A Statistical Method for Predicting Automobile Driving Posture

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A new model for predicting automobile driving posture is presented. The model, based on data from a study of 68 men and women in 18 vehicle package and seat conditions, is designed for use in posturing the human figure models that are increasingly used for vehicle interior design. The model uses a series of independent regression models, coupled with data-guided inverse kinematics, to fit a whole-body linkage. An important characteristic of the new model is that it places greatest importance on prediction accuracy for the body locations that are most important for vehicle interior design: eye location and hip location. The model predictions were compared with the driving postures of 120 men and women in five vehicles. Errors in mean eye location predictions in the vehicles were typically less than 10 mm. Prediction errors were largely independent of anthropometric variables and vehicle layout. Although the average posture of a group of people can be predicted accurately, individuals' postures cannot be predicted precisely because of interindividual posture variance that is unrelated to key anthropometric variables. The posture prediction models developed in this research can be applied to posturing computer-rendered human models to improve the accuracy of ergonomic assessments of vehicle interiors.

INTRODUCTION

The design of passenger car interiors is now commonly facilitated by the use of three-dimensional (3-D) human representations that can be manipulated in a computer environment (Porter, Case, Freer, & Bonney, 1993). These computer-aided-design (CAD) human models have increased in sophistication in recent years with advances in computer hardware and software, but their effective use is hampered by the lack of valid methods to set the posture of the models in the simulated vehicle interior.

In the mid-1950s, Dempster (1955) introduced an approach to ergonomic assessment for seated vehicle occupants using an articulated, two-dimensional (2-D) template. A similar template design and a weighted 3-D manikin for measurements in actual vehicles were standardized in the mid-1960s for passenger car interior design by the Society of Automotive Engineers in Recommended Practice J826. In this text SAE J*n* refers to a Society of Automotive Engineers (SAE) Recommended Practice, published in the *Automotive Engineering Handbook* (SAE, 2001). These two tools, the 2-D template and the 3-D H-point machine, are still widely used for designing vehicle interiors but are supplemented by statistical tools that predict the distributions of particular posture characteristics for the U.S. population. These task-oriented percentile models, based on posture data from a number of studies, are available for driver-selected seat position (SAE J1517), eye position (J941), reach (J287), and head location (J1052). See Roe (1993) for a thorough review of the use of these tools in contemporary occupant packaging.

Although the existing task-oriented percentile models are very useful for vehicle design, they

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are not directly applicable to the posturing of human figure models because they address the population distribution of particular posture characteristics, rather than predict the posture for any particular anthropometric category. For example, the SAE "eyellipse" provides a prediction of the mean and distribution of driver eye locations but does not predict the eye location for women 1550 mm tall or men 1800 mm tall. This more detailed information is necessary to establish an accurate posture for a particular instance of a CAD human model, which necessarily represents a single set of anthropometric variable values.

As computer technology has developed, CAD models have been created to simulate the 2- and 3-D physical manikins, supplemented by more complete 3-D human representations. Porter et al. (1993) briefly reviewed the features of 13 human-modeling systems in use prior to 1993 with potential application to vehicle design. Software development moves rapidly, however, and the two models most widely used for vehicle interior design at the time of this writing – Jack (EDS-PLM Solutions, Cypress, CA) and Tecmath's RAMSIS (Human Solutions, GmbH, Kaiserslautern, Germany) – were not mentioned in the Porter et al. review.

One impediment to more widespread use of human models for vehicle design has been a lack of valid posture prediction. Without posture-prediction capability built into the model or available through other external data or statistical models, many of the most useful applications of the CAD human models are unreliable. For example, vision and reach assessments require an accurate starting posture for the particular manikin dimensions being used. In the absence of accurate posture prediction, CAD human models are valuable primarily for visualization rather than for ergonomic assessment.

Few published studies are applicable to posture prediction for vehicle occupants. In many early studies data were presented only in the aggregate or in terms of a population distribution, so the findings are not applicable to human model posture (Hammond & Roe, 1972; Meldrum, 1965; Phillipart, Roe, Arnold, & Kuechenmeister, 1984). Seidl (1994) presented the most complete approach to whole-body driving posture prediction to date. Using posture data collected in a laboratory vehicle mockup, he developed an optimization-based approach that is now used with the RAMSIS human model. The Seidl approach selects a posture consisting of the set of joint angles that is empirically most likely within the specified kinematic constraints. This technique uses posture data collected from three vehicle configurations and can be interpreted as representing an analogue of the driver's inherent posture selection process, but it has several important limitations. The posture prediction model is proprietary, and hence its validity cannot be independently assessed except through the use of the RAMSIS software. In addition, the posture prediction model cannot be applied to a human figure model having a different linkage.

