Automatic Generation of Personalized Human Models based on Body Measurements

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Abstract

The objective of this study is to evaluate the (number of) input parameters (set of anthropometrical features) on the accuracy of human body models for integration into ergonomic design of sleep systems. A generic surface model is used that can be personalized based on a chosen set of anthropometric input parameters. The modeling framework consists of three steps: construction of a database, extraction of the influencing parameters and model generation. For our database a total of 60 subjects participated in a series of body measurements. 29 one-dimensional body measures, including sex, age and weight, were manually measured. Afterwards, the MakeHuman project interface is used to select some of the measured body parameters as model inputs and return a corresponding body shape model as an output, based on morphing techniques. Results indicate that when using six input parameters - namely sex, age, length, weight, pelvis width and acromion circumference - the resulting models have sufficient accuracy (root mean square error of 5.0 ± 3.5 %) while still giving a smooth representation of the human body as needed for posture recognition in sleep ergonomics.

Keywords: Body measurements

1. Introduction

Although our living environment is evolving towards high-tech systems to provide optimal comfort, little research focuses on the sleep environment. However, proper body support – which is posture-dependant – plays an important role in spinal recovery. Therefore a new approach in the development of state-of-the-art sleep systems consists of continuously monitoring posture, based on mattress indentation, to estimate spinal shape (Verhaert et al., 2011a; Verhaert et al., 2011b).

Previous research showed that main postures - lateral, supine or prone position - can be recognized from mattress indentation measurements based on a limited number of features in 92% of the cases when using support vector machines (Verhaert et al. 2009). The problem arises when people adopt a so-called *in-between posture* (a combination of the main postures, e.g. lying in a lateral position while the shoulders are turned towards a prone or supine position). Since persons' body contours vary a lot, it appears to be very difficult to recognize these intermediate postures based on a limited set of features. Therefore, a personalized human model is needed that can serve as a base model for a particle filter to estimate the exact posture and position of a person in bed and the resulting spinal shape. Similar research, based on pressure images instead of indentation measurements, has shown that it is possible to estimate the posture and position in bed using a personalized human model (Harada et al., 2000). The models should meet some specific requirements: first of all such models must be *smooth* and sufficiently *accurate* for simulating mattress indentation but also *simple* to make the simulations treatable and to be able to obtain real-time posture-feedback during the night. On the other hand it is also desirable for the models to require as less body measures as possible to assure a wide applicability of the work (no need for expensive 3D whole body scanners or a lot of measuring time) for spinal shape follow-up during the night.

A lot of digital human models (DHM's) have been described in literature, most of them in visualization (e.g. try-on clothing) and animation environments (Magnenat-Thalmann, 2004). More recently human body models are used for simulation and follow-up of real-life situations e.g. in markerless human motion tracking (Harada et al., 2001; Azad et al., 2004) and ergonomics (Woldstad, 2006; Verhaert et al., 2011). Human models can be categorized in three groups: (1) skeleton models, (2) body shape (surface) models and (3) hybrid models. Skeleton

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models describe the structure of joints and links of the human body in order to simulate moving, whereas shape models describe the surface mesh of the human body. Surface models can further be divided into several categories based on their modeling technique: (1) Direct models, based on e.g. 3D whole body scans (Ma et al., 2004), (2) Indirect models, generated by deformation of a general template (Kasap and Magnenat-Thalmann, 2007), (3) Image/Video based models (Buys et al., 2011) , and (4) Statistics based models (Baek S-Y 2011). 3D whole body scanning methods are the most accurate, but require expensive scanning equipment and extensive data processing, which does not meet our requirements. Instead, indirect models based on a general template will be used.

2. Materials and Methods

2.1. Data collection

A total of 60 subjects participated to this study (30 men and 30 woman, mean age of 26.4 ± 10.0 y, and mean BMI of 22.6 ± 3.15). For each subject a set of 29 one-dimensional body measures were manually measured, including heights, widths, depths and circumferences at different anatomical sites such as acromion, shoulder, breast, waist, pelvis, hip and thigh (see Figure 1), as well as sex, age and weight. No information was collected regarding parameters with little importance in sleep ergonomics applications such as measures of knees, ankles, arms and hands.

