Proceedings of the Twenty-Second Innovative Applications of Artificial Intelligence Conference (IAAI-10)

Design Privacy with Analogia Graph

Yang Cai
Carnegie Mellon University
ycai@cmu.edu

Joseph Laws
Carnegie Mellon University
Joe.laws@gmail.com

Nathaniel Bauernfeind
Carnegie Mellon University
Nate.bauernfeind@gmail.com

Abstract

Human vision is often guided by instinctual commonsense such as proportions and contours. In this paper, we explore how to use the proportion as the key knowledge for designing a privacy algorithm that detects human private parts in a 3D scan dataset. The Analogia Graph is introduced to study the proportion of structures. It is a graph-based representation of the proportion knowledge. The intrinsic human proportions are applied to reduce the search space by an order of magnitude. A feature shape template is constructed to match the model data points using Radial Basis Functions in a non-linear regression and the relative measurements of the height and area factors. The method is tested on 100 datasets from CAESAR database. Two surface rendering methods are studied for data privacy: blurring and transparency. It is found that test subjects normally prefer to have the most possible privacy in both rendering methods. However, the subjects adjusted their privacy measurement to a certain degree as they were informed the context of security.

1. Introduction

The rapidly growing market of three-dimensional holographic imaging systems has created significant interest in possible security applications. Current devices operate using a millimeter wave transceiver to reflect the signal off the human body and any objects carried on it. The device penetrates less dense items, like clothing and hair. Unlike current metal detectors, the system can also detect non-metal threats or contraband, including plastics, liquids, drugs and ceramic weapons hidden under clothing as seen in Figure 1.

The technology has also been used to create body measurements for custom-fit clothing. The holographic imager creates a high-resolution 3-D body-scan, allowing shops to provide tailored measurements to designers or provide recommendations on best-fit clothing. These high resolution scanned images reveal human body details and have raised privacy concerns. Airport and transport officials in several countries are refusing to run a test trial with the scanners until a more suitable way to conceal certain parts of the human body is found.

The scanner creates a three-dimensional point cloud around the human body. Since the millimeter wave signal cannot penetrate the skin, a three-dimensional human surface can be found. Furthermore, since the typical pose of a subject is standing, with arms to the side, we can segment the 3-D dataset into 2-D contours, which significantly reduces the amount of data processing. The goal of this study is to develop a method that can efficiently find and conceal the private parts of a human.

Figure 1. The 3D holographic imaging systems can detect contraband beneath clothing, yet they raise privacy concerns due to the detailed human figure that is revealed.

2. Related Work

From a computer vision point of view, detecting features from 3D body scan data is nontrivial because human bodies are flexible and diversified. Function fitting has been used for extracting special landmarks, such as ankle joints, from 3D body scan data [26, 27], similar to the method for extracting special points on terrain [14]. Curvature calculation is also introduced from other fields such as the sequence dependent DNA curvature [9]. These curvature calculations use methods such as chain code [21], circle fit, ratio of end to end distance to contour length, ratio of moments of inertia, and cumulative and successive bending angles. Curvature values are calculated from the data by fitting a quadratic surface over a square window and calculating directional derivatives of this surface. Sensitivity to the data noise is a major problem in both function fitting and curvature calculation methods because typical 3D scan data contains loud noises. Template matching appears to be a promising method because it is invariant to the coordinate system [26, 27]. However, how to define a template and where to match the template is challenging and unique to each particular feature.

In summary, there are two major obstacles in this study: robustness and speed. Many machine learning algorithms are coordinate-dependent and limited by the training data space. Some algorithms only work within small bounding boxes that do not warrant an acceptable performance since the boxes need to be detected prior to the execution of the algorithm and are, often, not amenable to noise. For example, if a feature detection algorithm takes one hour to process, then it is not useful for a security screening system. In this paper, we present a fast and robust algorithm for privacy protection.

