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ABSTRACT

Recent research in the ASPECT (Automotive Seat and Package Evaluation and Comparison Tools) program has led to the development of a new method for automobile driver posture prediction, known as the Cascade Model. The Cascade Model uses a sequential series of regression functions and inverse kinematics to predict automobile occupant posture. This paper presents an alternative method for driver posture prediction using data-guided kinematic optimization. The within-subject conditional distributions of joint angles are used to infer the internal cost functions that guide tradeoffs between joints in adapting to different vehicle configurations. The predictions from the two models are compared to in-vehicle driving postures.

INTRODUCTION

The widespread use of human figure models to develop and evaluate vehicle interiors has created a need for accurate vehicle occupant posture prediction. Vision, reach, and other analyses performed with figure models in virtual vehicle mockups are limited by the accuracy of the manikin postures. A recent program to develop new tools for vehicle design (ASPECT) included the measurement of vehicle occupant postures in hundreds of vehicle and seat conditions (1, 2). As part of that program, a new approach to posture prediction for automobile occupants was developed (3).

The Cascade Prediction Model (CPM) places the highest priority on accurate prediction of hip and eye locations, two of the posture characteristics that are most important for vehicle interior assessment. Regression equations created from laboratory data and adjusted using in-vehicle data are applied to predict hip and eye locations from occupant anthropometry, vehicle interior configuration, and seat characteristics. An inverse-kinematics approach is used to fit torso and limb segments to the calculated landmark locations within the kinematic constraints of the driving task. Reed et al. (3) demonstrated that the CPM accurately predicts driver postures in vehicles.

An important earlier model to predict driving postures was developed by Seidl (4). The Siedl approach used a kinematic optimization guided by the distributions of joint angles observed in laboratory testing. As part of the recent ASPECT work, a conceptually similar approach was explored as an alternative to the Cascade Model. The Optimization Prediction Model (OPM) identifies the most likely posture among the kinematically feasible postures based on the observed distribution of joint angles from laboratory experiments. This paper presents the development of the OPM and compares the results to the Cascade Model. The development and performance of the OPM provides insight into the posture-selection behavior of automobile drivers.

METHODS

DATA SOURCES – The CPM and OPM were developed using the same data from a laboratory study of driving posture (2, 3). An anthropometrically diverse group of 68 men and women selected their preferred driving postures in a vehicle mockup that was configured to represent a wide range of vehicle interior conditions. External body landmark data recorded with a sonic digitizer were used to calculate joint locations defining a three-dimensional kinematic-linkage representation of the body (5). The resulting lengths, positions, and orientations of the linkage segments were used in the development of the posture prediction models.

GENERAL MODEL FORMULATION

VEHICLE GEOMETRY DEFINITIONS AND MODEL INPUTS – Posture prediction is conducted in a vehicle package coordinate system, defined by several commonly used vehicle reference points. Complete definitions of these points can be found in Society of Automotive Engineers Recommended Practice J1100 and associated practices (6). The X axis in the package coordinate system runs positive rearward, the Y axis positive to the driver's right, and the Z axis positive up. The origin is defined by a different point on each axis. The origin X coordinate is defined by the Ball of Foot

(BOF) reference point, while the origin Z coordinate is defined by the Accelerator Heel Point (AHP). In general terms, vertical dimensions are measured from the floor and fore-aft dimensions are measured from a point on the accelerator pedal. For the current analysis, the origin Y coordinate is the centerline of the driver seat. Figure 1 illustrates these reference points on a sideview schematic of the driver's station.

A number of vehicle package dimensions are used as inputs to the posture prediction models. These parameters have been varied systematically in testing or are those whose specification is necessary to sufficiently characterize the locations of components. The weighted, contoured H-point manikin (SAE J826) measures a reference point on the seat known as the H-point (a hip-joint location estimate). When the seat is moved forward and rearward along its adjustment track, the orientation of the path of the H-point relative to the horizontal defines the seat track angle. The seating reference point (SgRP) is the H-point location that lies on the 95th-percentile selected seat position curve given by SAE J1517 (3). This curve is a second-order polynomial describing the horizontal position of the 95th-percentile of the seat position distribution as a function of seat height. Seat height is defined by the vertical distance between the SgRP and the AHP, and is termed H30, following the dimension definitions in SAE J1100.

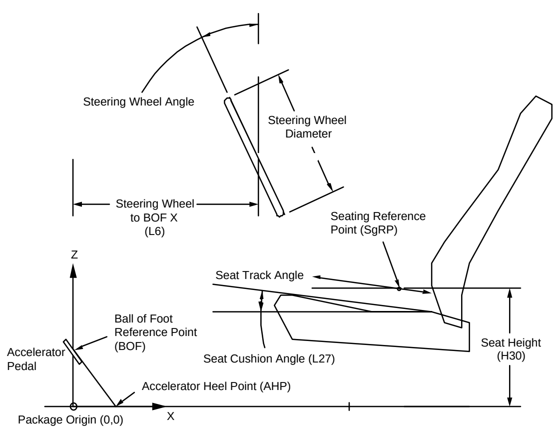


Figure 1. Vehicle package geometry. Expressions in parentheses are Society of Automotive Engineers nomenclature from SAE J1100 (3).