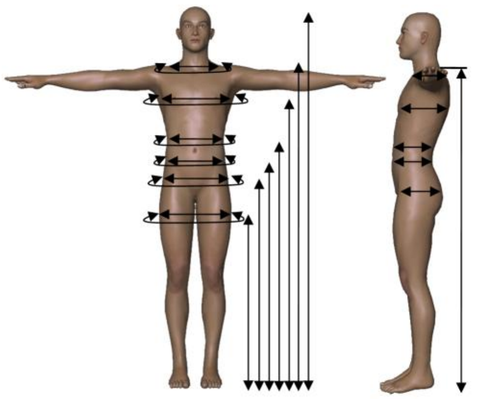

Figure 1: Body measures as used in the database

2.1.1. Human base mesh

In this study Makehuman (MH), a Free and Open Source Software (Bastioni and Flerackers 2000), was used for creating a human mesh. The mesh contains 15340 vertices. The authors defined well-chosen vertices on this base mesh that represent the body measures from the database (heights, widths and circumferences as presented in Figure 1). The sum of distances between these points (in the pre-defined order) can be calculated to obtain an estimation of the different body measures of the model. From the above database, we searched for the largest correlations between the different measurements to take into account when generating the mesh.

2.2. Mesh personalization by morphing

For every subject the base mesh is adapted by morphing. This technique was recently used and described by Volz et al. 2007 in order to generate avatars for use in sales support systems that focus on virtual ‘try-on’ clothing. Morphing is a technique in which the shape of three-dimensional objects can be altered by displacing its (or part of its) vertices along a (linear) deformation path between two extreme target positions (Figure 2). Vertices of both target positions are grouped in a matrix, called the morph targets (t_1 and t_2). Subsequently, a scalar u among the interval [0,1] can be defined to indicate the impact of the vertex relocations between the two extreme target shapes as given in equation (1.1) and presented in Figure 2.

$$t(u) = t_1 + u(t_2 - t_1) \quad (1.1)$$

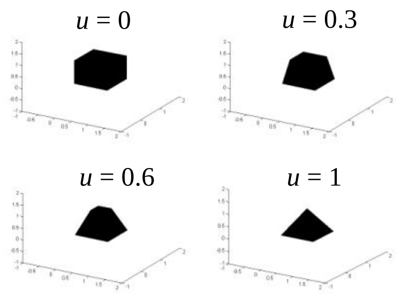

Figure 2: Morphing a square ($\mathbf{t_1}$) into a pyramid ($\mathbf{t_2}$)

This scalar thus only influences the length of the deformation vectors $(t_2 - t_1)$. An example of vector relocations in waist and hip zone of a mesh is given in Figure 3, where only the left side of the mesh has been altered.

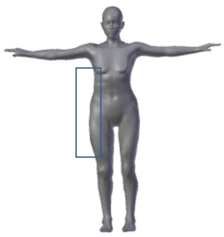

Figure 3: Female base mesh (MH) after altering waist and hip zone at the left side of the body

The above described morphing technique has been implemented in the MakeHuman (MH) Software, specialized in the generation of nice-looking three-dimensional humans. A wide range of morph targets are inherently implemented in MH, ranging from macrodetails as sex, length, weight or age to microdetails like nose or ear shape, etc. At the moment MH is not (yet) focusing on the reproduction of individualized (real) human body models since no functionality is available to enter

absolute body measures as input neither to collect them as output. For this study the MakeHuman project interface was adapted in order to make human models based on real body measures.
 gives an example of a man when increasing the scalar for the weight target in the MH project.

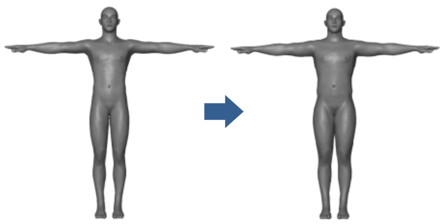

Figure 4: Increasing weight factor for male base mesh

2.3. Iterative modeling

An automatic process iteratively performs a deformation of the human base mesh according to the given model inputs. For each subject the number of inputs to the model is increased, starting with sex, age, weight and length which are the most *easy-to-get* body parameters. Afterwards pelvis circumference, acromion circumference, pelvis width, hip width and/or shoulder width are added since these parameters play the most important role in the determination of a mattress configuration for optimal body support (Haex, 2004).
The database shows that weight can give an indication for the width of the torso (shoulder, breast and waist width), which we thus included in the model adaptation. For some adaptations (e.g. for waist zone vertices), a distinction was made between men and women. Waist zone vertices for men, for example, are selected somewhat downwards since an increased torso for men leads to a somewhat lower located waist region in terms of vertex positions.

