Calibration of Kinematic Simulations of Pedestrian Injury Using Field Data

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ABSTRACT – Computer simulations have been widely used for occupant and pedestrian injury prediction as a result of vehicle impacts; however, their validity is often limited by the testing data being validated against. This article describes a machine learning method to improve prediction accuracy by calibrating the simulated pedestrian injury risks with field crash injury data. The concept is to construct a surrogate model of the kinematic-based simulation model to generate fast predictions in the full input space and then search for the optimal simulation parameters and model discrepancy that match the predicted injury risks from the surrogate model with the injury outcomes in the field data. Consequently, the calibrated surrogate model integrates the field data with the kinematic-based simulation model and field data, returning more accurate predictions throughout the input space. The effectiveness of the proposed method is demonstrated by a case study where the MADYMO simulations were calibrated by the pedestrian injury data from Pedestrian Crash Data Study (PCDS).

INTRODUCTION

Pedestrian injuries are a major public-health problem worldwide. In the U.S., the proportion of pedestrian injuries in motor-vehicle-crash-induced injuries have been increasing in recent years and will likely continue to increase in the near future [1]. To better understand the pedestrian injury distribution and mechanism, MADYMO simulations [2, 3] have been developed to predict injury risks under varying crash scenarios. However, the simulation model is established on rigid-body-based scalable pedestrian models, which may not accurately predict crash injury risks in real crashes. Finite element (FE) human body models may be more accurate than MADYMO models, but in addition to numerical limitation in FE models, there are other limitations associated with the experimental data used to develop and validate the models. As a result, modeling results are always associated with certain levels of errors.

Recently, machine learning methods have been investigated to improve simulation models' accuracy using field data, which are often referred to as computer model calibration techniques [4]. The basic concept is to provide statistical estimates of unknown simulation parameters and model discrepancies that optimally match simulated and actual responses under the same input. For example, Kennedy and O'Hagan (2001) [4] utilized a full Bayesian framework to simultaneously estimate unknown simulation parameters and model discrepancies for scalar outputs. Sung et al. (2020) [5] proposed a statistical framework for model calibration with binary responses. However, calibration of crash simulations has been seldom explored.

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In this study, we first build a fast surrogate model of the pedestrian crash simulations based on dynamics and kinematics associated with pedestrian impacts, then calibrate the surrogate model with field crash data to improve its accuracy. Specifically, the pedestrian injury data from the Pedestrian Crash Data Study (PCDS) is selected for validating and improving the model. The PCDS dataset involves 521 pedestrian crashes from 1994 to 1998. Investigation for each crash was conducted within 24 hours of the crash. Each case includes detailed crash scenarios and injury descriptions. Data analytics have been conducted on the PCDS dataset in the past years [7]. However, to the best of our knowledge, there is no systematic machine learning model trained to calibrate crash simulations using the PCDS dataset. An overview of the proposed method is shown in Figure 1.

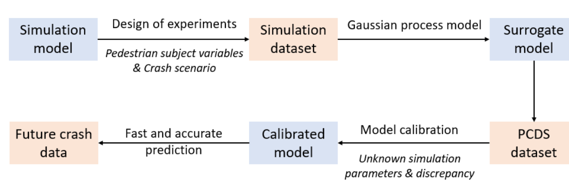

Figure 1. Method Flowchart

METHODS

Pedestrian Impact Simulation

MADYMO is used for all pedestrian impact simulations. The methods for simulation setup are similar to those reported in our previous study [8]. In this study, three vehicles are selected, including a sedan, an SUV, and a pickup truck. The vehicle model geometries are transferred from FE vehicle models to ensure accuracy. Contact stiffness values for windshield, hood, hood-leading edge, and bumper are defined separately based on MADYMO template models. The MADYMO scaler was used to generate pedestrian models with different combinations of height and weight for men and women.

ModeFrontier (ESTECO, Italy) is used to automatically integrate MADYMO vehicle and pedestrian models to generate large-scale simulations. The simulation matrix is determined using the Maximum Projection design of experiments [9], which has shown better results than the conventional uniform Latin Hypercube sampling. To balance the simulation time and model accuracy, a total of 9,000 simulation runs are generated to explore the injury measures and risks under different crash conditions. The input variables include pedestrian subject variables (gender, age, stature, and BMI), crash scenario (impact location, impact orientation, pedestrian speed, vehicle speed and vehicle type) and unknown simulation parameters (vehicle stiffness and impact location scale). The vehicle stiffness and impact location scale are considered unknown simulation parameters to be calibrated because they have significant impact on the injury measures while being unavailable in the field data. Among the injury measures, we focus on injuries on head, chest, tibia, and femur. The pelvis injury is not included in the data analytic step due to its high dependency on the initial impact location of the crash, which is very sensitive to a small perturbation on the crash scenario and thus becomes difficult to predict.