Seat cushion angle (L27) specifies the orientation of the lower part of the seat (seat pan) with respect to horizontal, and is measured using the H-point manikin with a procedure described in SAE J826. Seat cushion angle does not generally correspond to any measure of the unloaded centerline contour of the seat, but instead represents the cushion orientation experienced by a standardized sitter. The steering wheel is characterized by the coordinates of the center of the front surface of the wheel, the angle of the front surface of the wheel with respect to vertical, and the diameter of the wheel. The horizontal distance from the center of the steering wheel to BOF is a key package dimension and is denoted L6 in SAE J1100.

Table 1 lists vehicle geometry inputs to the posture prediction model in two categories: parameters that solely affect kinematic constraints imposed on the models, and those that are variables in the predictive equations. Only three variables are used in the posture prediction models: H30, L6, and L27. Notably, the vertical position of the steering wheel and the degree of forward vision restriction imposed by the instrument panel or vehicle cowl are not included. The vertical position of the steering wheel is highly constrained in vehicle design, because of the conflicting requirements of sufficient leg space beneath the wheel and sufficient vision above the wheel. The leg depth of large drivers and the eye height of small drivers tend to constrain the vertical steering wheel position to a small range relative to the SgRP location. Restrictions on forward vision, in the range that is reasonable for vehicle design, do not have important effects on posture (7).

Table 1. Vehicle Geometry Inputs

Prediction Variables	Kinematic Constraints
Seat Height (H30) Steering-Wheel to Ball-of-Foot X: SWBOFX (L6) Cushion Angle (L27)	Seating Reference Point (X,Y,Z) Steering Wheel Center (X,Y,Z) Steering Wheel Angle Steering Wheel Diameter Seat Track Angle Center of Accelerator Pedal Y Coordinate (with respect to seat centerline)

The driver's characteristics are represented in the models using four parameters: gender, stature, weight, and sitting height. Additional anthropometric data, such as arm or leg lengths, do not provide substantially better prediction. Because stature, weight, and sitting height are correlated in the data set, two transformations of the variables were used as regressors. The ratio of sitting height to stature (SH/S), a measure of body proportion, was used in lieu of sitting height, and the Body Mass Index (BMI), the ratio of mass (kg) to stature (m) squared, was used instead of mass. Each of these two ratio variables is only moderately correlated with stature in this dataset (r = –0.34 and 0.32 for SH/S and BMI, respectively). The predictive ability of regressions using these variables, assessed using the adjusted R^2 value, was within 0.01 of the values obtained using sitting height and mass directly, while reducing the problems associated with correlated regressors.

In the CPM, driver anthropometric characteristics are used as input to regression equations that calculate the most important postural degrees of freedom. The OPM uses anthropometry primary to scale the kinematic linkage (i.e., figure model). Subject stature and sitting height are used in one part of the algorithm to tune the optimization (see below).

KINEMATIC MODEL – Driving posture is represented using a kinematic linkage model of the human body. The linkage and its derivation from external body landmark data are described in detail elsewhere (3, 5). Figure 2 shows the linkage and defines variables that are used in the posture prediction models.

MODEL SIMPLIFICATIONS AND RESTRICTIONS – Several simplifying assumptions are made to reduce the model complexity. Normal driving posture is considered to be sagittally symmetric, with the posture of the left side of the body mirroring the right. In the data collection used to develop the models, subjects were asked to choose a "normal, comfortable driving posture" with their hands located at the 10-o'clock and 2-o'clock position on the steering wheel. By observation, the only important deviations from sagittal symmetry occurred when left lower-extremity postures did not match the right lower-extremity, which was constrained by the requirement of operating the accelerator pedal. Data from the right upper and lower extremities were used exclusively for developing the models, since the geometric task constraints imposed by the accelerator and brake pedals operate solely through the right lower-extremity (no vehicles or laboratory mockups with foot-operated clutches were used in this part of the study). The hand-position constraint in testing was imposed so that the elbow angle would be a reliable measure of the distance between the steering wheel and torso. The performance of the models in predicting postures measured in conditions with free hand placement suggests that this constraint provides useful upper-extremity posture data without otherwise affecting posture (see Results). To simplify limb kinematics calculations, the hands are assumed continuous with the forearms. Foot posture is neglected in favor of direct prediction of ankle joint location. Prediction of foot and ankle positions is based on data from Schneider et al. (8).