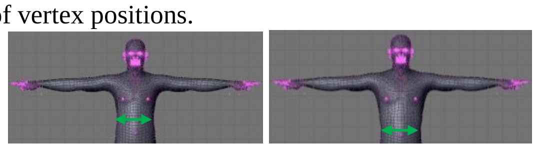

Figure 5: Lower waist zone vertices for men

The result of the iterative modeling procedure is a model that fits the input measures according to a given iteration threshold, chosen at 2.5 mm. Furthermore, more than one morph target can be altered for a given input parameter. As an example both the pelvis and waist widths as well as their depths are altered based on the pelvis width or circumference input since the data reveals that these measures are well correlated (correlation coefficient>0.8). The same applies for shoulder or waist dimensions.

2.4. Validation

To validate the presented models and the influence of the chosen inputs, *i* model inputs are selected from the 29 body measures of a person (we actually used only 17 parameters for validation since 1) age, sex and weight cannot be directly measured from a surface model, 2) some dimensions were measured in a different position than the MH base mesh making them irrelevant for validation, and 3) circumference measurements were not included in the validation since they incorporate error on width as well as depth measures). The remaining 17-i measures are calculated after generating the model. These calculated body dimensions are than compared to their real (manually measured) values from the database. This procedure is repeated for every subject while varying the number of inputs *i* to the model as presented in Figure 6.

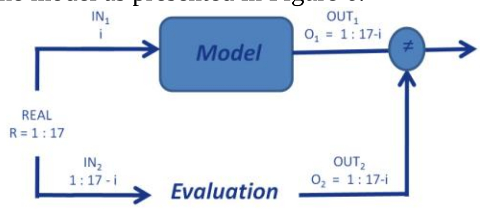

Figure 6: Validation of the models

2.5. Incorporation of a skeleton

The MH software has a build-in function that enables the user to export the surface models in combination with a skeleton as a MakeHuman eXchange (.mhx) file. These files can be imported into the Blender software, a Free and Open Source Software for modeling, rigging, simulating, animating and creating 3D applications (Roosendaal, 2002). A combination of the personalized surface model and this skeleton model will be used in the future for simulating mattress indentation for use in a particle filter as to recognize sleep postures. An example of an individualized model imported in Blender is given in Figure 7. On the right side, the model has adopted a left lateral sleeping posture.

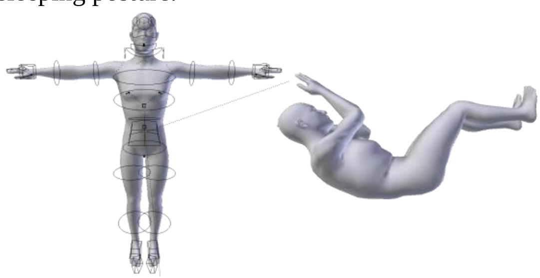

Figure 7: Individualized MakeHuman model incorporated in Blender software (left), posed in a lateral sleeping posture (right)

3. Results

Table 1 gives the mean and standard deviation of 22 measures of interest for the database models.
A comparison of the estimated model parameters with the real measures is given in Table 2 and 3 for two different combinations of input parameters.

Using sex, age, weight and length as input, the resulting models have a mean RMS error of 20.5 ± 6.8 mm. When incorporating also pelvis width and acromion circumference, RMSE is decreased to 17.9 ± 6.2 mm. This result is related to a percentage RMSE of 5.0 ± 3.5 %. Heights are predicted most accurate (2.3 ± 1.4 %), followed by widths (4.9 ± 2.3 %). When looking at the percentage RMSE, depth measurements result in the highest errors (9.9 ± 2.6 %).