3. Analogia Graph

Analogia (Greek: αναλογία, analogia "proportion") Graph is an abstraction of a proportion-preserving mapping of a shape. Assume a connected non-rigid graph G, there is an edge with a length u. The rest of edges in G can be normalized as $p_i = v_i / u$. Let X and Y be metric spaces d_X and d_Y. A map $f: X \rightarrow Y$ is called Analogia Graph if for any $x,y \in X$ one has $d_Y(f(x),f(y))/u = d_X(x,y)/u$.

Analogia Graph is common in arts. The Russian Realism painter Ropin said that the secret of painting is "comparison, comparison and comparison." To represent objects in a picture realistically, a painter has to constantly measure and adjust the relationship among objects. "You should use the compass in your eyes, but in your hands," Ropin said. Instead of using absolute measurement of the distances and sizes, artists often use intrinsic landmarks inside the scene to estimate the relationships. For example, using number of heads to estimate the height of a person and using number of eyes to measure the length of a nose, and so on. Figure 2 is an Analogia Graph of a human body.

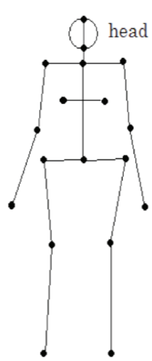

Figure 2. Analogia Graph of a human figure.

Why Analogia Graph is important to our visual experience? Most of us are not aware that our eyes make rapid movements, so called *saccades*, at four times per second, which help to cover the full visual field. When people are looking at an object, the saccades follow the shape of the object similar to the way as blind people obverse an object by touching it. The trajectory of those saccadic movements forms a graph. According to the philosopher George Berkeley, *seeing is like touching at a distance*. This idea was resurrected by neural scientist Rodney Cotterill [28]. Driven by our instinct, vision enables us to react quickly from dangerous situations at a distance. Analogia graph is one of the visual reasoning routines based on instinctual knowledge and heuristics about objects such as human figures.

4. Proportions as Commonsense

We often take everyday commonsense for granted. Our knowledge about proportions is an excellent example. Intrinsic proportion measurements have also been used in architecture and art for thousands of years. Roman architect Vitruvius said that the proportions of a building should correspond to those of a person, and laid down what he considered to be the relative measurements of an ideal human. Similarly in art, the proportions of the human body in a statue or painting have a direct effect on the creation of the human figure. Artists use analogous measurements that are invariant to coordinate systems. For example, using the head to measure the height and width of a human body, and using an eye to measure the height and width of a face.

Height of an adult human body:	6–8 heads
Width of an adult human body:	2-3 heads
Location of chest area:	2-3 heads
Length of an arm:	4 heads

Using this artistic approach, we can create a graph where nodes represent regions and are connected to each other by edges, where the weight is defined as the distance between the nodes in proportion to the height of the head. Initially, we stretch the graph such that it overlays the entire body. We then create a link between each node and its respective counterpart. We link the head, shoulders, arms, elbows, hands, neck, breasts, waist, legs, knees, and feet to their respective regions. There is some tweaking required to assure that the waist region does indeed cover that area. Here we run a quick top-down search through the plane slices until there is at least two disjoint areas, which we consider to be the middle of the waist. This change also makes modifications to where the knees and breasts are, and how large their regions are.

Figure 3 shows a sample of the vertical proportion in a typical art book and the actual distribution of head to body proportions calculated from our CAESAR data set [1]. The results show that on average a human is six to eight heads tall. Based on our observations from one hundred 3D scan data sets of adults from sixteen to sixty-five years old, including subjects from North America, Europe and Asia, we found that the length of one and a half head units from the bottom of the head is enough to cover the chest area. In addition, the chest width is about three heads wide. Figure

4 shows an output from the intrinsic proportion calculation based on the sample from CAESAR database.