CASCADE PREDICTION MODEL

Figure 3 shows a schematic of the CPM, as presented previously (3). The vehicle and seat geometry, along with the subject anthropometry, are input to a series of regression equations. The fore-aft hip location and hip-to-H-point offset are calculated independently, then combined with the seat track geometry to predict hip location. Eye location is calculated relative to hip location, using independent regression equations for horizontal and vertical position. The torso is then fit between the calculated hip and eye locations using data-guided inverse kinematics (3). Upper extremities are fit between the calculated hip/shoulder locations and the pedal/steering wheel positions, again using inverse kinematics with heuristics developed from measured posture data.

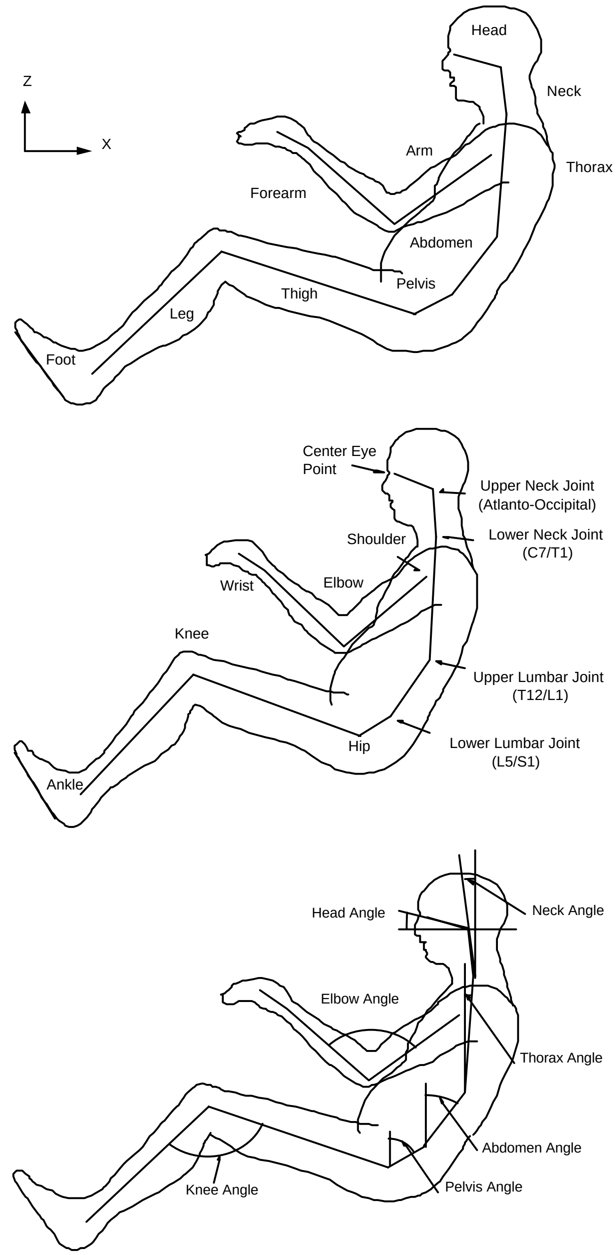


Figure 2. Definitions of kinematic linkage and posture measures (5). Angles referenced to horizontal or vertical are XZ (sagittal) plane angles. Angles between segments (elbow angle, knee angle, and ankle angle) are measured in the plane formed by the segments (included angles). Note: Neck angle is negative as shown. All other angles are positive as shown.

OPTIMIZATION PREDICTION MODEL

The optimization prediction model (OPM) uses a completely different approach to posture prediction from the regression-based methods used with the CPM, and has antecedents in a number of previous posture prediction schemes. Many researchers have proposed that there are joint angles, various called comfort angles or neutral postures, that result when the moments across the joint are passively balanced (9-17). If there are comfort costs associated with deviations from these angles, then posture might be predicted by assuming that people select postures that allow as many joints as possible to be close to these neutral angles (13). There are three essential components to this approach. The neutral angles, the cost functions associated with deviations from the neutral posture, and the manner in which these costs are traded off or optimized must be determined.

The neutral angles have been identified in a number of ways, most notably by observing postures underwater and in zero-g environments (16), and by assuming that the average postures observed over a wide range of task conditions represent the preferred or neutral posture (13, 15, 17). The cost functions and optimization procedure, which are interdependent, have generally been parameterized a priori, using, for example, a minimization of the deviations from the neutral angles (13).