Table 1: Mean values and standard deviations of anthropometric data from the database

	Mean [mm]	Std [mm]	Std [%]
Body Length	1723.8	105.3	6.10859
Neck Height	1465.4	94.4	6.44192
Acromion Height	1421	91.1	6.41097
Breast Height	1250.1	92.9	7.43140
Waist Height	1087.9	62.2	5.71743
Pelvis Height	985.3	68.9	6.99279
AcromionWidth	349.4	26.2	7.49856
Schoulder Width	425.7	31.3	7.35259
Breast Width	283.4	22	7.76287
Waist Width	263.1	23.7	9.00798
Pelvis Width	309.7	22.4	7.23280
Hip Width	346.6	19.5	5.62608
Acromion Depth	145.9	14.5	9.93831
Schoulder Depth	184.9	19	10.2758
Breast Depth	223.5	23.7	10.6040
Waist Depth	189.7	21.9	11.5445
Pelvis Depth	220.3	22	9.98638

Table 2: Root mean square error between estimated and manual measurements when input parameters consist of **sex**, **age**, **weight** and **length**

	RMSE [mm]	RMSE [%]
Body Length	1.182	0.0685
Neck Height	14.061	0.9595
Acromion Height	20.249	1.425
Breast Height	23.557	1.8843
Waist Height	24.017	2.2076
Pelvis Height	26.416	2.681
AcromionWidth	29.089	8.3244
Schoulder Width	28.869	6.7814
Breast Width	19.795	6.9854
Waist Width	16.641	6.326
Pelvis Width	19.766	6.382
Hip Width	27.02	7.796
Acromion Depth	17.946	12.302
Schoulder Depth	22.74	12.2977
Breast Depth	20.011	8.9524
Waist Depth	23.335	12.3005
Pelvis Depth	14.131	6.4148

Table 3: Root mean square error between estimated and manual measurements when input parameters consist of **sex**, **age**, **weight**, **length** as well as **pelvis width** and **acromion circumference**

	RMSE [mm]	RMSE [%]
Body Length	1.419	0.0823
Neck Height	13.595	0.9277
Acromion Height	20.259	1.4257
Breast Height	22.251	1.7798
Waist Height	24.325	2.2359
Pelvis Height	26.409	2.6803
AcromionWidth	17.046	4.878
Schoulder Width	19.827	4.6574
Breast Width	20.329	7.1737
Waist Width	17.83	6.7778
Pelvis Width	9.936	3.199
Hip Width	17.589	5.0749
Acromion Depth	16.549	11.3437
Schoulder Depth	21.109	11.4155
Breast Depth	26.2	11.721
Waist Depth	18.271	9.631
Pelvis Depth	12.03	5.4608

4. Discussion

Results show that a limited number of input parameters can be sufficient for creating human surface models to use in sleep ergonomics design when using the Open Source software from the MakeHuman project. According to the authors' belief, the presented accuracy is sufficient for individualized posture simulation and estimation in the scope of mattress design ergonomics.

Largest errors between modeled and manually measured parameters occur in circumference measures (up to 50 – 60 mm, not presented in the tables), which is a normal phenomenon since these measures incorporate errors on width as well as depth measures. Only 1D-measures in one single direction are therefore incorporated in the validation of this study, resulting in a maximal error of 26.4 mm on the prediction of pelvis height. The highest percentage RMS errors arise in depth measures. This is, however, not surprising since the variation of these measures is also largest when looking at the standard deviation in the database. The same applies for other studies where inter-user variability is larger for depth measures (Klipstein-Grobusch et al., 1997). Moreover, this forms no problem for the use of the presented models in the scope of mattress design since depth estimations are less important in this context: sagittal and coronal body contours in combination with weight distribution are the most influencing human factors when looking at mattress support properties.

Results of this study show that the best outcome is achieved when including both pelvis width as well as acromion (or shoulder) circumference as model inputs (when the user wants to limit the number of input parameters to six). Since it might be easier to measure circumference measures (using a measuring tape) instead of width measures – for which a caliper is needed – pelvis perimeter can be used for model personalization instead of pelvis width. Results are similar (5.0 ± 3.7 %).

Finally, other researchers (Buys et al, 2011) use the presented models to generate personalized human models based on 3 to 4 good fit camera measurements.

5. Conclusion

The presented study shows that the MakeHuman project can provide sufficiently accurate results for generating personalized human models, based on a limited set of six input parameters, for the use in sleep ergonomics applications. The main advantages of the proposed technique include the smooth representation of the models and its generic character, limiting the number of inputs needed.

Future work consists of integrating back shape data (sagittal contour or kyphose and lordose angle) into the models as to further individualize them for sleep ergonomics related research - where back shape information influences the modeling of supine postures - and to incorporate them in a particle filter for more detailed posture recognition, such as in-between postures, are specific leg-movement information, etc.

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