

Effect of Obesity on Seated Posture Inside a Vehicle Based on Digital Human Models

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Jared Gragg and Jingzhou (James) Yang
Texas Tech Univ

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ABSTRACT

Seated posture inside a vehicle influences driver performance and control of a vehicle. Many vehicles do not properly allow for a natural seated posture for all drivers. Some vehicles are difficult to drive due to the fact that the driver is inadequately accommodated in the driver seat. For people of extreme stature, tall or short, and for people of extreme width, obese or pregnant populations, it can be difficult to safely operate a vehicle if there is not enough room in the cab or if some controls cannot be reached. This paper employs digital human models to study the effect of obesity on seated posture inside a vehicle. Eight digital human models, four non-obese and four obese, are subjected to reach tests inside a virtual vehicle cab. These tests are used to determine how obesity affects the clearance between the steering wheel and driver body and whether additional factors contribute to discomfort associated with obese people seated inside a vehicle. In order to model the obese subjects, factors such as increased waist circumference and limited joint range of motion due to obesity are included in the simulations. Also given is an indication of discomfort level through the output values of the multi-objective function in the optimization formulation. The benefit of using this method is that the human aspect of design can be included early in the design process, reducing or eliminating prototypes. If adjustments to the layout of the vehicle cab are needed the resulting postural differences can be quickly observed.

KEYWORDS

Posture prediction, multi-objective optimization, seat adjustment range, digital human models, obesity, boundary manikin, population sampling, discomfort

1. INTRODUCTION

A good vehicle design incorporates varying driver anthropometry, allowing for drivers of different size and shape to safely operate the vehicle. One important aspect of an ergonomic vehicle design is that the vehicle allows for drivers with extreme anthropometric characteristics, short, tall, and obese, to reach all important controls. Each of these extremes causes specific design challenges. Short drivers must be able to reach the accelerator pedal, sit far enough back from the steering wheel to have enough clearance, and see over the steering wheel. Tall drivers must be able to fit inside the vehicle cab, not bump their head on the roof, and have enough leg room. Obese drivers present unique challenges in that obesity is not limited to drivers of a certain stature. Obesity is present in drivers of all statures and therefore presents challenges associated with both short and tall drivers. For obese drivers it is important that the driver is able to touch the accelerator pedal, have ample clearance between the stomach and the steering wheel, and safely reach all the important controls. This can be especially challenging due to the fact that obese people have a smaller range of motions in most joints. For a quality vehicle design, it is important to incorporate the varying anthropometric differences in the driver population.

Obesity rates in the US continue to rise despite efforts to increase the awareness of the harmful side effects that obesity has on human health. Body mass index (BMI) is typically used to classify a person as normal, overweight, or obese. A person's BMI is found by dividing the individual's mass in kilograms by the square of the individual's height in meters. A normal BMI is considered to be in the range of 18.5 and 25. An overweight BMI is from 25 to 30 and an obese BMI is over 30. Obesity is becoming more prevalent in today's society. It has been found that since the early 1960's the average adult weight has increase by 24 pounds (US DHHS,

2004). As recently as 2002, it was estimated that 65% of adults were overweight and more than 30% were obese (Hedley et al., 2004). Obesity has been linked to numerous physical ailments. Obesity is reported to increase the risk of coronary heart disease, hypertension, type 2 diabetes, stroke, and certain forms of cancer (US DHHS, 2004; 2005). The problems associated with increasing obesity rates are not limited to individual health risks. Obesity can also lead to significant financial burdens as well as health risks. In 1998, 9.1% of the total US health expenditures were tied to treating complications of obesity (Finkelstein et al., 2003).

