An Evaluation of Objective Rating Methods for Full Body Finite Element Model Comparison to PMHS Tests

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This paper has not been screened for accuracy nor refereed by any body of scientific peers and should not be referenced in the open literature.

ABSTRACT

Objective evaluation methods of time history signals are used to quantify how well simulated human body responses match experimental data. As the use of simulations grows in the field of biomechanics, there is a need to establish standard approaches for comparisons. There are two aims of this study. The first is to apply three objective evaluation methods found in the literature to a set of data from a human body finite element model. The second is to compare the results of each method, examining how they are correlated to each other, and the relative strengths and weaknesses of the algorithms.

In this study, the methods proposed by Sprague and Geers (Magnitude and Phase error, SGM and SGP), Rhule et al. (Cumulative Standard Deviation, CSD) and Gehre et al. (CORrelation Analysis, CORA Size, Phase, Shape, Corridor) were compared. A 40 kph frontal sled test presented by Shaw et al. was simulated using the Global Human Body Models Consortium mid-sized male full body finite element model (v. 3.5). Mean and standard deviation experimental data (n = 5) from Shaw et al. was used as the benchmark. Simulated data were output from the model at the appropriate anatomical locations for kinematic comparison. Force data were output at the seatbelts, seat pan, knee, and foot restraints.

Objective comparisons from 53 time history data channels were compared to the experimental results. To compare the different methods, all objective comparison metrics were cross-plotted and linear regressions were calculated. The following ratings were found to be statistically significantly correlated (p<0.01): SGM and CORA Size, R^2 =0.73, SGP and CORA Shape, R^2 =0.82, and CSD and CORA's Corridor factor, R^2 =0.59. Relative strengths of the correlated ratings were then investigated. For example, while correlated to CORA Size, SGM carries a sign to indicate whether the simulated response is greater than or less than the benchmark signal. A further analysis of the advantages and drawbacks of each method is discussed.

The results demonstrate that a single metric is insufficient to provide a complete assessment of how well the simulated results match the experiments. The CORA method provided the most comprehensive evaluation of the signal. Regardless of the method selected, one primary recommendation of this work is that for any

comparison, results should be reported to provide separate assessments of a signal's match to experimental variance, magnitude, phase, and shape. Future work planned includes implementing any forthcoming ISO standards for objective evaluations.

INTRODUCTION

Finite element analysis (FEA) has become an important tool in the field of injury biomechanics. Mathematical models have been used in this field for decades (Yang, et al. 2006) with Finite Element Models of full human bodies becoming more widespread recently (Robin 2001; Ruan, et al. 2003; Ruan, et al. 2005). Advances in computing power have allowed for more complex models and, as a result, modern full human body finite element models (FEMs) have been created with an increased focus on anatomical accuracy (Shigeta, et al. 2009; Vavalle, et al. 2013). Even with accurate anatomical representation, an FEM must be rigorously validated against experimental data before it can be used to study injury. To do this, models are often compared to mean responses and corridors created from post-mortem human surrogate (PMHS) testing. Objective comparisons of models are critical when evaluating validation. A comparison made based on mathematics and not human judgment is the preferred method for determining model validity. This approach offers the most robust means of evaluating model performance during development (to quantitatively track improvements) or validation (to quantify the degree to which a model agrees with experimental data).

A new full body FEM of the mid-sized male (M50) was recently developed by the Global Human Body Models Consortium (GHBMC). The GHBMC model is the result of a collaboration between the automotive industry, government agencies, and academia with a goal to create a set of advanced full human body FEMs. The purpose of full body models (FBMs) is to study blunt injury in motor vehicle crashes (MVCs) and to be used as a tool for the community to enhance the safety of vehicles. The development of the M50 model, has been discussed in the literature (Gayzik, et al. 2011; Gayzik, Moreno, Danelson, et al. 2012; Vavalle, et al. 2013) and will be briefly reviewed here. To obtain accurate anatomical geometry for the model a multi-modality medical imaging approach was taken (Gayzik, et al. 2009). Magnetic resonance imaging (MRI), upright MRI, computed tomography (CT), and laser surface scanning with bony landmark identification were used to obtain model geometries.