PCDS Dataset Processing

The PCDS dataset is pre-processed to match the simulation dataset. While the pedestrian subject variables, vehicle speed, and vehicle type in the PCDS dataset share the same data format a.s in the simulation dataset, part of the crash scenario information, including impact location, impact orientation, and pedestrian speed, are described in text and require to be converted to quantitative values. In particular, we use the general area of damage (PGADEV1) and injury source (PINJSOU) to find the impact location and assign negative, zero and positive location values to the crashes on the right, center and left of the vehicle, respectively. We set the pedestrian speed as 0 km/h, 5 km/h and 8 km/h for standing, walking, and running pedestrians, respectively. The impact orientation is assumed to be -135, -90 and -45 degrees when the pedestrian is facing away from vehicle, side to vehicle, and facing vehicle, respectively. We further remove cases with missing variables and obtain a dataset of 392 samples.

Model Calibration

The model calibration involves two steps – surrogate model training and calibration parameter estimation. The first step trains a statistical model that maps simulation inputs to outputs without running the actual simulation model. Here we employ the Gaussian process model [10] to construct the surrogate model, where the powered exponential covariance function is chosen to measure the sample correlations and the Gaussian process parameters are estimated through the maximum likelihood estimation. More details can be found in [10].

Next, we formulate the model calibration following the framework in [3]. Let x_i denote the vector of pedestrian subject variables and crash scenario of i-th case in the PCDS dataset. Let θ_i denote the unknown simulation parameter. $\eta_j(x_i, \theta_i)$ represents the j-th dimension of the simulated injury measures. Let $y_{i,j}$ denote the observed injury indicator on the j-th body region in the i-th case where $y_{i,j} = 1$ represents the injury cases (AIS≥ 3 on head and chest or AIS≥ 2 on lower extremity). The injury evaluation functions J_j in [2] are used to link the injury measures to the injury risks as:

$$P[y_{i,j} = 1] = J_j\left(\eta_j(x_i, \theta_i) + \delta_j\right),$$

where δ_j is the model discrepancy on the j-th body region. This formulation implies the assumption that the model discrepancy is constant for a fixed body region throughout all the cases.

In the calibration step, simulation parameters are identified via solving the optimization problem under the assumption that no model discrepancy exists, which is formulated as:

$$\hat{\theta}_i = argmax_\theta \sum_j y_{i,j} \log\left(J_j(\eta_j(x_i, \theta))\right) + (1 - y_{i,j}) \log\left(1 - J_j(\eta_j(x_i, \theta))\right),$$

where the rationale behind the formulation is to assign high injury risks to injury cases and assign low injury risks to non-injury cases. Next the constant model discrepancy is estimated based on the estimated simulation parameters, which is to compute

$$\hat{\delta}_j = argmax_\delta \sum_i y_{i,j} \log\left(J_j\left(\eta_j\left(x_i, \hat{\theta}_i\right) + \delta\right)\right) + (1 - y_{i,j}) \log\left(1 - J_j\left(\eta_j\left(x_i, \hat{\theta}_i\right) + \delta\right)\right).$$

With the simulation parameters and model discrepancy calibrated, for case x_i, the simulation injury measures are updated as $\eta_j(x_i, \hat{\theta}_i) + \hat{\delta}_j$, which is expected to reflect the crash injury more accurately in the actual crash case.

RESULTS

The accuracy of the surrogate model is evaluated based on the mean squared errors in a 5-fold cross-validation setup. Simulation runs are divided into five folds, each of which is used to generate predictions from the model trained at the left-out fold. The scatter plot in Figure 2 between the predicted and true values among all the test samples is provided to illustrate the accuracy of the surrogate model. The subplot in panels (a) and (b) depicts the prediction performance of the logarithm of the HIC and sternum acceleration, respectively. Most of the points are close to the line y=x, indicating that the predicted values are close to the true values in the test dataset. It is worth noting that the low sample density at the low HIC region leads to low accuracy due to the nature of Gaussian process modeling. The prediction accuracy can be quantified by the ratios between the explained variance and the total variance, which are 92.4% and 76.4%, respectively.