In the current research a model to predict automobile driver postures was developed using driving posture data obtained from a laboratory study of 68 men and women in vehicle and seat configurations that span a large range of passenger car interior geometry (Reed, Manary, Flannagan, & Schneider, 2000). 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. The CPM was also developed specifically to be suitable for use with any human figure model and to be capable of representation in closed form. As such the performance of the CPM as implemented in a figure model can be verified by reference to published functions, an important check that is not possible with the RAMSIS posture prediction approach. The prediction accuracy of the CPM was assessed using the original laboratory data and data from a separate study of driving posture in five vehicles.

METHODS

Model Development Methodology

Figure 1 shows the model development approach schematically. Data from a laboratory study with 68 drivers were used to develop the posture prediction model. The model was subsequently validated by comparison with the postures of 120 drivers in five vehicles.

The laboratory study methods and results

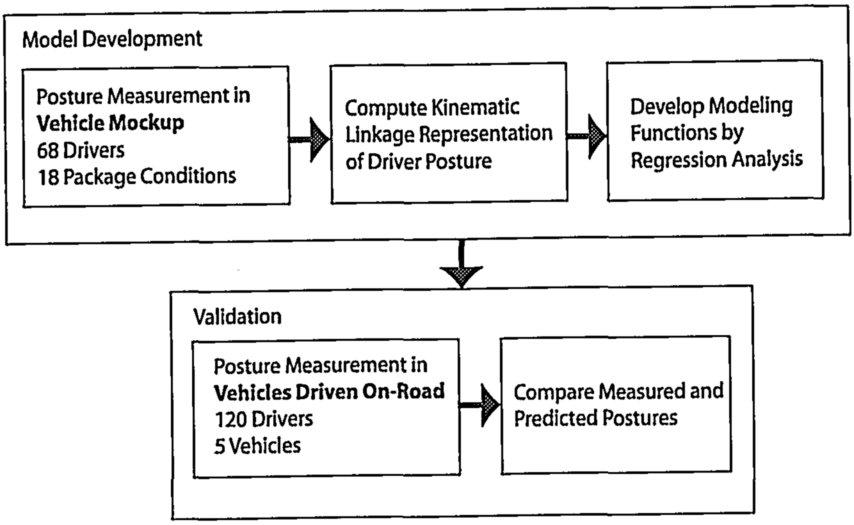

Figure 1. Schematic of model development and validation.

were described in a previous paper (Reed et al., 2000). 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. The participants were approximately evenly distributed in stature, from under 1500 mm to over 1900 mm tall. The preferred driving posture for each participant was recorded for 18 combinations of seat height, seat cushion angle, and fore-aft steering wheel position. The vehicle package configurations ranged from those typical of small, sporty cars to those typical of minivans and sport utility vehicles (SUVs). The steering wheel fore-aft position was varied over a 200-mm range for seat heights (SAE H30; Society of Automotive Engineers, 2002) of 180, 270, and 360 mm.

Driver posture was recorded by using a sonic digitizer to record the 3-D locations of 23 body landmarks. The external landmark data were used to calculate internal joint locations using methods described in Reed, Manary, and Schneider (1999). For example, the locations of the hip joints were calculated from the measured locations of the left and right anterior-superior iliac spine and pubic symphysis landmarks using offset vectors developed from cadaveric studies (Bell, Pedersen, & Brand, 1990; Reynolds, Snow, & Young, 1981; Seidel, Marchinda, Dijkers, & Soutas-Little, 1995). The joint locations define a kinematic linkage representation of the human body shown in Figure 2. Additional details concerning the data collection methodology are in Reed et al. (2000).

Vehicle Package Geometry

Driver posture prediction is conducted in a coordinate system defined by several commonly used vehicle reference points. The layout of the driver workstation is referred to as the vehicle *package.* Complete definitions of these points can be found in SAE J1100 and associated practices (SAE, 2001). The *x* axis in the package coordinate system runs positive rearward, the *y* axis runs positive to the driver's right, and the *z* axis runs positive upward. 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, whereas the origin *z* coordinate is defined by the accelerator heel point (AHP).

For the current analysis the origin *y* coordinate is the centerline of the driver seat. Figure 3 illustrates these reference points in a side-view schematic of the driver's station. In general terms vertical dimensions are measured from the floor and fore-aft dimensions are measured from a point on the accelerator pedal. Dimensions that are inputs to the posture prediction model are seat height (H30), seat cushion angle (L27), and fore-aft steering wheel position (L6).

