# The use of a generic human model to personalize bed design

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## Abstract

This study explores how digital human models (DHMs) can be used to assess quality of spine support on bedding systems. A generic surface model has been developed that can be personalized based on a set of anthropometric input parameters. Shape assessment of the personalized surface models was performed by 3D surface scans of the trunk. Results showed a mean unsigned distance of 9.77 mm between modeled and scanned meshes. The surface model is combined with an inner skeleton model, allowing the model to adopt distinct sleep postures. Evaluation of spinal alignment is achieved by combining the personalized model with mattress indentation measurements. An automatic fitting algorithm sets the appropriate degrees of freedom to position the model on the measured indentation in the adopted sleep posture. Root mean square deviation between modeled and measured spine shape was 11.5 mm, indicating the usefulness of DHMs to increase efficiency in early stage bed design.

*Keywords: Measurement, Anthropometry, Comfort/Discomfort.*

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## 1. Introduction

The main function of bedding systems is to provide body support during sleep while allowing muscles and intervertebral discs to recover from nearly continuous loading by day (Nachemson and Elfström 1970). Optimal recovery is achieved when the spine is in its natural physiological shape, yet with a slightly flattened lumbar lordosis due to the changed working axis of gravity (Dolan et al. 1988; Krag et al. 1990).

Several techniques have been described to evaluate spinal alignment during sleep, such as marker based anatomical landmark detection (Lahm and Iaizzo 2002), the use of geometrical instruments (McGorry and Hsiang 2000), or spine modeling from back shape data by means of active shape and active contour approaches (Huysmans 2004). The use of markers and geometrical instruments requires palpation of bony structures, which is time consuming and error prone, whereas back surface scanning does not require contact with the subject's body (Huysmans et al. 2006). However, the main shortcoming of the existing techniques is that they are not suited to be used in a bedroom environment because of their interference with the actual sleep process. The current study tries to overcome this by combining unobtrusive mattress indentation measurements, integrated in the bedding system, with a model of the sleeper containing relevant anthropometric information.

Digital human models (DHMs) are increasingly being used in a wide spectrum of applications, e.g. in animation development (Hasler et al. 2010; Azuola et al. 1994; Remondino 2004), garment design (Wang et al. 2003; Kim and Park 2004) and the ergonomic evaluation of early stage product design (Jung et al. 2009; Lämkull et al. 2007). Several ergonomic software packages are commercially available, allowing three dimensional modeling of humans (e.g. RAMSIS, Jack, Safework). Most of these simulation systems are developed to visualize the interaction of a human and a system, for instance reach and visibility in a car interior. The rise of 3D whole body scanning technologies (Daanen and van de Water 1998) has enabled accurate and fast acquisition of human body shapes. Several authors (Allen et al. 2004; Paquet and Viktor 2007) use whole body scans or

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derived measures to morph a template model to the scanned subject, resulting in highly realistic body shape models. However, 3D scanning based methods require expensive scanning equipment and extensive post-processing of the scanned point clouds (Weyrich et al. 2004).

Although the use of DHMs to evaluate automotive seating comfort has been widely studied (Verver 2004), few research groups apply DHMs to evaluate sleep comfort. Harada and co-workers (Harada et al. 1999; Harada et al. 2001) combined a full body human model (surface model and skeleton) with pressure distribution images in order to track human motion in bed and automatically detect adopted sleep postures. The model was manually scaled based on the subject’s body height to account for anthropometric differences. No further personalization was considered. Joint rotation and translation parameters were optimized to minimize the difference between the model based pressure distribution and the measured pressure distribution. However, the study did not incorporate the evaluation of personalized comfort parameters related to bed design (such as spinal alignment, maximal contact pressure,…), yet merely focused on motion tracking.

The current study proposes a generic human body model to be used in combination with integrated mattress indentation measurements for the unobtrusive evaluation of spinal alignment during sleep. The generic model can be personalized based on a standard set of body measures.