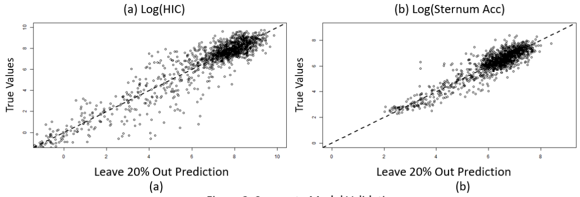

Figure 2. Surrogate Model Validation

The proposed model calibration method is performed on the generated simulation dataset and the pre-processed PCDS dataset. Figure 3 shows the comparison of predicted injury risks before ((a) and (c)) and after calibration ((b) and (d)), where the subplots (a) and (b) compare the head injury risks while the subplots (c) and (d) compare the chest injury risks. The injury (left) and non-injury cases (right) are separated by the vertical dashed lines. Significant reductions of injury risks are observed for non-injury cases after the proposed calibration method for both body regions. We further compare false alarm rates (injury risks greater or equal than 0.5 for non-injury cases) misdetection rates (injury risks less than 0.5 for injury cases) before and after calibration in Table 1. We observe 6.89% and 8.67% reductions in the misdetection rates of head and chest injuries, respectively, with 5.57% and 2.85% increments in the false alarm rates. The misdetection rate of femur injury increases by 5.6% with an improvement of false alarm rate by 1.27%. Figure 3 indicates that the calibrated model tends to predict injury risks around the hard boundary 0.5 for these misclassified samples when compared to the uncalibrated model.

Body regions	False alarm rates		Misdetection rates	
	Before	After	Before	After
Head	6.63%	12.2%	7.91%	**1.02%**
Chest	4.85%	7.14%	12.5%	**3.83%**
Tibia	14.5%	16.6%	13.8%	**11.2%**
Femur	3.57%	**2.30%**	12.0%	17.6%

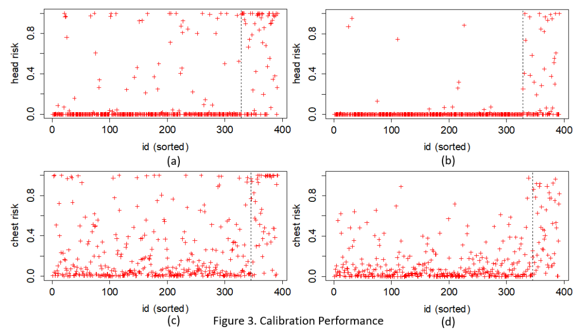

Figure 3. Calibration Performance

DISCUSSION

The model is calibrated based on individual simulation parameters and a constant model discrepancy term, which may not fully represent the gap between the simulated and actual responses. More complicated discrepancy terms, for instance, Gaussian-process-based nonlinear discrepancy terms, will be utilized in the future calibration work.

CONCLUSION

The study presents a quantitative method to improve the surrogate model of pedestrian injury simulations based on the field data. The case study on the PCDS data shows a high accuracy of the surrogate model and significant improvements after calibrating the simulation parameters and estimating the model discrepancy.

ACKNOWLEDGMENTS

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REFERENCES

[1] https://www.ghsa.org/resources/news-releases/GHSA-Pedestrian-Spotlight23

[2] Hu, Jingwen, Jun Wu, Kathleen D. Klinich, Matthew P. Reed, Jonathan D. Rupp, and Libo Cao. "Optimizing the rear seat environment for older children, adults, and infants." Traffic injury prevention 14, no. sup1 (2013): S13-S22.

[3] Hu, Jingwen, Kai Zhang, Matthew P. Reed, Jenne-Tai Wang, Mark Neal, and Chin-Hsu Lin. "Frontal crash simulations using parametric human models representing a diverse population." Traffic injury prevention 20, no. sup1 (2019): S97-S105.

[4] Kennedy, Marc C., and Anthony O'Hagan. "Bayesian calibration of computer models." Journal of the Royal Statistical Society: Series B (Statistical Methodology) 63, no. 3 (2001): 425-464.

[5] Sung, Chih-Li, Ying Hung, William Rittase, Cheng Zhu, and C. F. J. Wu. "Calibration for computer experiments with binary responses and application to cell adhesion study." Journal of the American Statistical Association 115, no. 532 (2020): 1664-1674.

[6] Higdon, Dave, James Gattiker, Brian Williams, and Maria Rightley. "Computer model calibration using high-dimensional output." Journal of the American Statistical Association 103, no. 482 (2008): 570-583.

[7] Longhitano, Douglas, Basem Henary, Kavi Bhalla, Johan Ivarsson, and Jeff Crandall. "Influence of vehicle body type on pedestrian injury distribution." SAE transactions (2005): 2283-2288.

[8] Joseph, V. Roshan, Evren Gul, and Shan Ba. "Maximum projection designs for computer experiments." Biometrika 102, no. 2 (2015): 371-380.

[9] Hu, Jingwen, Carol Flannagan, Sailesh Ganesan, Patrick Bowman, Wenbo Sun, Iskander Farooq, Anil Kalra, and Jonathan Rupp. "Understanding the new trends in pedestrian injury distribution and mechanism through data linkage and modeling." Accident Analysis & Prevention 188 (2023): 107095.

[10] Williams, Christopher KI, and Carl Edward Rasmussen. Gaussian processes for machine learning. Vol. 2, no. 3. Cambridge, MA: MIT press, 2006.