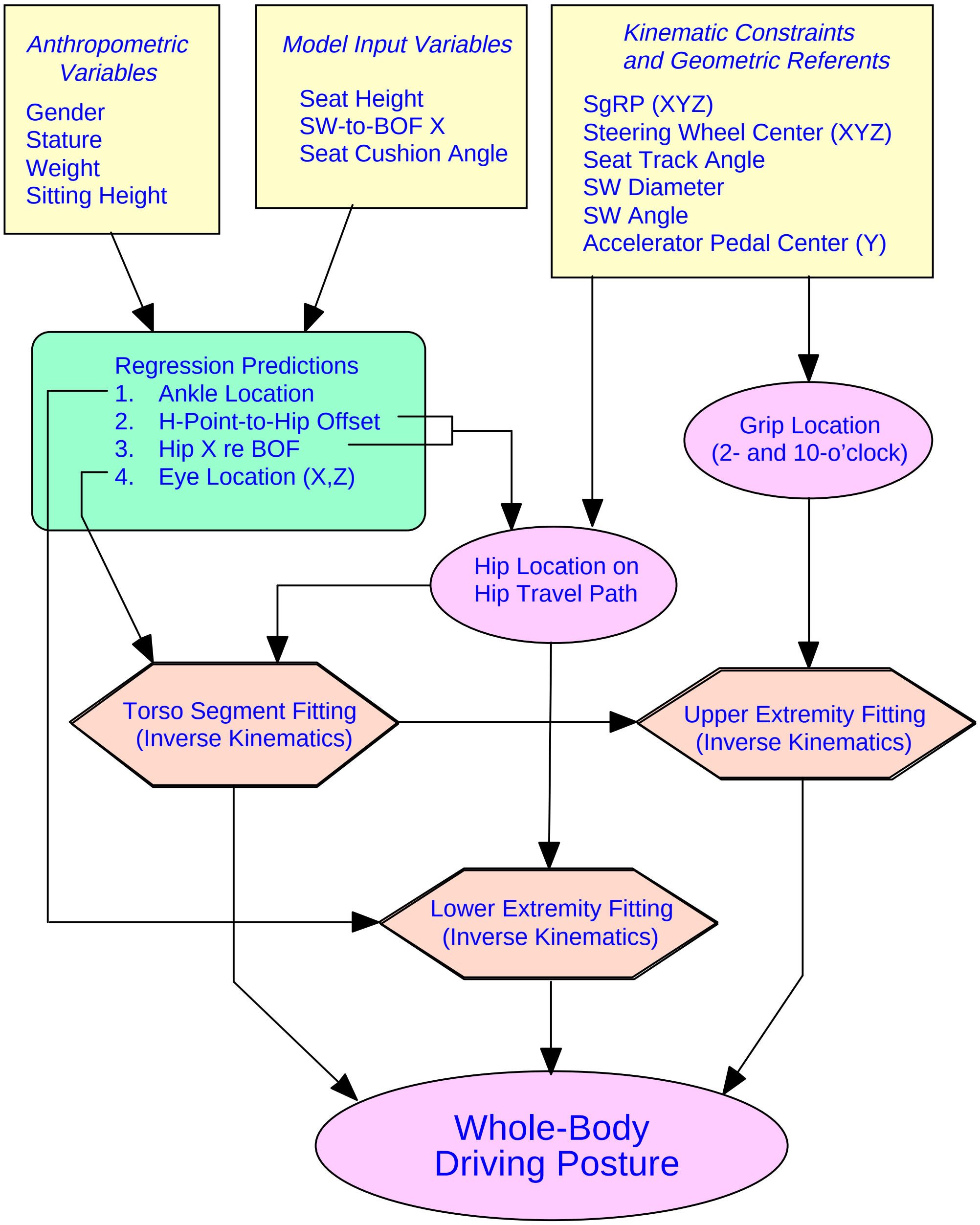


Figure 3. Schematic of Cascade Prediction Model (CPM).