The health sector is not the only area that sees increased costs due to rising obesity rates. A number of studies have been conducted that tie obesity to increased costs associated with the operation of a vehicle. In general, the amount of fuel consumed by a vehicle increases with the increased weight of a vehicle. Thus, it stands to reason that rising obesity rates will cause a rise in fuel consumption, but is the increase in fuel consumption associated with obesity significant? Currently, the US is responsible for 25% of the world's crude oil consumption, with 66% of the crude oil consumption being devoted to the transportation sector (US Department of Transportation, 2007). Jacobson and McLay (2006) estimated that cars and light trucks consume as much as 938 million additional gallons of gasoline each year due to the average weight gain in the US since the 1960s. Furthermore, Jacobson and King (2008) estimate that as many as one billion gallons of gasoline consumed in the US can be attributed to excess weight in the US population. These estimates account for .8% of the 139 billion gallons of gasoline consumed each year in the US and an additional .5% of the CO₂ emissions produced from fossil fuel combustion (Jacobson and King, 2008). Clearly, obesity has a significant impact on the automobile industry and the US driver population in general. While efforts to limit further increase in obesity rates are being taken, the process is slow. Currently, obese and overweight individuals make up a significant percentage of the US driver population, with obesity rates still on the rise. While it is important to combat increasing obesity rates, the effects of the current obesity trend must be addressed. Since obese drivers make up a significant portion of the driver population, it is important to include obese individuals in any study related to current vehicle design.

In previous study (Gragg et al., 2010), the boundary manikin method was used to predict the optimum driver seat adjustment range for a midsize sedan. The boundary manikin approach tested two boundary digital humans (a 5% female and 95% male) inside a virtual environment, determining the optimum driver seat adjustment range as the difference between the predicted distances of each driver from the accelerator pedal. This paper extends the previous boundary manikin method to incorporate diverse drivers, including obese drivers of varying stature. In this study, eight digital humans are subjected to reach tests inside a midsize sedan.

For each percentile studied, 5% female, 50% female, 50% male, and 95% male, two subjects are chosen, one obese subject and one non-obese subject. For each simulation, the predicted posture of each obese subject will be compared to the non-obese subject from the same percentile. This enables the study of how obesity affects posture inside of a vehicle. In addition to incorporating diverse drivers, the paper improves upon the posture prediction algorithm employed in the previous study (Gragg et al., 2010). Additional constraints are added to the simulation along with a self-collision avoidance algorithm, to enhance the realism of the simulation. This study looks at the postural differences of obese drivers when compared to non-obese drivers of the same stature, as well as predicting how obesity affects how far back an obese driver must adjust the seat position to remain comfortable.

A multiple-objective optimization (MOO) based posture prediction was developed by Yang et al. (2004). Gragg et al. (2010) applied this MOO method to predict postures for two boundary manikins (5% female and 95% male) inside a vehicle cab. The basis for the posture prediction algorithm is that human movement is governed by human performance measures. When humans assume a posture, it is assumed that the person naturally limits certain human performance measures, such as joint displacement, joint torque, delta-potential energy, musculoskeletal discomfort, visual displacement, etc. (Yang et al., 2004). The posture prediction algorithm developed for previous work incorporated joint displacement and visual displacement as objective functions in the MOO simulation (Yang et al., 2004). For this paper, musculo skeletal discomfort is included along with the aforementioned human performance measures in the MOO simulation.

The paper is organized as follows: Section 2 describes the digital human model, Section 3 describes the posture prediction formulation, Section 4 describes the digital obese human subjects, Section 5 provides the results of the eight simulations, and Section 6 provides essential discussion and a summary of the paper as a whole.

2. DIGITAL HUMAN MODEL

The digital human model is comprised of two parts, the underlying skeletal structure and deformable skin. Deformable skin is attached to the skeletal structure of the digital human to aid in the realistic appearance of the digital human, but has no impact on the dynamics or kinematics of the model (Gragg et al., 2010). The kinematics of the digital human are tied to the skeletal structure, which is modeled as a series of revolute joints according to the Denavit-Hartenberg (DH) method (Denavit and Hartenberg, 1955). Each human degree-of-freedom (DOF) is modeled as a single revolute joint. This allows each joint to be described by a single real number, or joint angle. Requiring each joint in the kinematic chain to only have one associated DOF simplifies the

kinematics of the full joint chain but does not cause loss of generality. Physical joints that have more than one associated DOF, such as the shoulder and the hip, are modeled as single revolute joints set at zero link length apart. Certain sections of the skeleton are shared by multiple limbs, such as the spine, so that posture calculations for the common section only need to be determined once. Fig. 1 details the full skeletal model for the human body, with the global coordinate frame located at the right heel.

