the median. Then, we use 29 measurements for each sample (see Table I) to direct the creation of each template 3D human model. To represent the variation of the height and girth distribution as shown in Figure 3, we divide the height into 5 groups and girth into 7 groups respectively. We combine some of the outlier quadrants with small numbers of samples. Then 3 samples are drawn randomly from each quadrant at least r distance apart to avoid resemblance. After careful examination, one sample is kept to represent each bucket and is used as templates for generating the crowd. Due to the large sample count around the median (row 2, column 2), more distinctive samples are needed to maximize variety.

We use Daz3D to create realistic 3D models as it provides useful tools and morphs for creating body shapes, although any model generation tool with similar properties could be used. A set of mesh deformers P is used to morph the template mesh T to the desired measurement M_d. Thus we can generate models with measurements that closely match the CAESAR samples (see Figure 2). Note that some measurements require the avatar to be seated and in these cases we take the measurement from the template mesh by setting the joint rotation of the avatars. We wrote a script to apply the Daz3D mesh deformers $P = \{p_1, p_2, \cdots, p_n\}$ to morph the template mesh T using weights w_i. The post morph measurement M_t of the model is shown in 1. Our script adjusts the morphs iteratively and different measurements are recorded and compared against the desired measurements.

$$M_t = Measure(T + \sum_{i=0}^{n} w_i * p_i(T)) \tag{1}$$

To conform the avatar to the CAESAR subject measurements, we use conjugate gradient descent to minimize the error between the template mesh measurements and the desired ones: $\varepsilon = \|M_d - M_t\|$. A set of clothes for the template female and male meshes were created by an artist, and morphed in Daz3D to fit each of our selected models. The models are exported to Morpheme where retargeting and animation occurs, and finally they are imported into our crowd system. There they are rendered with color variation to create our final varied crowd simulation.

IV. Experiments

We conducted an online perceptual experiment to investigate the influence of body measurements on the perception of body shapes that are close to the median, as these are the templates that will be most often replicated in a crowd. We are particularly interested in the distinctiveness of the different body shapes, and as previous research shows how attractiveness is closely related, we also explore this metric. We also ran a laboratory-based experiment with a different method and smaller number of participants to gain further insights.

Stimuli: We select 32 male and female CAESAR samples with girth and height closest to the median (see Figure 3) and generate the 3D models that match their measurements, as described in Section III. We also generate average male and female models, as previous research in face and body motion

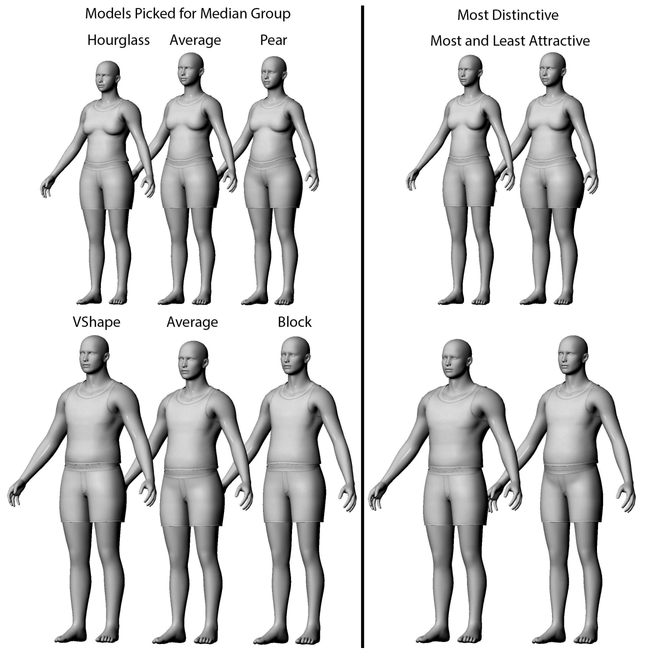

Fig. 4. Example models used in Experiment 1, sampled near the median: models picked to represent the median group (left); most distinctive and most/least attractive models (right).