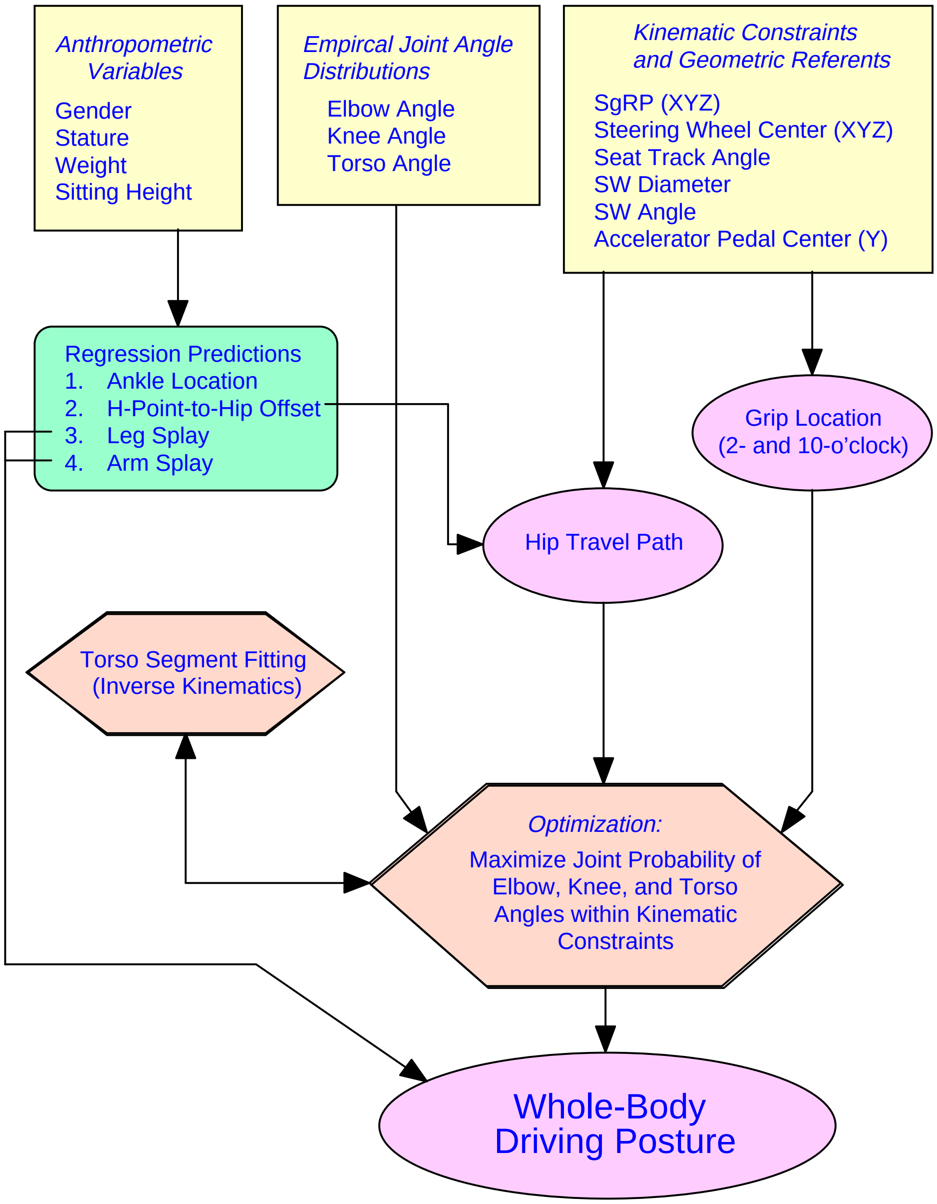


Figure 4. Schematic of Optimization Prediction Model (OPM).

More recently, Seidl (4) proposed a novel method of simulating the joint-angle comfort tradeoffs that are frequently assumed to underlie posture selection behavior. The actual distributions of joint angles measured over a range of task conditions (vehicle package geometries) are used to determine the joint cost functions. A posture is selected within those kinematically possible that simultaneously maximizes the likelihood of each of the joint angles with respect to the observed distributions. This procedure, developed for the RAMSIS software manikin, applies this method globally to all joints in the model for each posture prediction.

The OPM uses a modified version of Seidl's approach, illustrated schematically in Figure 4. To begin, the kinematic linkage is scaled and the ankle location, grip location, and hip travel path are calculated as with the CPM. The OPM algorithm calculates the most likely posture, based on the input data, that is consistent with the specified kinematic constraints.

The kinematic optimization is conducted using the three-dimensional linkage depicted in side view in Figure 5. Intersegment motion in the torso is governed by the same motion distribution parameter values used in the CPM (3, 7). Three angles are used in the optimization process: elbow angle, knee angle, and torso angle. The elbow and knee angles are the angles formed by the adjacent model segments at the respective joints (larger angles represent greater extension), and torso angle is the XZ-plane angle of the vector from hip to shoulder with respect to vertical.

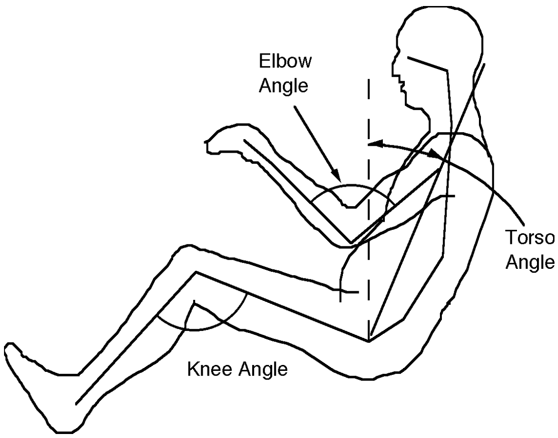


Figure 5. Posture variables used in OPM.

In the reference dataset, the mean values of knee angle and torso angle are not significantly related to the anthropometric variables, but mean elbow angle is a function of stature and the ratio of sitting height to stature. The mean values and predictive equation, used to determine the neutral values in the optimization, are given in Table 2. While Seidl used the pooled angle values from all subjects to model the distribution of angles, a more direct interpretation of the relative sizes of the angle distributions can be obtained by first subtracting off each subject's mean values. The spreads of the resulting distributions reflect the average within-subject joint-angle tradeoffs. Shapiro-Wilk W-test values given in Table 2 indicate that, for each variable, the within-subject angle distribution is not significantly different from normal.