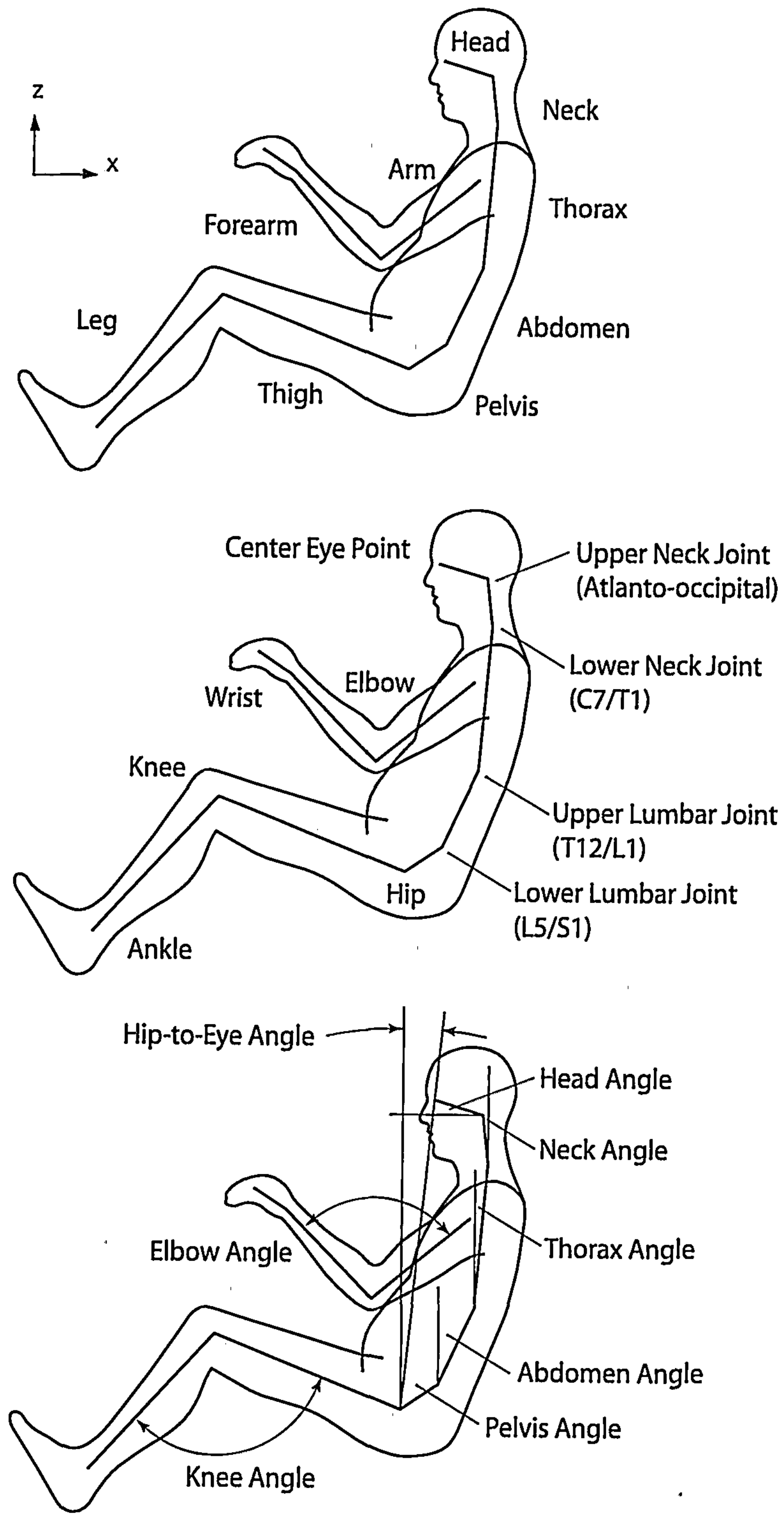

Figure 2. Definitions of kinematic linkage and posture measures. Angles referenced to horizontal or vertical are *x,z* (sagittal) plane angles. Angles between segments (elbow angle, knee angle, and ankle angle) are measured in the plane formed by the segments (included angles). Note: Neck angle is negative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