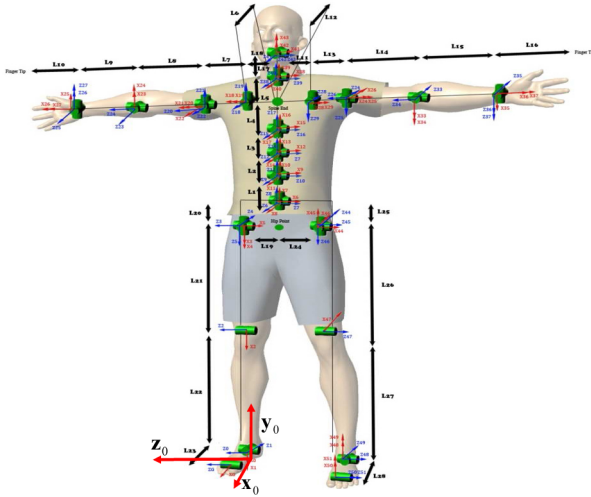


Fig. 1. Detailed DH skeletal model

The kinematics of the joint chain are determined by the DH method. With the i^{th} joint, we associate the joint variable, q_i , and rigidly attach a local coordinate system. The set of all angles, $\mathbf{q} = [q_1 \dots q_n]^T \in R^n$, represents a specific posture. $\mathbf{x}(\mathbf{q}) \in R^3$ is the position vector in Cartesian space that describes the location of an end-effector with respect to the global coordinate system. $\mathbf{x}(\mathbf{q})$ is determined using the DH method and is expressed as the product of the individual transformations associated with each joint. The 4×4 transformation matrix, $\mathbf{T}_j^i$, denotes the position and orientation of joint i with respect to joint j . $\mathbf{x}(\mathbf{q})$ and $\mathbf{T}_j^i$ are expressed as follows:

$$\mathbf{x}(\mathbf{q}) = \left(\prod_{i=1}^n \mathbf{T}_i^{i-1} \right) \mathbf{x}_n \quad (1)$$

$$\mathbf{T}_i^{i-1} = \begin{bmatrix} \cos \theta_i & -\cos \alpha_i \sin \theta_i & \sin \alpha_i \sin \theta_i & a_i \cos \theta_i \\ \sin \theta_i & \cos \alpha_i \cos \theta_i & -\sin \alpha_i \cos \theta_i & a_i \sin \theta_i \\ 0 & \sin \alpha_i & \cos \alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

where $\mathbf{x}_n$ is the position of the end-effector with respect to the n^{th} frame and n is the number of DOFs. The rotational

displacement q_i changes the value of θ_i . The constants α , a , and d are the DH parameters link twist, link length, and link offset and along with θ are used to define the geometric relationships between the joint $i-1$ and joint i . The global coordinate frame is placed at the right heel to ensure that the digital human's right foot stays affixed to the accelerator pedal. Thus, the body has four natural end-effectors: the right hand, the left hand, the left foot, and the head. The main advantage of placing the global coordinate frame at the right heel instead of the conventional hip-point is that the hip-point can be treated as an "end-effector" rather than the origin of movement. The digital humans are viewed utilizing the program Autodesk Maya and the Maya Simulation Environment (MSE) developed for the purpose of visualization (Gragg et al., 2010).

3. POSTURE PREDICTION AS AN OPTIMIZATION PROBLEM

The simulation is constructed as an optimization problem with three human performance measures. The MOO problem is solved by a nonlinear function optimization problem solver, SNOPT (Gill et al., 2002). The general form of the optimization problem is as follows:

- *Find:* Joint angles that represent a specific posture
- *Minimize:* Human performance measures
- *Subject to:*
 - Distance constraints on the end-effectors
 - Self-collision avoidance
 - Obstacle avoidance

The three human performance measures employed in the simulation are visual displacement, joint displacement, and musculoskeletal discomfort (Yang et al., 2004; Yang et al., 2010). The distance constraints on the end-effectors ensure that the digital human is able to safely reach all important controls. The self-collision avoidance algorithm ensures that the digital human's limbs do not pass through each other and the obstacle avoidance algorithm ensures that there is enough clearance room between the digital human's stomach and the steering wheel. The following paragraphs detail the human performance measures and simulation constraints.