Table 2. Angle Distribution Parameters for OPM

Angle	**Between-Subject Mean (degrees)**	**Within-Subject Standard Deviation (degrees)**	**Shapiro-Wilk Test for Normality (W, p)***
Torso	23.8	2.8	0.994, 1.00
Knee	118.0	7.9	0.986, 0.35
Elbow	-297.0 + 0.12 Stature + 406.6 SH/S†	11.6	0.987, 0.63

*p values less than 0.05 (or some other Type-I error level) would support a conclusion that the distribution is not normal.
†Regression on stature (mm) and the ratio of sitting height to stature, $R^2 = 0.32$, RMSE = 19 degrees.

In the within-subject analysis, the relative sizes of the angle distributions represent quantitatively the joint angle tradeoffs used by the subjects in adjusting to a wide range of vehicle and seat geometries. Angle changes at the elbow were largest, followed by knee angle, with only small angle changes occurring in the torso.

The objective of the OPM is to select, from the postures that meet the kinematic constraints, the posture that is most likely. This means choosing the vector of joint angles

$$\Phi = \{\text{knee angle, elbow angle, torso angle}\} = \{\phi 1, \phi 2, \phi 3\} \quad (1)$$

such that the joint (conditional) probability of Φ is maximized. In the original approach developed by Seidl, the range of test conditions was restricted in a way which reduced the correlation among the variables to the point where they could be neglected. In that case, the combined probability is simply the product of the probabilities at the individual joints. However, in the broader dataset used for the development of the OPM, there are potentially important correlations among the joint angles, notably between the elbow and knee angles ($r = -0.39$). Therefore, the likelihood of a particular angle at one joint is dependent on the value of another joint. To compute the overall likelihood of a posture, it is necessary to consider the conditional probability.

Using the marginal normality findings from Table 2, the three individual joint angle distributions can be considered as a single multinormal distribution characterized by mean vector $\boldsymbol{\mu}$ and covariance matrix Σ. The probability density function for the random vector **Y**, where **Y** has multivariate normal distribution, is given by

$$f(\boldsymbol{\mu}, \Sigma) = \frac{1}{(2\pi)^{r/2}\sqrt{|\Sigma|}} \operatorname{Exp}[-\frac{1}{2}(\mathbf{Y}-\boldsymbol{\mu})^{T}\Sigma^{-1}(\mathbf{Y}-\boldsymbol{\mu})]$$

where $\boldsymbol{\mu}$ is the mean vector, r is the dimension of **Y** (3, in this case), Σ is the covariance matrix, $|\Sigma|$ denotes the determinant of Σ, and Σ^{-1} denotes the inverse. For the knee, elbow and torso angles used in the OPM, the mean values are given by the expressions in Table 2 and the covariance matrix is given in Table 3. The optimization problem, then, is to find the vector Y = Φ for which $f(\boldsymbol{\mu}, \Sigma)$ is a maximum.

Table 3. Covariance Matrix (Σ)

Angles	**Knee**	**Elbow**	**Torso**
Knee	62.41	-35.73	5.08
Elbow	-35.73	134.56	-1.29
Torso	5.08	-1.29	7.84

Because of the kinematic constraints imposed by the ankle location, grip location, hip travel path, and torso motion distribution, the kinematic linkage has only two degrees of freedom (neglecting arm and leg splay). If the knee angle and torso angle are given, the elbow angle can be computed from the constraints. This reduces the optimization problem to the search of a two-parameter space, and the objective function (posture likelihood) can be plotted as a surface for any particular vehicle-geometry/anthropometry combination, as shown in Figure 6. The single local maximum is also a global maximum, so a gradient-based approach is adequate to compute the posture. After determining the knee, torso, and elbow angles using the optimization algorithm, the torso segments are fit to the calculated hip and shoulder locations using the same inverse kinematics approach used with the CPM (3, 7).

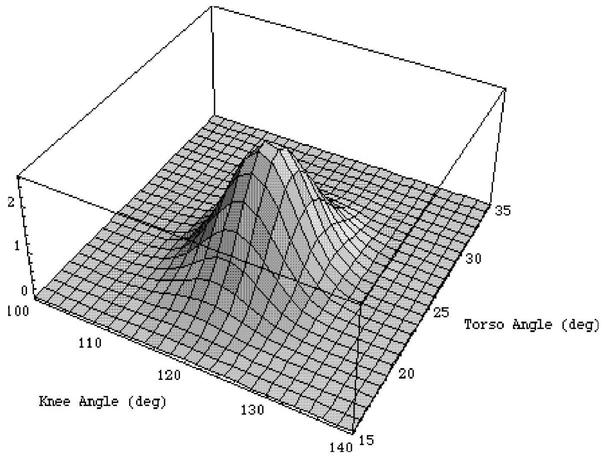
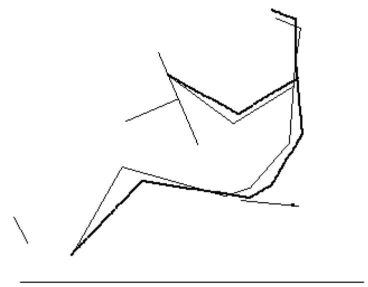


Figure 6. Empirical posture likelihood (arbitrary units) as a function of knee angle and torso angle for midsize-male anthropometry in a mid-range vehicle package.