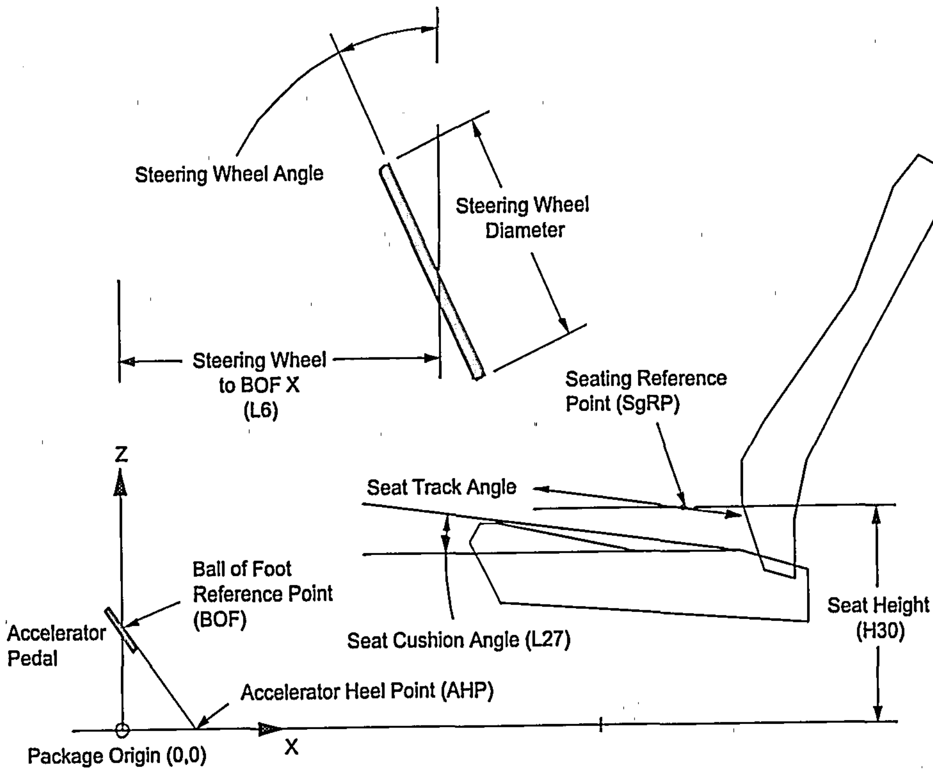

Figure 3. Vehicle package geometry. Expressions in parentheses are nomenclature from SAE J1100 (SAE, 2001).

Model Structure

The posture prediction model combines the regression functions presented in Tables 1 and 2 with inverse kinematics guided by additional information from the input data set. The model is intended to produce the best possible prediction of eye and hip locations while potentially sacrificing some accuracy in other model degrees of freedom. The posture of the trunk and the right limbs is predicted, after which the right-limb posture is reflected to the left side of the body, in keeping with a sagittally symmetric definition of normal driving posture.

The model is known as the *cascade prediction model* (CPM) because the predictions are obtained using a series of submodels, each based on the results of the previous model. The motivation for this approach is to provide the best possible prediction accuracy for the hip and eye locations, the posture characteristics that are most important for ergonomics assessments of the driver's station. Hip location is closely related to seat position and lower extremity posture, whereas eye location is critical for vision analyses. In addition, this approach allows the CPM to be used with many different human figure model linkages and also permits the core parts of the model that predict hip and eye locations to be used with other approaches to fitting the torso and extremities.

Figure 4 depicts the CPM algorithm schematically. The fore-aft hip location (Hip$x$ reBOF) is predicted directly using regression functions. The hip-to-H-point offset vector is calculated using regression functions, yielding a hip travel path in the x,z plane corresponding to fore-aft seat position adjustment. The point along this line with x value equal to the predicted fore-aft hip location is the predicted hip location in the x,z plane. The y coordinates of the left and right hip joints are set so that each hip joint lies equidistant from the seat centerline, placing the torso segments in the x,z plane of the seat centerline.

Eye location in relation to the hip is then

TABLE 1: Regression Models

Variable (mm or °)	Intercept	Stature (mm)	Sitting Height/ Stature	Seat Height (H30; mm)	SW to BOFx (L6; mm)	Cushion Angle (L27; °)	R^2_{adj}	*RMSE*
Hipx reBOF	84.8	0.4659	–430.1	–0.1732	0.4479	–1.04	.78	35.9
Hip-to-eye angle	–72.7	0.00642	115.7	—	0.0147	0.11	.20	3.9
Eyex reBOF	–836.6	0.5842	916.6	–0.1559	0.6101	—	.71	50.9
Eyez reAHP	–267.1	0.3122	679.9	1.0319	0.0292	—	.89	21.8
Eyex reHip	–916.0	0.1187	1347.2	—	0.1563	1.15	.23	41.7
Eyez reHip	–261.5	0.3336	675.8	—	–0.0544	—	.72	22.9
Anklex reBOF	–300.2	0.0400	467.6	0.1746	0.1358	1.3	.32	18.0
Anklex reAPedal	46.1	–0.0466	—	—	—	—	.05	23.2
Anklez reAHP	8.4	0.0312	—	0.1236	—	0.55	.25	13.1
Knee angle	69.1	–0.0071	61.3	–0.0321	0.0829	–0.59	.44	7.7
Head angle	–156.2	0.00919	137.5	—	—	—	.03	10.6
Neck angle	16.1	–0.01197	—	—	0.0109	—	.04	7.7
Thorax angle	–42.7	0.00497	45.2	—	0.0128	—	.03	6.1
Abdomen angle	–94.5	0.0109	184.5	—	0.0222	—	.09	9.7
Pelvis angle	–16.3	0.0102	90.2	—	0.0177	0.39	.04	10.0

Note: Linear model created by multiplying each term in the table by the value of the column variable and adding a constant intercept. BOF = ball of foot; AHP = accelerator heel point; APedal = accelerator pedal; SW = steering wheel.

calculated using the regression functions in Table 1. With respect to the original data set, predicting the eye location relative to the hip location and relative to AHP/BOF gives essentially identical results. However, the indirect procedure avoids potential errors associated with seat track angles different from the angle used in testing. The predicted eye location is the center eye point, a point on the midline of the body that has a *z* coordinate equal to the corner-of-eye landmark and an *x* coordinate equal to the infraorbitale landmark. This makes it possible to conduct calculations of all torso segments in a plane.