## 2. Materials and Methods

### 2.1. Measurements

A total of 65 subjects (32 male, 33 female, age: 27.3 ± 11.5 y, BMI: 22.2 ± 5.0) participated in the following series of measurements. First, two dimensional body contours in both the sagittal and frontal plane were automatically registered using an optical measurement system (Ikélo, Custom8, Leuven, Belgium). Subjects were asked to wear a tight fitting shirt. Lateral contours were determined in a standing posture with the back surface oriented towards the camera-pair and with the arms in front of the body and bent in such way that the angles between upper and lower arm and between upper arm and chest approximated 90°. Figure 1 clarifies the measurement procedure and silhouette extraction of lateral body contours. Sagittal contours were determined in a standing posture with the arms next to the body and the camera-pair at the right hand side. Based on the measured body contours, the system outputs the following set of body measures: 1) height, breadth and depth at shoulder, breast, waist, pelvis and hip, 2) acromion height, total body length, body weight, kyphosis and lordosis. Second, since silhouette extraction of body contours provides no information on body circumferences, manual measurements of body circumferences were performed at shoulder, breast, waist, pelvis and hip. Third, a subgroup of 20 subjects (12 male, 8 female, age: 22.9 ± 3.8, BMI: 22.3 ± 2.9) also underwent a three dimensional surface scan of the trunk region (zSnapper multiple, Vialux, Chemnitz, Germany). Finally, mattress indentation was measured in a two-dimensional grid of 170 points at a sampling rate of 1 Hz, using a sleep system equipped with integrated indentation sensors (DynaSleep, Custom8, Leuven, Belgium). The mattress core of this sleep system consists of pocket springs and comprises ten comfort zones. Eight of these comfort zones can be adjusted in stiffness by applying a vertical displacement of the zones’ spring bases. Validation of spine shape assessment is provided by means of a 3D surface scan of the back surface (zSnapper, Vialux, Chemnitz, Germany), performed simultaneously with the mattress indentation measurements. Prior research (Huysmans 2004) has shown that the line through the spinous processes can be accurately reconstructed based on an active contour model iterating on back surface curvatures (Figure 2).

### 2.2. Modeling body shape

A generic model has been developed that is constituted of five major body parts: a trunk, two arms and two legs. Each part consists of consecutive superellipses that represent the transverse cross sections of the human body.

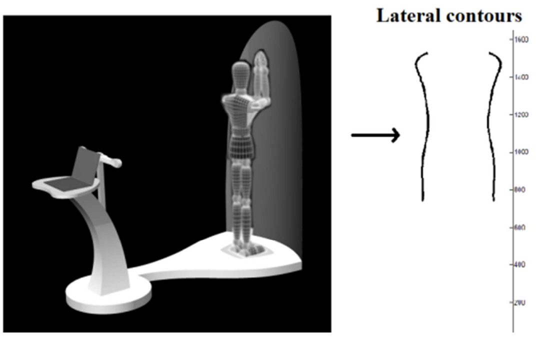

Figure 1: Silhouette extraction of lateral body contours using the Ikélo system.

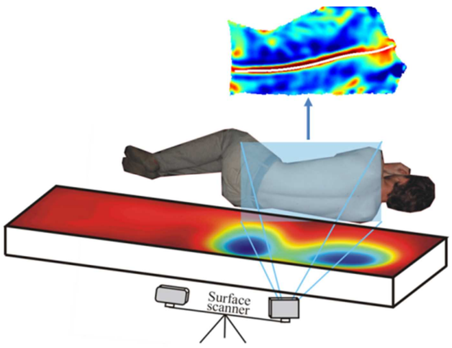

Figure 2: Simultaneous mattress indentation recordings and back surface scanning. An active contour model iterating on surface curvatures serves as gold standard for spine shape assessment.

Superellipses are geometrical shapes that are defined as the sets of points (x, y) that satisfy the equation

$$\left|\frac{x}{a}\right|^n + \left|\frac{y}{b}\right|^n = 1 , \qquad (1)$$

with a and b the semi-diameters, and n the ellipse order (Gielis 2003). The semi-diameters allow accommodating to different breadths and depths, whereas the ellipse order determines the extent to which the shape is more star-like ($0 < n < 1$), ellipsoidal ($n = 2$) or rectangular ($n > 2$) (Figure 3). In general, four input values are necessary to model a transverse cross section: height, breadth, depth and circumference. The height measure is used for caudocranial positioning of the superellipse, breadth and depth determine the semi-diameters, and the ellipse order is determined in such way that the ellipse circumference optimally corresponds to the measured circumference by means of a least square optimization.