We take into account that not every subject has all four limbs. Our algorithm still accepts the scan if such items are missing, such as half an arm or half a leg. It is also amenable to a complete loss of an arm or leg by looking at the expected ratio versus the real ratios when determining the length of each particular region.

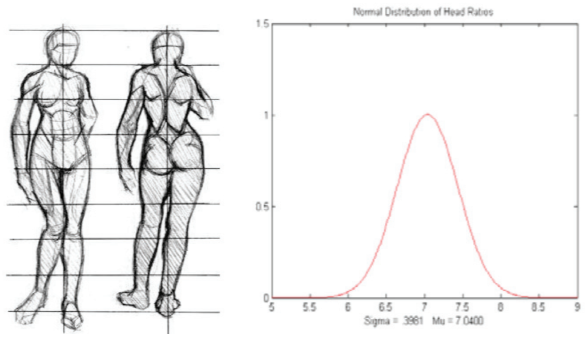

Figure 3. Body height measured by head example (left), normal distribution of heads per body (right).

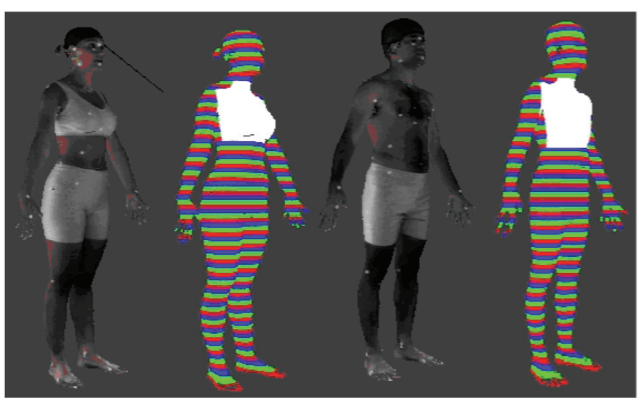

Figure 4. Detected waist region in white.

However convenient to find such broad range of regions, it is not possible to expand this algorithm to find more details like specific fingers, toes, ankle joints, or the nose. These searches are more complicated and require additional template fitting per feature and would significantly reduce the algorithm's run time. We found that the intrinsic proportion method can reduce the search space by an order of magnitude. For example, our algorithm is 60 times faster than the record in the study [27]. In addition, it reduces the risk of finding the local optima while searching the whole body.

5. Template Matching

Our objective is to reduce the search space of the 3D body scans with Analogia Graph. In this study, we assume that the body is standing with the arms hanging to the sides in a non-concealing way. If the arms are too close to the body, then the holograph imager cannot produce an accurate representation of the body and items on the side of the body could be completely missed because the area between the arm and the body would not be clearly defined. We start by dividing the 3D data points into 2D slices. The points are 'snapped' to the nearest planes enabling us to convert a 3D problem to a 2D one. Examining each slice from top to bottom is rather an expensive process. Here we present a novel approach to reduce the search space by making use of intrinsic proportions. It is a relative measurement that uses an object in the scene to measure other objects [22].

Template matching is image registration that matches a surface, of which all relevant information is known, to a template of another surface. The matching of the two surfaces is driven by a similarity function. We need to solve two problems before applying template matching on the regions of interest. First, a suitable template has to be created. Second, a similarity function has to be selected so that a minimization algorithm can align the template onto the region of interest. For each plane of the scan data, the back of the body contour can be removed. By assigning the X-axis between the two points with the greatest distance, we can obtain the front part of the body contour. This aligns the subject to our template such that the matching is never attempted on a twisted or backward body. We then use three Radial Basis Functions (RBF) to configure the template for a female breast pattern.

$$Y(x) = \sum_{i=1}^{3} a_i \bullet \exp(-(x - s_i)^2 / \sigma_i^2) \tag{1}$$

where, $a = a_1 = a_2$, $b = a_3$, $s = s_1 = s_2$, and $s_3 = 0$. We use non-linear regression on the variables *a, b, u* and *s* to match the template with the scan data. Figure 5 shows the matching results for the female and male samples.