An inverse kinematics submodel is used to fit the kinematic linkage representation of the torso to the predicted hip and eye locations. Regression analyses were performed using values of torso segment orientation and overall recline (hip-to-eye) angle after subtracting participant means. The slopes of the regression functions estimate the average change in *x,z* plane orientation of each torso segment with a change in overall recline. These values are used to determine the relative motion in the torso as the torso segments are manipulated to match the predicted hip and eye locations.

Once the torso segment orientations have been calculated using the inverse kinematics procedure, upper-extremity posture is calculated using inverse kinematics and employing the calculated shoulder locations and the hand grip locations. Consistent with observations from the laboratory study, note that the locations of the hands on the steering wheel do not affect the torso posture. Rather, the torso posture and hand grip locations determine the upper-extremity joint angles. An analogous process is used to fit the thigh and leg segments to the predicted hip and ankle locations.

TABLE 2: Regression Models for H-Point Location

Variable	Intercept	Stature (mm)	Body Mass Index (kg/m²)	Seat Height (H30; mm)	SW to BOFx (mm)	Cushion Angle (°)	R^2_{adj}	*RMSE*
Hipx reHPt	–131.5	0.0482	–2.677	—	—	5.00	0.34	27.6
Hipz reHPt	–143.4	—	2.009	0.0700	0.1375	0.49	0.40	13.7

Note: Linear model created by multiplying each term in the table by the value of the column variable and adding a constant intercept. SW = steering wheel; BOF = ball of foot; HPt = H point.

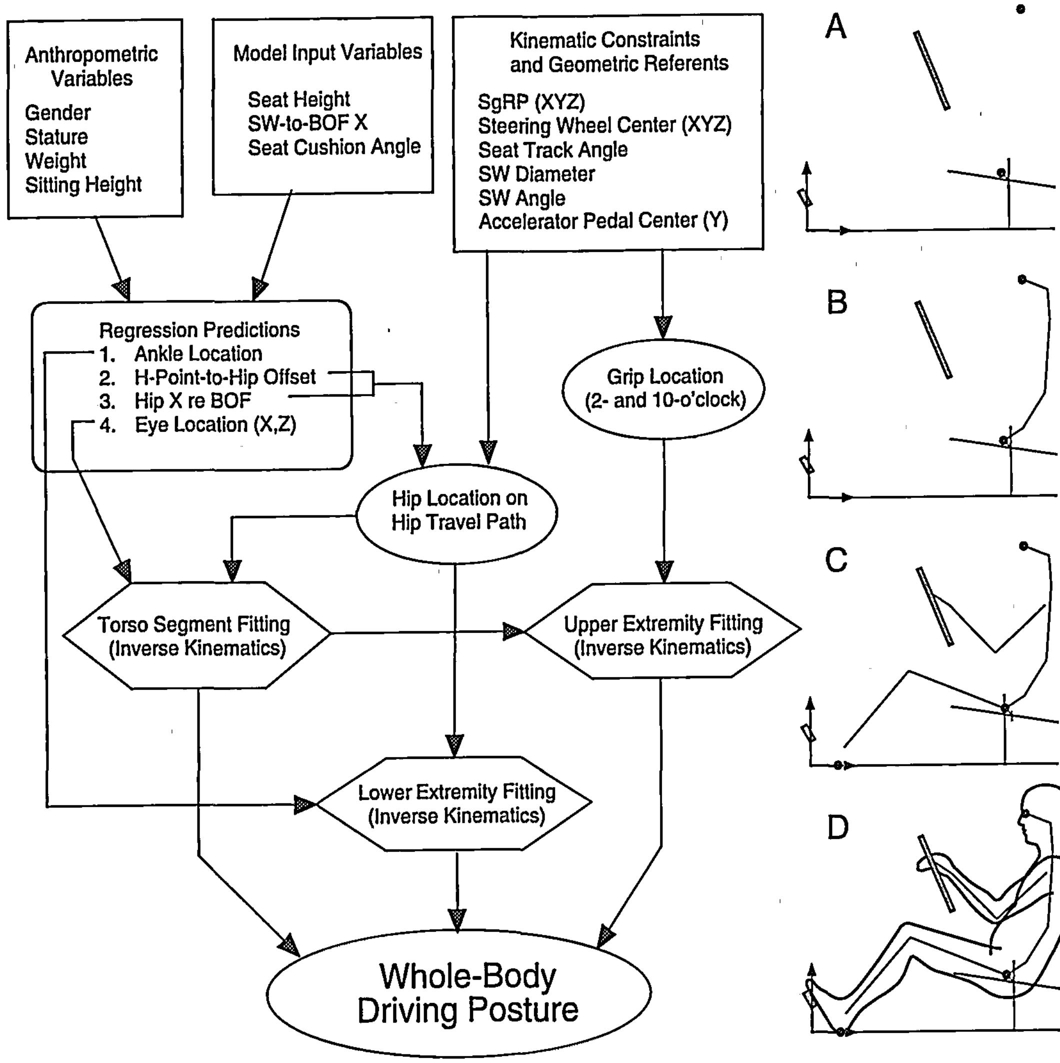

Figure 4. Information flow schematic of cascade prediction model (CPM) and step-by-step sequence. A: Predict hip and eye locations. B: Fit torso segments by inverse kinematics using data-based motion distribution. C: Fit limb segments by inverse kinematics using splay data. D: Fit full 3-D model to kinematic linkage. SW = steering wheel, SgRP = seating reference point, BOF = ball of foot.