The generic model is personalized based on the following anthropometric information: sex; age; body weight; body length; height, breadth and circumference at shoulder, breast, waist, pelvis and hip; and depth at shoulder, breast, waist and pelvis. Furthermore, input of information on back curvatures (e.g. the complete sagittal contour or discrete values of kyphosis and lordosis), allows personalized modeling of back curvatures. Intermediate superellipses (between the measured anatomical sites) are calculated by means of shape preserving piecewise cubic Hermite interpolation (Fritsch and Carlson 1980). In addition, since silhouette extraction does not provide information on body circumferences, it is impossible to automatically personalize the ellipse order based on linear measures derived from body contours solely. Therefore, the manually measured circumferences were used in a multiple linear stepwise regression to estimate body circumferences based on the anthropometric output available from silhouette extraction.

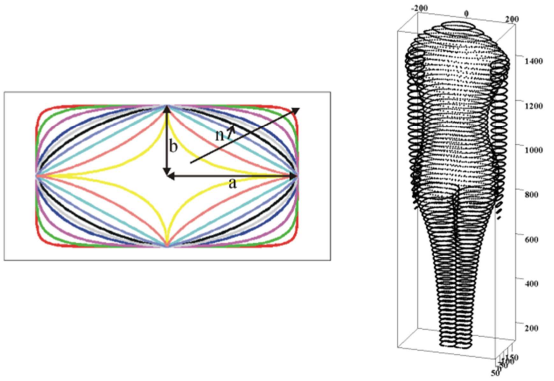

Figure 3: Effect of ellipse order on the shape of a superellipse (left) and modeled body shape by consecutive superellipses (right).

*2.3. Spine shape assessment*

For the purpose of modeling sleep postures a simplified skeleton has been integrated in the human body model. The skeleton consists of the following joints: two ankle joints, two knee joints, two hip joints, three spinal vertebrae (representing L5, L1, and C7 approximately), two shoulder joints, two elbow joints and two wrist joints. The pelvis is modeled as a triangular plate connecting both hip joints and the lower spinal vertebra (L5). The other joints are interconnected by rods.

Spinal alignment is evaluated by fitting the model into the indentation measurement. A limited set of DOFs is varied according to the adopted sleep posture. The fitting procedure is automated as follows.

Fitting the modeled body shape in the mattress indentation comes down to identifying appropriate values to a set of DOFs. The amount of DOFs that needs to be accounted for varies according to the adopted sleep posture. In case of a supine or prone posture the body shape is not deformed before it is lowered into the indentation matrix. Consequently, only three positioning DOFs of the model need to be determined: rotation in the plane of the mattress surface (θ), longitudinal (x) and lateral translation (y). The values of these parameters are set based on the location of two specific points on the mattress surface: the point of maximal indentation in the breast/shoulder zone ($P_1$) and the point of maximal indentation in the hip zone ($P_2$). The angle between the longitudinal axis and the connection line of $P_1$ and $P_2$ ($\overline{P_1P_2}$) determines the value of θ. Values of x and y are determined based on the alignment of the models buttocks with $P_2$ for supine postures and based on the alignment of the models breast with $P_1$ for prone postures. The fitting procedure for lateral sleep postures is more complicated. Next to three positioning DOFs, four deformation DOFs have to be determined as well: flexion of the knees, hips, lumbar spine and thoracic spine. In addition to $P_1$ and $P_2$, the saddle point ($P_3$) between $P_1$ and $P_2$ is determined as well. The three positioning DOFs (x, y and θ) are determined by the location of $P_3$ (x and y) and by the angle between the longitudinal axis and $\overline{P_1P_2}$ (θ). The angle between $\overline{P_1P_3}$ and the connection line of shoulder and L5 determines thoracic flexion, the angle between $\overline{P_3P_2}$ and the connection line of L5 and hip determines lumbar flexion. Starting from $P_2$, a 90° circle sector (with radius the length of the femur) is scanned to find the line of maximal indentation. This line determines hip flexion and the position of the knee ($P_4$). Knee flexion is determined analogously by scanning a 120° circle sector (with radius the length of the tibia) starting from $P_4$. Figure 4 illustrates the above described fitting procedure for a lateral and supine sleep posture.