CAD data was distributed to collaborating universities whose goal was to create regional FEMs (Beillas, et al. 2012; DeWit, et al. 2012; Fice, et al. 2011; Li, Kindig, Kerrigan, et al. 2010; Li, Kindig, Subit, et al. 2010; Mao, et al. 2012; Shin, et al. 2012; Yue, et al. 2011). The GHBMC seated male full body model was constructed by combining five regional models (head, neck, thorax, abdomen, and pelvis/lower extremity) (Thompson, et al. 2012). The version of the model used in this study (v 3.5) contained a total of 1.3 million nodes, 1.95 million elements, 961 parts, and represents a weight of 75.5 kg. The focus of this paper will be one validation case in which the experiments of Shaw et al. (Shaw, et al. 2009) were simulated. This particular case provided 53 channels of data for comparing objective evaluation (OE) methods.

OE methods to make comparisons between model response and experimental data are gaining favor. An ISO workgroup (ISO/TC 22/SC 10/WG 4) is working to standardize their use for FEM simulations, indicating a broad need for non-subjective means to calculate the level of correlation observed in the validation of FEMs. The ISO/TR9790 method for evaluating side impact ATDs has been used to evaluate the validation of an FEM in the past (Ruan, et al. 2006), but this method has been noted to be too subjective (Hsu, et al. 2005). The National Highway Traffic Safety Administration (NHTSA) also formulated a method for creating cadaveric corridors to which lateral impact ATDs can be compared (Maltese, et al. 2002). This method is an improvement over ISO/TR9790 in that it is more automated and less subjective, but there are still shortcomings that have been outlined in the literature (Hsu, et al. 2005; Irwin, et al. 2005). A third method for comparing side impact ATD responses to experimental results was developed by Nusholtz et al. (Nusholtz, et al. 2007) using cross-correlation. Rather than creating corridors from PMHS tests, this method compares inter-PMHS cross-correlations to cross-correlations between the ATD and each PMHS.

The methods used in the comparison presented in this study were biased towards those that employed averages and standard deviations of PMHS data points. This decision was made since those data are typically presented in the literature and are commonly accessible for computational model comparison. Individual test curves are required for the ISO/TR9790, Maltese, and Nusholtz methods. Individual traces are often not published, creating a higher barrier for groups outside of the lab that conducted the experiment to employ them. While these previous three methods are considered beyond the scope of this study, they are of great interest and reserved for future investigations. The overarching objective of the current work was to investigate several methods for OE. Since there are a number of methods available in the literature, the first aim was to select several commonly used methods and apply them to a robust dataset to determine how the methods are correlated, if at all. Methods proposed by Sprague and Geers (Sprague, et al. 2004), Rhule et al. (Rhule, et al. 2002), and Gehre et al. (Gehre, et al. 2009) were implemented. Correlations were used to investigate the relationships of the different metrics and the relative strengths and weaknesses of each method. This work provides an assessment of the method that provided the most complete evaluation of the model with regards to the literature data.

METHODS

The GHBMC average male seated model (M50) was used in this study. The subject used as the template for the model was a living male volunteer, 26 years old, 174.9 cm, and 78.6 ± 0.77 kg. The model has been validated in lateral (Vavalle, et al. 2013) and frontal impact (Gayzik, Moreno, Vavalle, et al. 2012). More details of the model and its development can be found in the GHMBC M50 manual (GHBMC 2011).