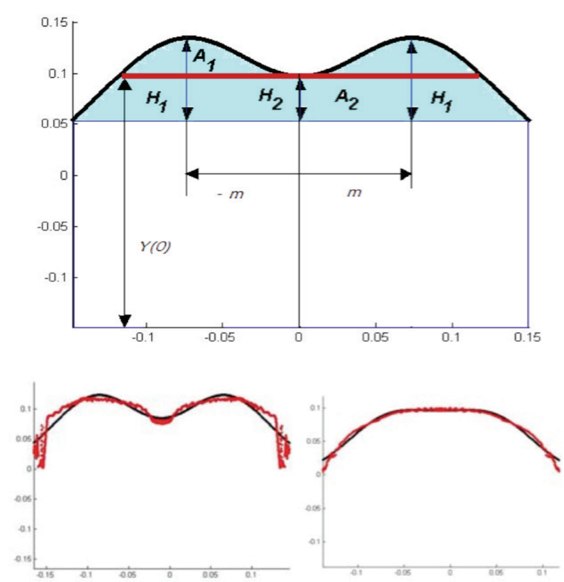

Figure 5. Variable definitions for the breast template (up), matching results for the female sample (bottom left) and male sample (bottom right). The solid black curves are the template contours. The red points are the 3D scan data.

Most shape descriptions depend on particular coordinate systems and particular viewpoints, meaning that the algorithm can only work within the same 'space' as the training data. Our shape invariant measurements are aimed to compute the shape properties from the ratio, rather than absolute values. This reduces this dependency onto a particular pose that is easily controlled, as opposed to creating an algorithm for each available holograph imager.

Template matching not only filters out noises, but also describes the characteristics of a shape. We define the following invariant similarity functions to the coordinate system: height ratio and area ratio. The height ratio is defined as:

$$H_r = \frac{H_2}{H_1} \tag{2}$$

The area ratio is defined as the ratio of the area of curvature feature *(A_1)* to the total area *(A_2)* of the model by the following formula:

$$A_r = \frac{A_2}{A_1} \tag{3}$$

where,

$$A_2 = \int_l \sum_{i=1}^{3} a_i \bullet \exp(-(x-s_i)^2/\sigma_i^2)\ dx \tag{4}$$

$$A_1 \approx A_2 - 4m \bullet Y(0) \tag{5}$$

We use the Taylor series to find an appropriate approximation of the areas, for example:

$$A_2 = \sum_{i=1}^{3} a_i \bullet (1 - (x-s_i)^2 + \frac{(x-s_i)^4}{2!} + \frac{(x-s_i)^6}{3!} + \frac{(x-s_i)^8}{4!} + \ldots \tag{6}$$

It is necessary to attempt to match the template to each slice within the detected area, where only the greatest ratio of curvature is kept and used as the final result.

Here we use the parameterized template to model the human body curvatures. The following is the heuristic template match process:

```
Calculate the length of the head;
Locate the chest area by moving down δ head;
For slice = 1 to k;
        Snap the points to the nearest slice grid;
        Find the slice at the center of the chest;
        Terminate the iteration;
End slice;
Minimize the Euclidean Distance between the
        template and the data points at the slice;
Calculate the ratios Hr and Ar;
Determine the gender based on threshold;
```

6. Results

We tested our algorithm with a subset of the CAESAR database, which contains 50 males and 50 females ages 16-65, where 50 of them are North American, 24 are Asian, and 26 are from the European survey of Italy and the Netherlands. We tested our algorithm to find the breast features from known female and male scan data samples. Figure 6 shows these test results. From the plot, we can see that there are two distinguishable groups, which happen to coincide with the particular gender of each subject. The male subjects tend to have no curvature features and lie in the lower left range of the graph, whereas female subjects do demonstrate these curvature features and lie in the upper right range of the graph. There is a 'dilemma' zone where some over-weight males do have the curvature features. However, the over-lapped zone is small, less than eight percent of the total one hundred samples.