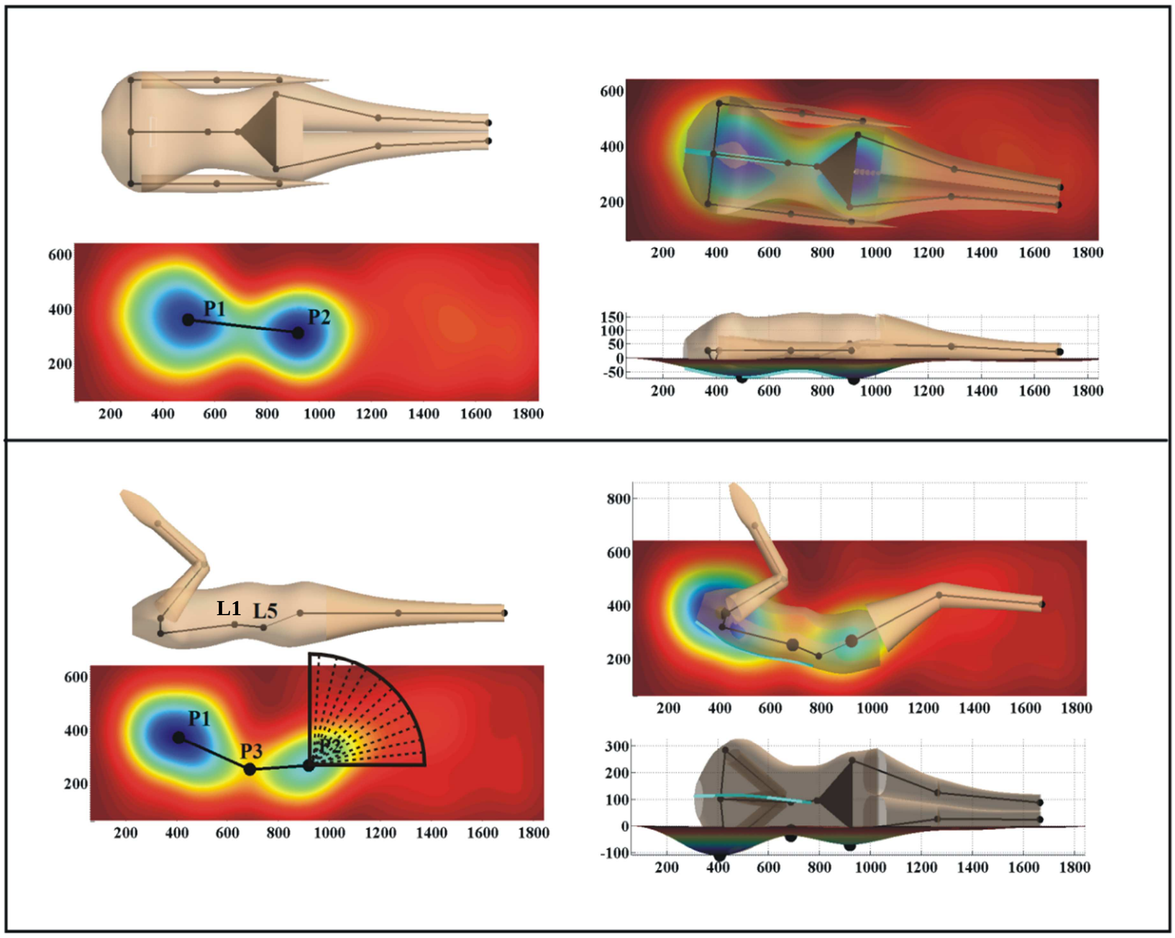

Figure 4: Fitting procedure and spine shape assessment for a supine (upper) and a lateral (lower) sleep posture.