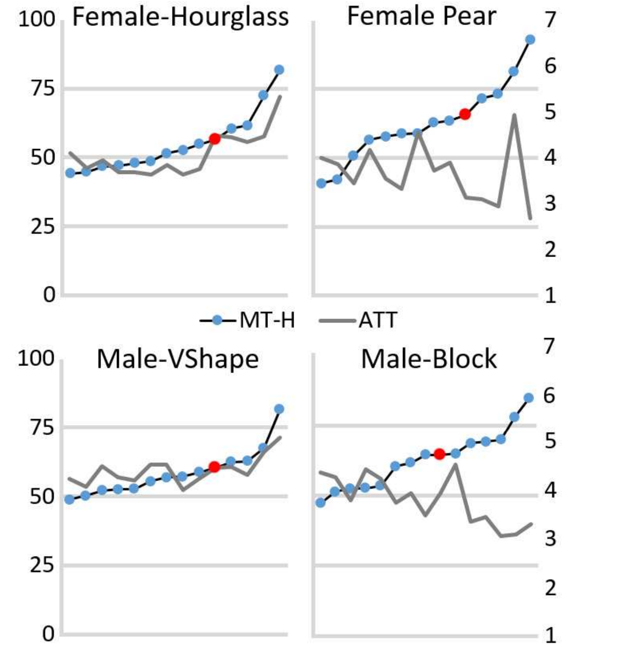

Fig. 5. Distinctiveness and Attractiveness results from Experiment 1: the red dots show the models we chose for the median group. The average Male and Female models were also chosen.

perception has shown that the average is usually amongst the least distinctive and most attractive. Some of the models used can be seen in Figure 4.

Method: In order to recruit as many participants as possible, we created several online surveys and posted the links on Mechanical Turk (MT). The HITs (Human Intelligence Tasks) were available only to 'master MTurkers', i.e., those who have a good performance track record. The study was approved by an institutional ethics review board and all participants provided informed consent. After first removing the responses of participants whose accuracy was too low (97 out of 479), we analyzed the results of 382 participants (206F/176M). Participants are shown a set of 99 pages, showing either all male or female models depending on the hit. A target model is shown on the left, and three smaller sample models are shown on the right. One of the sample models always matched the target, while the other two distractor models are chosen at random from the remaining 32. The task was to first rate the attractiveness of the target on a 7-point Likert scale from 1 (very unattractive) to 7 (very attractive); then to select the sample on the right that was the same as the target. Three repetitions of each target were shown, and the order of all pages was randomized. Each page was viewed for between 5-10 seconds so the experiment took approximately 15-20 minutes on average.

As it would be infeasible to generate all possible combinations of the 33 models as the time and/or number of participants needed would be prohibitive, we created two surveys each for male and female models. This means that each target was compared with a total of 12 distractor models. To ensure that we were not introducing bias with this limitation, we also ran a laboratory-based experiment with 17 participants (8M/9F). We followed a similar procedure to Hoyet et al. [6], where first a group of two side-by-side models was shown, then one target model, and the task was to indicate using one of two keys whether the target was Present or Absent from the previous group. In 50% of cases the model was present. One group of 9 participants viewed the Females and one group of 8 viewed the Males. There were 4 repetitions of each target model (2 present, 2 absent) and the distractor models were selected at random.

V. Results and Discussion

Analysis of Variance (ANOVA): To ensure that differences between models were indeed being noticed, we first performed repeated measures ANOVA on the average accuracy values and attractiveness ratings for the Mechanical Turk experiment. For accuracy (i.e., mean percentage of correct identifications), we found a main effect of Model for the 33 female models ($F(32,7680) = 50.06, p < .00005$)) and the 33 male models ($F(32,7520) = 30.65, p < .00005$). For the attractiveness ratings, we also found a main effect of Model for both Females ($F(32,7680) = 134.01, p < .00005$)) and Males $F(32,7520) = 136.83, p < .00005$). We also analyzed the factors of participant sex, age group and the self-reported display device used and found no significant effects.