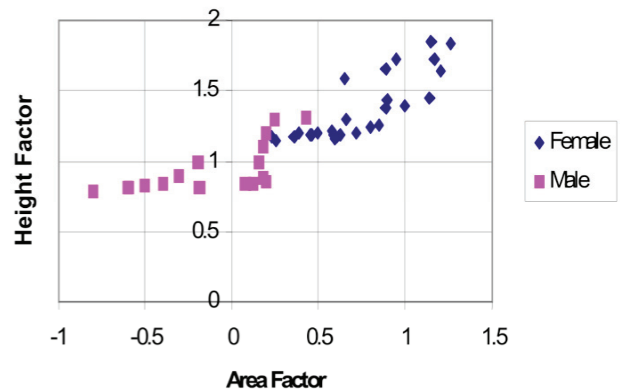

Figure 6. Classification test results from CAESAR samples.

After the area and height factors have been calculated, we determine the feature area. Once we find the feature area, we reduce the polygon resolution so that the area is blurred. Figure 7 shows the results of the blurring effects in wireframe mode. Figures 8–9 show scales of blurring and transparency respectively.

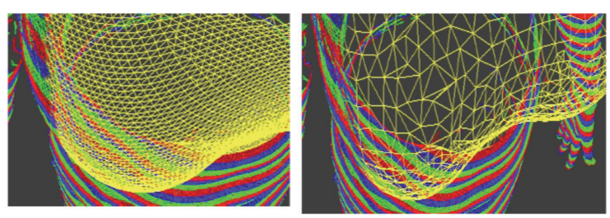

Figure 7. The blurred scale.

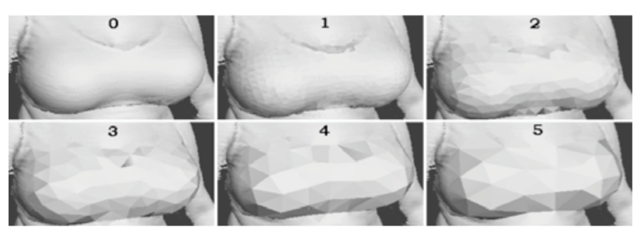

Figure 8. The blurred surface rendering.

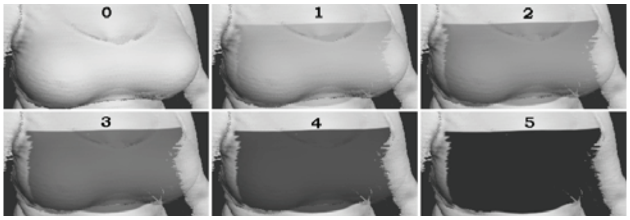

Figure 9. The transparent scale.

7. Usability Study

Here let's investigate the usability of the privacy-aware algorithm. It is common knowledge that most people disagree on how much privacy can be given up for security. It was also another goal of ours to find out what most end-users would give up for that security. We ran two sets of two tests. Both sets included Figure and Fig as scales where the subjects rated which they preferred given the particular privacy concerns discussed prior to showing them the images. Ten random males and ten random females, whose ages are from 19 to 53, including students, faculty members and residents, were interviewed in the lab.

In the first study, subjects were told to imagine that they (or their girlfriend or wife) were in an airport and had to walk through the three-dimensional holographic scanner, mentioned in the introduction, and that the resulted images would be displayed to the security officials on duty. They were asked to choose a blurred image, or a transparent image. The men averaged a 4.8 on the blurred scale and a 4.2 on the transparent scale. The women averaged a 4.0 on the blurred scale and a 3.8 on the transparent scale.

Table 1. User preferences without security concerns.