Once the appropriate DOFs are determined, the model is lowered into the mattress indentation by calculating the vertical distances of consecutive model segments to corresponding indentation values. In a final step, spine shape is determined by fitting a cubic smoothing spline through those model points on the back surface that correspond to the spinous processes.

## 3. Results

Table 1 gives an overview of the minimum set of body measures that is necessary to build the model along with the descriptive statistics for the measured subject population. Body circumferences were estimated by a multiple linear regression model based on sex, age and the measures of table 1. Mean adjusted $R^2$ values of the regression equations was 0.84 ± 0.08 and a leave one out cross validation revealed a percentage RMSE of 3.27 ± 0.50 %. Shape assessment of the modeled body shapes was performed by 3D distance maps between personalized models and surface scans of the trunk after registration of both meshes. Figure 5 illustrates the results of such a distance map on one of the subjects. Mean unsigned distance was 9.77 ± 9.31 mm, with the surface scan and the modeled mesh being the source and target mesh respectively. The majority of the scanned points (86.9 %) were within a range of [0, 20] mm distance of the modeled mesh points. More specifically, 39.2 % was within a range of [0, 5] mm, 24.6 % within [5, 10] mm and 23.1 % within [10, 20] mm. In addition, most points outside the [0, 20] mm range were located at body sites were the tight fitting shirt was not in contact with the subject's body. Simultaneous back surface measurements were performed along with the unobtrusive mattress indentation measurements allowing a synchronized, objective validation for spinal alignment in a lateral sleep posture. The adjustable comfort zones allowed evaluating spinal alignment on different

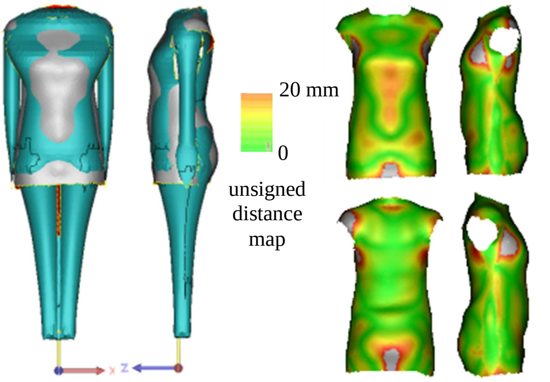

Figure 5: Shape assessment by 3D distance mapping between a personalized surface model and a surface scan of the trunk after registration of both meshes.

Table 1: Anthropometric data of the entire subject population (n = 65)

| | Mean ± std |
|---|---|
| Body length [mm] | 1716 ± 90 |
| Body weight [kg] | 64.3 ± 15.8 |
| Shoulder height [mm] | 1345 ± 73 |
| Breast height [mm] | 1246 ± 78 |
| Waist height [mm] | 1087 ± 61 |
| Pelvis height [mm] | 984 ± 63 |
| Hip height [mm] | 878 ± 57 |
| Shoulder breadth [mm] | 409 ± 30 |
| Breast breadth [mm] | 284 ± 23 |
| Waist breadth [mm] | 262 ± 30 |
| Pelvis breadth [mm] | 304 ± 23 |
| Hip breadth [mm] | 342 ± 19 |
| Shoulder depth [mm] | 181 ± 20 |
| Breast depth [mm] | 218 ± 23 |
| Waist depth [mm] | 189 ± 27 |
| Pelvis depth [mm] | 215 ± 23 |

types of sleep systems. Therefore, measurements were repeated on two mattress configurations. Configuration A is characterized by a heterogeneous stiffness distribution and configuration B by a homogeneous stiffness distribution, which often results in an impaired spinal alignment during lateral recumbency. Table 2 summarizes the comparison between modeled and measured spine shape. Overall, root mean square deviation between modeled and measured spine shape was 11.5 ± 4.9 mm. No difference was noted considering results on both mattress configurations separately. In addition, clustering the subjects according to their BMI (19.9 ± 1.0 vs. 23.8 ± 3.7) showed no effect on spine shape reconstruction, considering an RMS deviation of 11.38 ± 2.76 mm and 11.65 ± 6.82 mm for the low and high BMI cluster respectively.