We also performed repeated measures Analysis of Variance (ANOVA) on the accuracy results from the Laboratory experiment for Males and Females separately (a between-groups analysis showed no main effect of Model Sex). We found a main effect of both Female ($F(32,256) = 1.88, p < .005$))

and Male ($F(32,256) = 1.97, p < .00005$)) Models. We also evaluated whether presence or absence detection accuracy were different, and found that the former was significantly higher than the latter ($F(1,8) = 25.70, p < .0005$)). However, a two-way interaction between presence/absence and Model for the Female models ($F(32,256) = 1.49, p < .05$)) indicated that for some actors, absence detection was as good as presence detection, in one case (90%) whereas for others it was as low as 20%. There was much less variability in the scores for presence detection, with participants scoring above 80% on average.

Correlation Analysis: One of the main goals of our experiments was to determine which body shape features have the strongest effect on body shape perception. Hence we wished to assess the correlations between our results and the body measurements that we used to create the 3D models. Based on the observation that absence detection appeared to yield greater variability between models in the Laboratory experiment, we decided to use five metrics based on our results: the Mechanical Turk Hit rate (MT-H), which was calculated for each model as the percentage of times it was accurately matched; the Mechanical Turk False alarm rate (MT-F), i.e., for each model, we calculated the number of times it was wrongly selected divided by the number of times it was seen as a distractor (note that we could not do this on a per-participant basis, as the distribution of distractors was random); the Laboratory Hit (LAB-H) and False alarm (LAB-F) rates; and the average Attractiveness (ATT) ratings.

From viewing the images of the ranked models, it was clear that the women fell into one or other of two very visually distinct groups: those with symmetric upper and lower bodies (i.e., hour-glass) and those whose lower body was wider than the top (i.e., pear-shaped). Further analysis of the male images showed that the two main body types were V-shaped (i.e., shoulders larger than the lower body) and Block (upper and lower body widths more or less similar). Furthermore, from the cited literature we know that Waist to Hip Ratios (WHR) in women and Waist to shoulder or Chest Ratios (WCR) in men have been found to be strong predictors of Gender and Attractiveness. In order to determine whether the Females were more Hourglass or Pear-shaped, we also calculated WCR-WHR for the females (i.e., indicates symmetry between the upper and lower body). We also found high correlations with these measurements and factors as shown in Table II. We focus on the most salient features here, and include all other significant correlations in the supplemental material.

We selected Hourglass and Pear female models from those above and below the median of WCR-WHR; and VShape and Block males similarly, based on the median WCR. In Figure 5 we plot the average attractiveness (ATT) ratings against the average distinctiveness (MT-H) for these models. We can see that for the Hourglass group, attractiveness and distinctiveness are positively correlated (0.9), whereas for the Pear group they are not (the only reason there is not a significant negative correlation is due to an outlier pear model who was much thinner and lighter than all the others). Similarly, for the

Fig. 6. Close-up from the crowd simulation.

VShape males, there is a significant positive correlation between distinctiveness and attractiveness (0.8) and a negative one for the Blocks (-0.8). The most distinctive hourglass female was also the most attractive female overall, with the most distinctive pear the least attractive, with the same being true for the male VShape and Block models (see Figure 4:right).

Selection Strategy: These results confirm our intuition that these different body types are perceived very differently by participants, and hence we made our choice of the three representatives of the Median groups (Figure 4:left) by choosing the average Male and Female (both of whom had the median WCR or WCR-WHR and were amongst the least distinctive of all models), along with one of each of the Hourglass, Pear, VShape and Block models (chosen to be not overly distinctive but reasonably different from each other). For the non-median groups, as described in Section III, one sample is selected among three candidates to represent its body size group. As shown in Figure 1, we generated a set of crowd template for various size and shapes to simulate the real-world crowd.

VI. Conclusion

We have found that the most visually salient properties of body shape for models near the median are hips, chest and their ratios with waist size. Furthermore, the types of bodies that are defined by these ratios, i.e., V-shape or Block for males; Hourglass or Pear for females, are perceived differently. The template models that are selected using our perception based strategy are most representative of the median population in a crowd, which combined with the samples we selected from the other body sizes, allow the generation of a crowd that is both varied and representative of a real population (see Figure 6).

There are limitations to our work, in that we have only explored similarity for a very small group of body shapes, and we did not perform a full confusion analysis due to the nature of the experimental data. We also did not assess the overall variation perception of the full crowd, which is an interesting direction for future work.