Gender	Method	Rank										Ave
Male	Blurring	5	5	5	5	4	5	4	5	5	5	4.8
	Transparency	4	4	4	4	4	5	4	4	4	5	4.2
Female	Blurring	5	5	4	4	4	3	4	4	4	3	4.0
	Transparency	5	5	4	4	4	4	3	3	4	2	3.8

Table 2. User preferences with security concerns

Gender	Method	Rank										Ave
Male	Blurring	4	3	3	3	5	3	2	3	3	3	3.2
	Transparency	3	3	3	3	4	3	2	3	3	2	2.9
Female	Blurring	2	3	3	2	2	2	2	3	3	3	2.5
	Transparency	2	2	3	2	2	2	2	3	3	2	2.3

In the second study, subjects were told to rate their privacy on a scale versus security in a context which not only were they being observed, but others who may or may not be attempting to conceal weapons were also being observed. Such oddities as a pocket knife between the breasts would be more difficult to detect in a very blurred mesh. The men averaged a 3.2 on the blurred scale and a 2.9 on the transparent scale. The women, on the other hand, averaged a 2.5 on the blurred scale and a 2.3 on the transparent scale.

The two studies display how different contexts can affect a subject's response and personal choice. It is clear that in the first study the men were more concerned about having their girlfriends/wives seen than were the women concerned with how much they were seen. In the second study, it is clear that nearly every subject gave up more of their privacy for the benefits of security and the safety of their travels.

8. Conclusions

In this paper, we explored an algorithm to recognize body feature areas and hide them to protect a subject's privacy. The intrinsic human proportions are used to drastically reduce the search space and reduce the chance of local optima in detection. The Radial Basis Function is used as the feature template whose parameters are determined by non-linear regressions along each contour slice. Feature factors of the height and area are then used to classify the curvature feature as being male or female. The relative measurements are coordinate invariant, meaning that the algorithm is robust and is capable to work with multiple data sets. With the non-linear regression method, the template matching is effective and convergent within a given error range. We have tested one hundred body scans from the CAESAR database and found that the algorithm can successfully classify the male and female bodies based on the curvature features at a rate of over ninety percent.

Two surface rendering methods are studied for data privacy: blurring and transparency. It is found that test subjects normally prefer to have the most possible privacy in both rendering methods. However, the subjects adjusted their privacy measurement to a certain degree as they were informed the context of security.

Our future work includes the development of more robust coordinate invariant methods to detect more predefined body features, and to calibrate the algorithms for both protecting privacy and detecting concealed weapons. Ultimately, we will work with the real field data to fine-tune the algorithms.

9. Acknowledgement

This project is sponsored by National Science Foundation, US Army Research Office (ARO) and Cylab.

10. References

[1] Anthropometry Resource (CAESAR), Final Report, Volume I: Summary, AFRL-HE-WP-TR-2002-0169, United States Air Force Research Laboratory, Human Effectiveness Directorate, Crew System Interface Division, 2255 H Street, Wright-Patterson AFB OH 45433-7022 and SAE International, 400 Commonwealth Dr., Warrendale, PA 15096.

[2] Bansal, M. Analysis of curvature in genomic DNA. http://www.ibab.ac.in/bansal.htm

[3] Besl, P.J. and R. C. Jain, "Three-dimensional object recognition," ACM Comput. Surveys, vol. 17, no. 1, pp. 75-145, Mar. 1985.

[4] Brady, M., J. Ponce, A. Yuille, and H. Asada, "Describing surfaces," *Comput. Vision, Graphics, Image Processing*, vol. 32, pp. 1-28, 1985.

[5] Calladine C.R. Gaussian curvature and shell structures. The Mathematics of Surfaces, Oxford University Press, pages 179-196, 1985.

[6] Chen, H.H. and T. S. Huang, "Maximal matching of two three-dimensional point sets," in *Proc. ICPR*, Oct. 1986.