## 4. Discussion

This study describes how digital human models can be used to assess spine support on a bedding system without interfering with sleep. A generic model has been developed that consists of consecutive superelliptic cross sections. Personalization of the generic model is achieved by a set of anthropometric input parameters. The necessary input can be obtained using different types of anthropometric measurement equipment. Most input parameters are traditional anthropometric measures that can be acquired using caliper and tape measure, although personalized sagittal spine curvatures require measurement of the sagittal back contour or values of lordosis and kyphosis.

Results showed that body measures based on silhouette extraction provided reliable anthropometric information. Body circumferences were estimated through multiple stepwise regression models based on the detected body measures. Leave one out cross validation revealed that circumference deviations were within range of inter- and intra-rater variability in traditional anthropometric measurements (Klipstein-Grobusch et al. 1997). Shape assessment of the modeled body shapes by means of 3D distance maps with surface scans of the trunk revealed a mean unsigned distance below 10 mm.

Table 2: Deviation between modeled and measured spine shapes.

| | RMS deviation [mm] | Maximal deviation [mm] |
|---|---|---|
| Config. A (n=13) | 11.61 ± 4.41 | 22.35 ± 7.55 |
| Config. B (n=8) | 11.30 ± 6.44 | 21.38 ± 8.86 |
| Total (n=21) | 11.51 ± 4.95 | 22.05 ± 7.75 |

Spinal alignment was evaluated by the combination of the personalized model with mattress indentation measurements. A fitting algorithm has been developed that automatically determines the appropriate values for the DOFs that position the model on the measured indentation in the adopted posture. Validation of modeled spine shapes was performed by means of back surface measurements (Huysmans 2004). Comparison of modeled and measured spine shapes revealed an average root mean square deviation of 11.5 mm. In addition, results on different mattress configurations indicate that accuracy of spine shape evaluation is independent on the type of bedding system.

Prior research showed the feasibility of automatic posture recognition based on mattress indentation measurements (Verhaert et al. 2009). The combination of such posture detection techniques with the described evaluation technique allows a completely automatic, continuous assessment of back support during the night based not only on anthropometric, but also on behavioral features (e.g. preferred sleep postures).

Some limitations remain present. First, the evaluation of spinal alignment was only validated in a lateral sleep posture. The main reason is that the gold standard, spine modeling from back shape data, has only been validated for lateral sleep postures. Furthermore, it goes without saying that no back surface scans can be recorded in supine sleep postures. However, since in a supine posture the back surface is in direct contact with the mattress surface, there is no reason to believe that the described evaluation of spinal alignment for supine postures is less accurate than for lateral postures. For prone postures, further validation might be required. A second limitation involves that anthropometric input remains necessary, an issue that other techniques do not require.

Future work should therefore focus on how to overcome these limitations. For instance, a reduction of the necessary anthropometric input might be possible if part of this information could be derived from the indentation measurement itself. In addition, the possibility of combining more complex DHMs (such as the open source MakeHuman meshes (Bastioni and Fleracker 2000)) with mattress indentation measurements should be explored in terms of accuracy of spine shape assessment and reduction of necessary anthropometric input (Van Deun et al. 2011).

## 5. Conclusion

The present study provides a novel method to evaluate spinal alignment during sleep in an unobtrusive way. A generic human body model has been developed that can be personalized based on basic anthropometric information. The combination of the personalized model with mattress indentation measurements allows the evaluation of spinal alignment by means of an automatic fitting algorithm. The main advantage of the developed technique is that it does not interfere with sleep. Therefore, its use is not limited to snapshots of predefined postures in a pre-sleep testing environment, such as most other techniques (Lahm and Iaizzo 2002, McGorry and Hsiang 2000, Huysmans 2004). On the contrary, the technique allows overnight continuous measurements of spinal alignment in the bedroom environment without compromising the actual sleep process.

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