Regression Modeling

Hip and eye locations, which are the most important postural degrees of freedom for ergonomics analysis of the driver's station, are predicted by regression functions developed from the laboratory study data. These functions were created by a stepwise process following a thorough analysis of the study data (see Reed et al., 2000, for details of the factor effect assessments). Among the conclusions of the original analysis were that seat height, steering wheel position, and seat cushion angle all have significant independent effects on posture.

Data from all participants and trials were pooled in the analysis. A stepwise regression technique was applied with the potential regressors of stature, body mass index, sitting height divided by stature, seat height (H30), steering wheel to BOF distance (L6), and seat cushion angle (L27). Body mass index (weight in kilograms divided by stature in meters squared) was used rather than body weight to reduce the problems associated with correlated regressors. For the same reason, the ratio of sitting height to stature was used rather than sitting height itself.

An automated algorithm selected a model using $p < .25$ to enter and $p > .10$ to leave, after which manual selections were made to obtain a parsimonious model that maintained an adjusted R^2 value within .02 of the maximum value obtained by the automated procedure. Tables 1 and 2 summarize the regression models for posture variables of interest. All terms included in the models are significant with $p < .001$, as are the models themselves. No interaction terms are included in these models because no significant interactions between the potential predictors were found (see Reed et al., 2000, for more analysis of potential factor interactions in this data set).

In-Vehicle Study Methods

The validity of the posture prediction model was assessed by reference to data from a separate in-vehicle study reported in Manary, Flannagan, Reed, and Schneider (1998). As part of that study, 120 men and women ranging in stature from 1441 to 1952 mm tall drove five vehicles (a sports car, two sedans, a minivan, and an SUV) that ranged in seat height from 189 to 326 mm.

Each participant drove each vehicle over a 15-min road route, adjusting the seat track position and seat back angle to obtain a comfortable driving posture. Each car was equipped with automatic transmission and was tested with the seat track adjustment restricted to two-way (fore-aft) travel. After drivers returned from the road route, their posture was recorded using a mechanical coordinate measurement arm and procedures similar to those used in the laboratory. These procedures have been used extensively in other studies (e.g., Flannagan, Manary, Schneider, & Reed, 1998; Flannagan, Schneider, & Manary, 1996) and have been shown to produce reliable measures of normal driving posture. The in-vehicle data used in this analysis were also used in the development of the most recent revision to the SAE "eyellipse" (Manary et al., 1998).

RESULTS

Model Assessment: Original Data

There are two general areas of concern in assessing model performance. First, the ability of the models to match the original data used to construct the models is assessed. Second, the predictive ability of the models is evaluated using new data collected in vehicles. Because eye location is one of the most important characteristics of the posture prediction, quantitative assessments of the models will focus on eye location.

For the original data, observed and predicted eye locations differ by 0.9 mm in the x direction and –0.4 mm in the z direction. The standard deviation of the errors, a measure of the residual posture variance not accounted for by the model predictions, is about 51 mm for the x coordinate and about 20 mm for the z coordinate. These values are similar to the root mean square error (RMSE) values for the direct regression prediction of the eye location in Table 1, indicating that the model prediction precision is similar to the precision obtained by a direct prediction.

Figure 5 shows a plot of the CPM x and z axis errors along with a 95% density ellipse. The z axis errors are approximately normally distributed (Shapiro-Wilk W test), but the x axis errors have a broader-than-normal distribution. Nonetheless, the normal distributions overlying the marginal distribution plots in Figure 5 illustrate that the x,z plane prediction error distribution can reasonably be approximated as bivariate normal.

The correlation among the errors is attributable to the effects of the principal ways in which posture selection behavior can deviate from the prediction. People can select a seat position or recline angle that is different from that predicted. Both deviations tend to cause a movement of the eye along an inclined side-view path. Seat position prediction errors result in discrepancies along a path having the same slope as the seat track, and recline angle errors result in errors along a slightly more inclined path.