References

[1] R. McDonnell, M. Larkin, S. Dobbyn, S. Collins, and C. O'Sullivan, "Clone attack! perception of crowd variety," *ACM Trans. Graph.*, vol. 27, no. 3, pp. 26:1–26:8, Aug. 2008. [Online]. Available: http://doi.acm.org/10.1145/1360612.1360625

[2] M. Pražák and C. O'Sullivan, "Perceiving human motion variety," in *Proceedings of the ACM SIGGRAPH Symposium on Applied Perception in Graphics and Visualization*, ser. APGV '11. New York, NY, USA: ACM, 2011, pp. 87–92. [Online]. Available: http://doi.acm.org/10.1145/2077451.2077468

[3] D. Thalmann and S. R. Musse, "Modeling of populations," in *Crowd Simulation*, 2012, ch. 3, pp. 31–290.

[4] K. L. Johnson and M. Shiffrar, *People watching : social, perceptual, and neurophysiological studies of body perception*. Oxford University Press, 2013.

[5] R. McDonnell, M. Larkin, B. Hernández, I. Rudomin, and C. O'Sullivan, "Eye-catching crowds: Saliency based selective variation," in *ACM SIGGRAPH 2009 Papers*, ser. SIGGRAPH '09. New York, NY, USA: ACM, 2009, pp. 55:1–55:10. [Online]. Available: http://doi.acm.org/10.1145/1576246.1531361

[6] L. Hoyet, K. Ryall, K. Zibrek, H. Park, J. Lee, J. Hodgins, and C. O'Sullivan, "Evaluating the distinctiveness and attractiveness of human motions on realistic virtual bodies," *ACM Trans. Graph.*, vol. 32, no. 6, pp. 204:1–204:11, Nov. 2013. [Online]. Available: http://doi.acm.org/10.1145/2508363.2508367

[7] G. Rhodes, "The evolutionary psychology of facial beauty," *Annual Review of Psychology*, vol. 57, pp. 199–226, 2006.

[8] K. Johnson and L. Tassinary, "Perceiving sex directly and indirectly: Meaning in motion and morphology," *Psychological Science*, vol. 16, no. 11, pp. 890–897, 2005.

[9] ——, "Compatibility of basic social perceptions determines perceived attractiveness," *PNAS*, vol. 104, no. 12, pp. 5246–5251, 2007.

[10] A. C. Wellerdiek, M. Breidt, M. N. Geuss, S. Streuber, U. Kloos, M. J. Black, and B. J. Mohler, "Perception of Strength and Power of Realistic Male Characters," in *Proceedings of the ACM SIGGRAPH Symposium on Applied Perception*, ser. SAP '15. New York, NY, USA: ACM, 2015, pp. 7–14. [Online]. Available: http://doi.acm.org/10.1145/2804408.2804413

[11] B. Allen, B. Curless, and Z. Popovi, "The Space of Human Body Shapes: Reconstruction and Parameterization from Range Scans," in *ACM SIGGRAPH 2003 Papers*, ser. SIGGRAPH '03. New York, NY, USA: ACM, 2003, pp. 587–594. [Online]. Available: http://doi.acm.org/10.1145/1201775.882311

[12] S. Wuhrer and C. Shu, "Estimating 3d human shapes from measurements," *Machine Vision and Applications*, vol. 24, no. 6, pp. 1133–1147, Dec. 2012. [Online]. Available: http://link.springer.com/article/10.1007/s00138-012-0472-y

[13] D. Anguelov, P. Srinivasan, D. Koller, S. Thrun, J. Rodgers, and J. Davis, "SCAPE: Shape Completion and Animation of People," in *ACM SIGGRAPH 2005 Papers*, ser. SIGGRAPH '05. New York, NY, USA: ACM, 2005, pp. 408–416. [Online]. Available: http://doi.acm.org/10.1145/1186822.1073207

[14] S.-Y. Baek and K. Lee, "Parametric human body shape modeling framework for human-centered product design," *Computer-Aided Design*, vol. 44, no. 1, pp. 56–67, Jan. 2012. [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/S0010448510002289