RESULTS

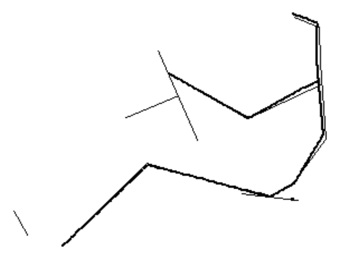
MODEL COMPARISONS – Figure 7 illustrates driver posture predictions from the CPM and OPM for four different body sizes in one typical passenger car configuration. The two models produce similar postures, with the greatest differences observed with small female anthropometry. In particular, the CPM predicts a more reclined torso posture for the small female than is predicted by the OPM.

Figure 8 shows the effects of a 200-mm change in fore-aft steering wheel position at a midrange seat height with midsize male anthropometry. There are small differences between models in the predicted postures, but the effects of the steering wheel position change are similar. Figure 8 illustrates the tradeoff between torso recline and limb posture that drivers adopt in adjusting to different steering wheel positions. Table 2 showed that the within-subject standard deviation of knee angle across a wide range of vehicle configurations is about 2.8 times as large as the standard deviation of torso angle. This indicates that drivers adapt to changes in fore-aft steering wheel position primarily by changes in limb posture, while torso recline changes only slightly.

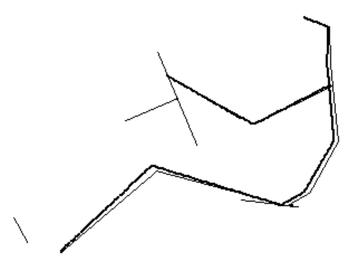


Small Female

Midsize Female



Midsize Male



Large Male

Figure 7. Comparison of postures predicted by CPM (thin lines) and OPM (thick lines) for a range of body sizes. Refer to Figure 2 for kinematic linkage description.

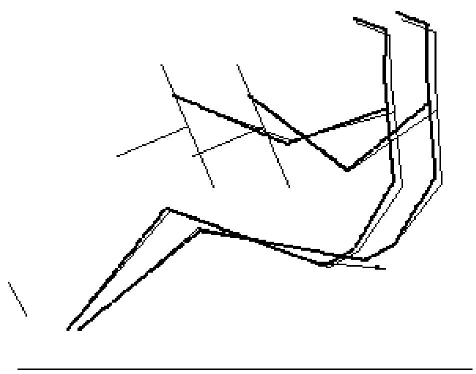


Figure 8. Illustration of effects of fore-aft steering wheel position on posture for midsize male for CPM (thin lines) and OPM (thick lines).

COMPARISON TO IN-VEHICLE DATA – The accuracy of both models for predicting driving posture was assessed using data from another study of driving posture. In this in-vehicle study, 60 men and 60 women ranging in stature from 1441 to 1952 mm drove five vehicles over a 15-minute road route, adjusting the seat track position and seatback angle to obtain a comfortable driving posture. Each car was equipped with an automatic transmission and was tested with the seat track adjustment restricted to two-way (fore-aft) travel. After returning from the road route, the driver's preferred posture was recorded using a FARO coordinate measurement arm and procedures similar to those used in the laboratory studies (2, 5). Table 4 lists some of the characteristics of the vehicles. The vehicles were selected to represent a substantial part of the range of the interior geometry available in current passenger cars.

The CPM and OPM were exercised using the vehicle configurations and individual subject anthropometry. The resulting eye position predictions were compared with the observed eye positions to assess the model accuracy. Table 5 lists the means and standard deviations of the prediction errors by vehicle for each posture model.

The CPM predicted the mean eye location for the five vehicles with considerable accuracy, as reported previously (3). The predicted horizontal coordinate was within 10 mm in all cases, with average errors of 3.6 mm. Both the CPM and OPM tended to predict eye locations higher than those measured. During the in-vehicle study, measurements of eye location taken before and after the drive indicated that eye locations averaged 9 mm lower after the drive, a difference attributed to seat compression. Applying this dynamic Z correction brings the average vertical prediction error for the CPM to about 2 mm and the OPM to about –12 mm. The standard deviation of the eye location errors were similar for the two models, but the overall range of average error across vehicles was larger for the OPM on the horizontal axis (22.3 mm compared with 8.7 mm for the CPM).