One important question concerning the prediction errors is whether the prediction precision varies substantially with the input variables. Is the prediction precision approximately the same for small people and large people, or for different seat heights? To address this issue we divided the participants into five stature groups using 100-mm bins from 1550 to 1850 mm (three groups), and creating two groups from those with statures above 1850 and below 1550 mm. The number of participants in each group

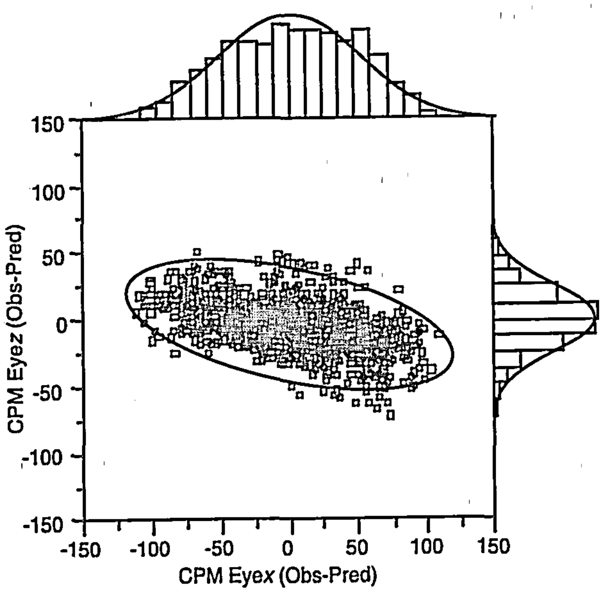

Figure 5. Observed-predicted eye locations for the CPM, showing marginal histograms and a 95% bivariate normal density ellipse. A normal distribution with equivalent variance is depicted overlying each histogram.

ranged from 9 to 26. Table 3 lists the group definitions and the within-group error standard deviations. The error variance from the CPM was compared among the groups using Levene's test for homogeneity of variance. Levene's test is an analysis of variance on the absolute differences between each observation and the group mean. No significant differences in variance were found among groups for *x*-coordinate errors, but there were small but significant differences in the distribution of *z*-coordinate errors. However, the standard deviations in Table 3 indicate that there is not a consistent trend with body size, and the differences are small enough to be of minimal practical importance. Similar trends are observed for other variables (seat height, steering wheel position, etc.). These findings suggest that the precision of the model predictions can reasonably be approximated as constant throughout the range of the input data.

Model Assessment: Vehicle Data

A measure of the posture prediction model performance that is more important than fit to the original data is the correspondence between the model predictions and the postures of drivers in actual vehicles. The posture prediction model was exercised using the vehicle configurations and driver body dimensions. The resulting eye position predictions were compared with the observed eye positions to assess the model's accuracy. Table 4 lists the means and standard deviations of the prediction errors by vehicle.

Errors in the prediction of horizontal eye

TABLE 3: Prediction Error Standard Deviations by Stature Group

Group	Stature Range (mm)	Number in Group	Eyex (Obs – Pred) *SD* (mm)	Eyez (Obs – Pred) *SD* (mm)
1	<1550	11	48.9	16.0
2	1550–1650	13	47.2	18.5
3	1650–1750	26	50.5	22.4
4	1750–1850	9	55.9	16.2
5	>1850	9	47.7	21.2

Note: Linear model created by multiplying each term in the table by the value of the column variable and adding a constant intercept. BOF = ball of foot; AHP = accelerator heel point; APedal = accelerator pedal.

TABLE 4: Comparison of Model Predictions versus Observed Eye Locations in Vehicle Data: Mean Observed minus Predicted (Standard Deviation)

Vehicle	Eyex (Obs–Pred; mm)	Eyez (Obs–Pred; mm)
Voyager	0.7 (52.2)	–4.8 (20.6)
LHS	0.0 (46.5)	–6.5 (18.1)
Avenger	2.5 (47.5)	–7.4 (18.8)
Grand Cherokee	5.9 (49.6)	–13.6 (18.9)
Laser	8.7 (46.2)	–2.2 (17.3)
Overall mean	3.6 (48.4)	–6.9 (18.7)
Dynamic *z* correction[a]	—	2.1
Overall range	8.7	11.4

[a] Eyez predicted location lowered by 9 mm (see text).

location averaged 3.6 mm across vehicles, with an average standard deviation of 48.4 mm. On the vertical coordinate the predicted mean eye locations were higher than those observed in all cases. Pilot testing in three vehicles demonstrated that eye locations after the 15-min drive were on average 9 mm lower than those measured immediately prior to the drive (Manary et al., 1998). The cause appears to be settling into the seat, not additional slumping.

Because the prediction models were generated from static vehicle mockup data, a 9-mm dynamic correction was made to the *z*-coordinate predictions. With the correction, the average vertical error across vehicles is 2.1 mm. The range of prediction errors, a measure of the consistency of the models across vehicles, was under 10 mm for the *x* coordinate and about 10 mm for the *z* coordinate. The standard deviations of the errors, a measure of the individual prediction accuracy, were essentially identical to the standard deviations computed with the original vehicle mockup data, suggesting that the error distribution for the vehicle data is similar to that observed in the laboratory.

DISCUSSION

Key Features of the CPM

The CPM represents an important advance in the prediction of driving posture in three main areas.

First, the model predicts postures for individual drivers, a feature that is necessary for posturing human figure models. Current SAE models (e.g., SAE J1517 and J941) predict only population distributions of seat position or eye location.