[15] Y. Zhang, J. Zheng, and N. Magnenat-Thalmann, "Example-guided anthropometric human body modeling," *The Visual Computer*, vol. 31, no. 12, pp. 1615–1631, Dec. 2015. [Online]. Available: http://link.springer.com/10.1007/s00371-014-1043-1

[16] N. Magnenat-Thalmann and H. Seo, "Data-driven approaches to digital human modeling," in *2nd International Symposium on 3D Data Processing, Visualization and Transmission, 2004. 3DPVT 2004. Proceedings*, Sep. 2004, pp. 380–387.

[17] N. Hasler, C. Stoll, M. Sunkel, B. Rosenhahn, and H.-P. Seidel, "A Statistical Model of Human Pose and Body Shape," *Computer Graphics Forum*, vol. 28, no. 2, pp. 337–346, Apr. 2009. [Online]. Available: http://doi.wiley.com/10.1111/j.1467-8659.2009.01373.x

[18] H. Seo and N. Magnenat-Thalmann, "An Automatic Modeling of Human Bodies from Sizing Parameters," in *Proceedings of the 2003 Symposium on Interactive 3D Graphics*, ser. I3D '03. New York, NY, USA: ACM, 2003, pp. 19–26. [Online]. Available: http://doi.acm.org/10.1145/641480.641487

[19] O. Freifeld and M. J. Black, "Lie Bodies: A Manifold Representation of 3d Human Shape," in *Computer Vision ECCV 2012*, ser. Lecture Notes in Computer Science, A. Fitzgibbon, S. Lazebnik, P. Perona, Y. Sato, and C. Schmid, Eds. Springer Berlin Heidelberg, Oct. 2012, no. 7572, pp. 1–14, dOI: 10.1007/978-3-642-33718-5_1. [Online]. Available: http://link.springer.com/chapter/10.1007/978-3-642-33718-5_1

[20] H. Seo and N. Magnenat-Thalmann, "An example-based approach to human body manipulation," *Graphical Models*, vol. 66, no. 1, pp. 1–23, Jan. 2004. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1524070303000778

[21] K. M. Robinette, S. Blackwell, H. Daanen, M. Boehmer, and S. Fleming, "Civilian american and european surface anthropometry resource (caesar), final report. volume 1. summary," DTIC Document, Tech. Rep., 2002.

Measurement	Explanation
Acromial Height, Sitting	Vertical difference from the sitting surface to the left acromion (shoulder)
Ankle Circumference	
Arm Length (Shoulder to Wrist)	
Hand Length	Distance from tip of middle finger to the end of the palm
Head Circumference	Circumference of the hand across knuckles of the index and little fingers
Hip Circumference, Maximum	Maximum hip circumference measured parallel to the standing surface
Hip Circumference, Maximum, Height	Vertical distance from standing surface to level of maximum hip circumference
Knee Height, Sitting	Vertical distance from foot support surface to the top of knee
Neck Base Circumference	Circumference of neck measured at the juncture of neck and shoulder
Shoulder Breadth	Horizontal distance between maximum protrusion of left and right shoulder
Sitting Height	Vertical distance sitting surface to the highest point of the head
Height	Vertical distance between the standing surface and the highest point of the head
Thigh Circumference	
Total Crotch Length	Distance from front to back of the waist passing through the crotch
Waist Circumference	
Waist Front Length	Distance from front neck base to front of waistline in the median plane
Waist Height	Vertical distance from waist to the standing surface
Weight	
Armscye Circumference	Circumference passing acromion (shoulder) and armpit
Chest Circumference	Circumference of the torso at nipple level
Bust/Chest Circumference Under Bust	
Buttock-Knee Length, Sitting	Horizontal distance from foremost point of kneecap to rearmost point of buttock
Chest Girth at Scye	Max circumference of torso passing under the arms and across upper chest
Crotch Height	Vertical distance between crotch and standing surface
Eye Height, Sitting	Vertical distance between sitting surface to outer corner of the eyes
Foot Length	Maximum distance from the rear of the heel to the tip of the longest toe
Hand Circumference	Circumference hand passing knuckles of index and little fingers