Table 4. Vehicle Characteristics*

Vehicle	Seat Height (mm)	SWtoBOFX (mm)	Seat Cushion Angle (deg)
Plymouth Voyager	326	504	14.0
Chrysler LHS	250	597	17.7
Dodge Avenger	189	577	16.6
Jeep Grand Cherokee	298	607	11.3
Plymouth Laser	194	550	11.3

* Some vehicles were modified from design intent.

Table 5. Comparison of Model Predictions vs. Observed Eye Locations in Vehicle Data: Mean Observed minus Predicted (Standard Deviation)

Vehicle	EyeX (Obs - Pred) (mm)		Eye Z (Obs - Pred) (mm)	
	CPM	OPM	CPM	OPM
Plymouth Voyager	0.7 (52.2)	-1.2 (50.4)	-4.8 (20.6)	-15.2 (20.4)
Chyrsler LHS	0.0 (46.5)	9.2 (46.3)	-6.5 (18.1)	-20.6 (18.3)
Avenger	2.5 (47.5)	20.0 (47.1)	-7.4 (18.8)	-22.7 (19.7)
Jeep Grand Cherokee	5.9 (49.6)	16.8 (50.3)	-13.6 (18.9)	-22.9 (18.9)
Plymouth Laser	8.7 (46.2)	21.1 (45.0)	-2.2 (17.3)	-24.9 (17.9)
Overall Mean	3.6 (48.4)	13.2 (47.8)	-6.9 (18.7)	-21.3 (19.0)
Dynamic Z Correction	--	--	2.1	-12.3
Overall Range	8.7	22.3	11.4	9.7

DISCUSSION

The posture prediction method developed by Seidl (4) used observed posture selection behavior to infer the relative costs of deviation from average, preferred joint angles. The OPM presented in this paper refines the approach by using a within-subject analysis and data-guided inverse kinematics to simplify the calculations. The resulting conditional joint angle distributions can be regarded as a measure of the within-subject tradeoffs between limb and torso posture changes when adapting to different vehicle configurations. Drivers adapt to changes in steering wheel position (relative to the pedals) primarily by changes in limb posture (elbow and knee angles) with only small changes in torso recline.

When developed using the same data, the CPM and OPM produce essentially equivalent predictions, although the CPM is slightly more accurate for predicting in-vehicle postures. It is likely that the OPM could be refined to replicate the accuracy of the CPM. The primary advantage of the CPM is that the predictions for important postural characteristics, such as hip and eye location, are written as closed-form, linear equations, the coefficients of which quantify the relative effects of stature, steering wheel position, and other inputs. This closed-form approach allows the predictions to be used independent of any particular human figure model. In contrast, the OPM must be implemented using some type of computerized search algorithm, and is tied to a particular kinematic linkage.

In spite of its limitations, the OPM provides some interesting insights into posture-selection behavior. When confronted with a range of workstation geometries, people select postures that can be interpreted as an optimization of an internal, unknown cost function. Provoking a wide range of postural responses by testing with an large variety of workstation geometries will elicit a range of angles at each joint that imply the relative cost to the worker of deviations from the average, preferred postures. Looked at in this way, the experiments with automobile driving postures suggest that changes in torso posture typically have greater internal cost than changes in limb posture.

One potential advantage of the OPM is that it may provide greater generalizability to novel tasks. The CPM can adjust the predicted posture only in response to changes in the specific input parameters, such as seat height and steering wheel position. However, the OPM will produce a different posture whenever the kinematic constraints at the hands and feet are changed. This is actually a liability for prediction of normal driving postures, because driving postures are not significantly different when a driver's hands are constrained to grasp the steering wheel at different locations (3). For other tasks, such as reaching and grasping shifters, brake levers, or other controls, the OPM method provides greater adaptability. Yet, the predictions are not likely to be accurate unless movements of this type were included in the input database. In general, the CPM approach will always be more accurate for well-studied tasks, because it is not constrained by the limitations of a kinematic model.

Both of the models included here have limitations arising from test data on which they were developed and validated. The models are applicable only to seats with fore-aft adjustment, although comparison to in-vehicle data collected with height- and angle- adjustable seats shows that the CPM is similarly accurate under those conditions. In all conditions, drivers were free to select a preferred seatback angle. Fixed or imposed seatback angles would result in torso postures substantially different from those predicted. Finally, fore-aft adjustable pedals that have recently been introduced in popular vehicle models provide an additional adjustment degree of freedom that was not included in the development of these models. Addition study will be necessary to determine the resulting effects on posture.

The accuracy of ergonomic analyses using computer manikins is strongly dependent on the accuracy of the manikin postures. The CPM and OPM compared in this paper are two accurate ways of predicting normal driving posture that may be used to facilitate vehicle interior assessment.

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