HUMAN PERFORMANCE MEASURES

The three human performance measures (visual displacement, joint displacement, and musculoskeletal discomfort) are included into the overall objective function using the concept of MOO (Yang et al., 2004). Each human performance measure has desirable qualities, but the most desirable posture is the one that incorporates the tendencies of each human performance measure in a single weighted objective

function. The weighted objective function is defined as follows:

$$F(\mathbf{q}) = \left\{ \left[w_1 \left(\frac{VD}{VD^{\max}} \right) + 1 \right]^2 + \left[w_2 \left(\frac{JD}{JD^{\max}} \right) + 1 \right]^2 + \left[w_3 \left(\frac{MD}{MD^{\max}} \right) + 1 \right]^2 \right\}^{\frac{1}{2}} \quad (3)$$

VD stands for visual displacement, JD for joint displacement, and ME) for musculoskeletal discomfort. The superscript max represents the maximum possible value of the objective function. The weights, w_i , influence the relative importance of one objective function versus another.

The visual displacement function (VD) minimizes the sight angle between the vision vector and a target point (Yang et al., 2010). Visual displacement is based on visual acuity, but modified to incorporate the tendency to look at an object even when it is out of the field of view. The formula for visual displacement is:

$$VD = 10 \left(1 - \cos \left[\frac{\theta(q)}{2} \right] \right) \quad (4)$$

where the term $\cos^{\theta/2}$ is calculated as the dot product between the normalized vision vector and the normalized sum of the vision vector and the eye-to-target vector.

The joint displacement function (JD) limits the movement of each joint according to joint weights (Yang et al., 2004). Joint displacement is defined as follows:

$$JD = \sum_{i=0}^{48} w_i \left(\frac{q_i - q_i^N}{q_i^U - q_i^L} \right)^2 \quad (5)$$

It assumes that humans tend to minimize movement away from a comfortable neutral posture. This neutral posture is considered to be a natural, comfortable posture. Joint weights help to further minimize movement of joints that are especially sensitive to movement. Humans tend to move certain joints, such as the spinal column, hips, and neck, less than others such as the elbows, knees, and shoulder. The higher the weight value for a particular joint, the more limited the movement of the joint. There is no established value for joint weights, but ongoing research is being conducted to determine standard joint weights for the human body (Zou et al., 2010). The joint displacement function value is considered as a measure of discomfort. The exact value of the function is not important, rather the relative value between different postures.

The musculoskeletal discomfort (MD) function is based on three factors describing musculoskeletal discomfort: the tendency to move segments of the body sequentially, the tendency to obtain a relatively neutral position, and that discomfort is associated with movement of joints at their respective limits (Yang et al., 2004). This approach to discomfort solves for posture sequentially, by taking a lexicographic approach to posture (Yang et al., 2004). That is, in general humans tend to move certain joints more than others when attempting to reach something. First, humans tend to move their arms, then bend at the hips, and finally use the clavicles and spinal joints if the object still cannot be reached. Since the lexicographic method is computationally expensive, a weighted sum method can be used to approximate the approach (Yang et al., 2010). The formulation of musculoskeletal discomfort is:

$$MD = \frac{1}{\zeta} \sum_{i=1}^{DOF} \alpha_i (\Delta q_i \text{ norm})^2 + \zeta QU_i + \zeta QL_i \quad (6)$$

$$QU_i = (0.5 \sin \left(\frac{5.0(q_i^U - q_i)}{q_i^U - q_i^L} + 1.571 \right) + 1)^{100} \quad (7)$$

$$QL_i = (0.5 \sin \left(\frac{5.0(q_i - q_i^L)}{q_i^U - q_i^L} + 1.571 \right) + 1)^{100} \quad (8)$$

$$\Delta q_i \text{ norm} = \frac{(q_i - q_i^N)}{q_i^U - q_i^L} \quad (9)$$

where $(\Delta q_i \text{ norm})^2$ is a normalization of the design variable, α_i are the weights used to approximate the lexicographic approach, and $\zeta = 10^6$. Also, joints in which the limits present no stretching of ligaments or tendons, such as the elbows and clavicles, are not penalized for being near their upper limits. As with joint displacement, the value of musculoskeletal discomfort is not relevant but rather the relative value of musculoskeletal discomfort between different postures. Together, visual displacement, joint displacement, and musculoskeletal discomfort form a weighted objective function in the MOO simulation.

SIMULATION CONSTRAINTS

There are several important constraints necessary for the simulation. Most of the constraints are special constraints related to sitting inside a vehicle, while the others are collision avoidance constraints. Fig. 2 shows a pictorial representation of the constraints.