TABLE I

THE 27 CAESAR BODY MEASUREMENTS USED TO GENERATE OUR 3D MODELS

Female Correlations	All Females					Hourglass Females					Pear Females				
	MT-H	MT-F	LAB-H	LAB-F	ATT	MT-H	MT-F	LAB-H	LAB-F	ATT	MT-H	MT-F	LAB-H	LAB-F	ATT
MTurk Hit Rate (MT-H)	-	-0.5	-	-0.6	-	-	-0.8	-	-0.7	0.9	-	-	-	-0.6	-
MTurk False Alarm Rate (MT-F)	-0.5	-	-	0.6	-0.5	-0.8	-	-	0.8	-0.8	-	-	-	-	-0.5
Lab Test Hit Rate (LAB-H)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Lab Test False Alarm Rate (LAB-F)	-0.6	0.6	-	-	-	-0.7	0.8	-	-	-0.7	-0.6	-	-	-	-
Attractiveness Ratings (ATT)	-	-0.5	-	-	-	0.9	-0.8	-	-0.7	-	-	-0.5	-	-	-
Chest Circumference (mm)	-	0.4	-	0.4	-0.4	-	-	-	-	-0.6	-	0.8	-	-	-0.7
Hip Circumference, Maximum (mm)	-	0.5	-	-	-0.9	-0.7	0.9	0.1	0.6	-0.9	-	-	-	-	-0.9
Waist Circumference, Pref (mm)	-	-	-	-	-0.6	-	-	-	-	-	-	-0.6	-	-	-0.7
Waist to Chest Ratio (WCR)	-	-0.4	-	-0.5	-	-	-	-	-	0.6	-	-0.8	-	-	0.6
Waist to Hip Ratio (WHR)	-	-0.6	-	-	0.8	0.7	-0.9	-0.2	-0.7	0.8	-	-	-	-	0.8
WCR-WHR	0.4	-	-	-	-0.4	-	-	-	-	-	0.6	-	-	-	-

Male Correlations	All Males					VShape Males					Block Males				
	MT-H	MT-F	LAB-H	LAB-F	ATT	MT-H	MT-F	LAB-H	LAB-F	ATT	MT-H	MT-F	LAB-H	LAB-F	ATT
MTurk Hit Rate (MT-H)	-	-0.8	-	-0.5	-	-	-0.9	-	-0.5	0.8	-	-0.7	-	-	-0.8
MTurk False Alarm Rate (MT-F)	-0.8	-	-0.4	0.6	0.4	-0.9	-	-	0.6	-0.7	-0.7	-	-0.6	-	0.6
Lab Test Hit Rate (LAB-H)	-	-0.4	-	-	-	-	-	-	-	0.5	-	-0.6	-	-	-
Lab Test False Alarm Rate (LAB-F)	-0.5	0.6	-	-	-	-0.5	0.6	-	-	-0.6	-	-	-	-	-
Attractiveness Ratings (ATT)	-	0.4	-	-	-	0.8	-0.7	0.5	0.6	-	-0.8	0.6	-	-	-
Chest Circumference (mm)	-0.1	0.4	-0.1	0.4	0.8	0.8	-0.7	0.4	-0.6	0.9	-0.4	0.7	-0.4	0.4	0.6
Waist Circumference (mm)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Hip Circumference, Maximum (mm)	-	-	-	0.5	-	-	-	-	-	-	-	-	-	-	-
Waist to Chest Ratio (WCR)	0.2	-0.3	0.1	-0.4	-0.8	-0.8	0.8	-0.2	0.6	-0.8	0.6	-0.6	0.3	-0.3	-0.7

TABLE II

ALL SIGNIFICANT CORRELATIONS BETWEEN THE BODY MEASUREMENTS AND OUR FIVE METRICS: HIT (H) AND FALSE ALARM RATES (F) FOR OUR TWO EXPERIMENTS (MT AND LAB), AND ATTRACTIVENESS RATINGS (ATT). ALL OTHER SIGNIFICANT CORRELATIONS ARE PROVIDED IN THE SUPPLEMENTARY MATERIAL.