Second, the model can be represented in closed form, it is applicable to any kinematic linkage, and its implementation can be independently verified. The model in the widest use, the optimization-based technique in RAMSIS, cannot be expressed in closed form, works only with the RAMSIS linkage, and cannot be independently verified. Moreover, the RAMSIS model can be validated (compared with actual driving postures) only through the use of the RAMSIS software, whereas the closed-form functions for the CPM can be compared with any source of driving posture data using a simple spreadsheet.

Third, the direct prediction of hip and eye locations means that these variables, which are the most important for driver workstation design, are maximally representative of the underlying data (that is, the regression functions give best, unbiased estimates of the expected value for the outcome variables, given the input conditions and the modeled data set). Posture prediction methods that rely on cost-function optimization through a kinematic linkage (e.g., Porter & Gyi, 1998) cannot be more accurate for predicting hip and eye location and are likely to be less accurate. The potential inaccuracy of joint-angle-based prediction methods stems in part from the fact that factor effects can be modeled only kinematically. For example, the only way to account for the substantial effect of steering wheel position on fore-aft hip location is through upper-extremity angles. With such models changing the steering wheel grip location changes the torso posture. However, the laboratory and vehicle data show that people grip steering wheels at many positions as they drive, with no important changes in torso and lower-extremity posture.

Model Evaluation

A good predictive model of driving posture will have a number of useful characteristics for any degree of freedom of interest. Taking the prediction of eye location as an example: (a) The model will be accurate and precise, on average, across vehicles, meaning that the mean predicted eye location will deviate only a small amount from the mean observed eye locations across vehicles. This implies that the error in mean eye location prediction for each vehicle will be small and, also, that the errors will offset so that across vehicles, the average error is small. (b) The model will have the accuracy characteristics described in (a) for any population composition (e.g., for a group of small women or large men). (c) The model will have minimal error variance for individual predictions, meaning that the absolute deviations of individuals from the predictions for people with matching anthropometry on the key variables are small.

The CPM shows good accuracy based on criteria (a) and (b), but the error variance for individual predictions with all three models is fairly large (criterion c). Individual prediction performance is constrained by the consistency of driving postures chosen by different people with similar anthropometry. In effect, the only opportunity for improving the model's ability to predict individuals is to add anthropometric descriptors as input to the models. However, such additions are unlikely to be useful for general vehicle design because the intended user population is anthropometrically diverse and, hence, cannot usefully be described by more than a few variables.

Restrictions and Limitations of the CPM

As with any other predictive model, the CPM's generalizability is constrained by the limitations of its underlying database – in particular, the range of test conditions used in the original study. Other limitations are as follows:

1. The model is for use with seats that have two-way (fore-aft) seat track adjustment and seat back angle adjustment but no seat height or seat pan angle adjustment. Further validation is under way to quantify the performance of the model in vehicles with seat height adjustment.
2. The model assumes an automatic transmission (no clutch), which covers more than 85% of passenger cars sold in the United States.
3. The in-vehicle posture data used to evaluate the model performance were obtained after a 15-min drive. Although the measured postures probably represent the most prevalent, normal driving postures for these drivers, it is likely that they shifted their postures as they drove, so the results are not representative of all on-road postures. However, Reed and Schneider (1996) demonstrated that posture changes in long-term sitting are small relative to between-subjects variance.
4. The model validation presented in this paper was conducted using data from only five vehicles. This data set is too small to allow an accurate estimate of the distribution of prediction errors across vehicles. However, comparison of the model predictions with those given by a seating accommodation model that was developed using data from 44 vehicles (Flannagan et al., 1998) indicates that the model's accuracy for other vehicles is not likely to deviate substantially from the accuracy observed in the validation vehicles.
5. The drivers whose postures were used to develop the model ranged in age from 21 to 75 years, but their behavior may not be representative of that in certain population segments, such as the very old or those with visual or other impairments.

Practical Implications

The CPM is the first model for predicting driving posture that is based on a large set of data and is publicly available in an implementable form. Because the input dimensions are readily obtained from any vehicle package drawing, the regression functions that constitute the core of the model can be used directly to predict eye locations, hip locations, or seat positions for people of various sizes. However, the full value of the model comes when it is integrated into a digital human modeling software package, so that the prediction results can be viewed immediately as whole-body postures within the vehicle package. The CPM can also be used as an independent check of prediction models that have been developed using other databases and methods.

CONCLUSIONS

Using the CPM, whole-body driving postures can be predicted with considerable accuracy, within the limitation of interindividual variability that is not accounted for by body dimensions.

With this modeling approach the predictions of key degrees of freedom are independent of the kinematic model definition and linkage scaling. The model prediction errors are largely independent of driver size and vehicle geometry, allowing a straightforward interpretation of prediction precision. The cascade model approach allows the most important degrees of freedom to be predicted directly, with reasonable accuracy on other degrees of freedom obtained using inverse kinematics assisted by motion distribution heuristics.

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