[7] Coleman, R., M. Burr, D. Souvaine, A. Cheng, An intuitive approach to measuring protein surface curvature, Proteins: structure, function and bioinformatics, vol. 61, no.4, pp 1068-1074

[8] Fan, T.G., G. Medioni, and R. Nevatia, "Description of surfaces from range data using curvature properties," in *Proc. CVPR*, May 1986.

[9] Forsyth, D.A. and Fleck, M. M., Automatic detection of human nudes, *International Journal of Computer Vision* , Vol. 32, No.1, 63-77, August, 1999

[10] Forsyth, D.A. and Fleck, M.M., Body Plans, Proc. CVPR-97, 678-83, 1997.

[11] Forsyth, D.A.; Fleck, M.M., Identifying nude pictures, *Proceeding. Third IEEE Workshop on Applications of Computer Vision*. 103-108, 1996.

[12] Goldgof, D.B., T. S. Huang, and H. Lee, "Curvature based approach to terrain recognition," Coord. Sci. Lab., Univ. Illinois, Urbana-Champaign, Tech. Note ISP-910, Apr. 1989.

[13] Goldgof, D.B., T. S. Huang, and H. Lee, "Feature extraction and terrain matching," in Proc. IEEE Comput. Soc. Conf. Comput. Vision Pattern Recognition, Ann Arbor, MI, May 1988.

[14] Goldgof, D.B., T.S.Huang, H.Lee, A Curvature-Based Approach to Terrain Recognition, November 1989 (Vol. 11, No. 11) pp. 1213-1217

[15] Gordon G. Face recognition based on depth and curvature features. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Champaign Illinois), pages 108-110, 1992.

[16] Haralick, R.M., S.R. Sternberg, and X. Zhuang, "Image analysis using mathematical morphology," IEEE Trans. Pattern Anal. Machine Intell., vol. PAMI-9, no. 4, pp. 532-550, 1987.

[17] http://www.dace.co.uk/proportion.htm

[18] Jones, P.R.M. and Rioux, M. 1997. Three-dimensional surface anthropometry: applications to the human body. Optics and Lasers in Engineering, 28, 89-117.

[19] Li, P., Corner, B.D., Paquette, S. Evaluation of a surface curvature based landmark extraction method for three dimensional head scans. International Ergonomics Conference, Seoul, 2003.

[20] Liu, X. W. Kim, and B. Drerup, 3D Characterization and Localization of Anatomical Landmarks of the Foot, Proceeding (417), Biomedical Engineering , Acta Press, 2004, http://www.actapress.com/PaperInfo.aspx?PaperID=16382

[21] M.M. Fleck, D.A. Forsyth and C. Bregler, Finding naked people, *Proc. European Conf. on Computer Vision* , Edited by: Buxton, B.; Cipolla, R. Berlin, Germany: Springer-Verlag, 1996. p. 593-602

[22] Ratner, P. 3-D human modeling and animation, John Wiley & Sons, Inc. 2003

[23] Robinette, K.M., Blackwell, S., Daanen, H.A.M., Fleming, S., Boehmer, M., Brill, T., Hoeferlin, D., Burnsides, D. 2002. Civilian American and European Surface Anthropometry Resource

[24] S. Ioffe and D.A. Forsyth, Probabilistic methods for finding people, *International Journal of Computer Vision* , Volume 43, Issue 1, pp45-68, June 2001

[25] Sonka, M. et al. Image processing, analysis and machine vision, PWS Publishing, 1999

[26] Suikerbuik C.A.M. Automatic Feature Detection in 3D Human Body Scans. Master thesis INF/SCR-02-23, Institute of Information and Computer Sciences. Utrecht University, 2002

[27] Suikerbuik, R., H. Tangelder, H. Daanen, A. Oudenhuijzen, Automatic feature detection in 3D human body scans, Proceedings of SAE Digital Human Modeling Conference, 2004, 04-DHM-52

[28] Kringelbach, M.L. The Pleasure Center, Oxford University Press, New York, 2009