The model was simulated in a frontal sled test configuration presented by Shaw et al. (Shaw, et al. 2009). The simulation was conducted using MPP LS-Dyna R 4.2.1 running on a Red Hat Linux computational cluster using 48 cores. The seat buck was modeled per the data in the above reference and adjusted from personal communications with the authors of that study. The buck was modeled as a rigid body. Belt properties were made to match descriptions of the webbing of the belt reported by Shaw et al. (26 kN of force for 7% strain). No pre-tensioners or load limiters were modeled. Friction was not included between the body and the buck. The model was gravity-settled for 90 ms prior to executing the sled pulse. Belts were fit and final adjustments were made for components of the buck (i.e. knee bolster) following the settling simulation. This particular buck was designed to focus loading on the thorax as the knees are in contact with rigid bolsters at the outset of the simulation. This limited forward excursion of the PMHS in the experiment. The 40 kph change in velocity pulse reported in the study was applied as a velocity history to the buck in the simulation.

All data were recorded in binary output files at a sample rate of 10 kHz. The SAE J1733 coordinate system was used for all kinematic output and seat pan reaction forces. The forces at the upper and lower shoulder belt, and outer lap belt correspond to forces along the belt. Reaction forces at the knee bolsters and foot rest were recorded in the global coordinate system and transformed to local coordinate system as reported in the literature (Ash, et al. 2012). All kinematic data was reported in the global coordinate system with the exception of chest deflection data, which utilized a local coordinate system defined on T8 (Shaw, et al. 2009). The time history of the model output is available in the literature (Gayzik, Moreno, Vavalle, et al. 2012). Data extracted from the model were compared against an average and standard deviation of n = 5 PMHS tests (Shaw, et al. 2009). The subjects were all male and had an average mass and age of 75.5 kg and 54 years. Since the average mass of the subjects were equal to that of the model, mass scaling was not explicitly performed.

Study Name	Evaluation Metric	Best match value	Worst match value	Notes
Sprague and Geers	Magnitude, SGM	SGM = 0, equal magnitude of experiment	SGM = -1 (much less than experiment) $SGM = \infty$ (much greater than experiment)	Mean comparison only.
	Phase, SGP	SGP = 0, no phase differences between simulation and experiment	SGP = 1 (180° out of phase of experiment)	Mean comparison only. Result is normalized by π .
Rhule et al.	Cumulative Standard Deviation, CSD	CSD = 0, sum of squared difference between experiment and simulation is zero	Positive valued only CSD = n (n standard deviations from the mean) $CSD = \infty$ (many standard deviations from the mean)	Accounts for standard deviation, $CSD = \sqrt{R}$, square root used to report results in terms of a cumulative standard deviation rather than cumulative variance. BioRank utilizes \sqrt{R} .
Gehre et al.	CORA Corridor, C _{cor}	$C_{cor} = 1$, with inner corridor	$C_{cor} = 0$, outside of outer corridor	Comparison based on user- provided inner and outer corridors.
	CORA Phase, C _{phase}	$C_{phase} = 1$, required shift is less than user-defined δ_{min}	$C_{phase} = 0$, required shift is greater than user-defined δ_{max}	Mean comparison only. Phase shift value is interpolated between a min and max permissible shift.
	CORA Size, C _{size}	$C_{size} = 1$, Area under the curve of simulated and experimental results are equal	$C_{size} \rightarrow 0$, Area under the curve of simulated and experimental results are very different	Mean comparison only.
	CORA Shape, C _{shape}	$C_{shape} = 1$, Shape of curves is similar	$C_{shape} \rightarrow 0$, Shape of curves is very different	Mean comparison only. Utilizes a normalized cross- correlation.

Table 1. Comparison of objective evaluation methods used in the study.

The model and simulated case are critical background for this study. However, the focus was to compare and contrast various OE techniques using this simulation. To that end, it is necessary to briefly describe the three methods of quantitative comparison that were used. Equations are readily available in the literature for these methods so a general overview of each method will be provided instead. A summary of the differences in these methods is found in Table 1. The first of these methods, introduced by Sprague and Geers, utilizes two metrics; Magnitude and Phase error factors (Sprague, et al. 2004; Vavalle, et al. 2013). The Magnitude factor (SGM) is insensitive to phase shifts and the Phase factor (SGP) is insensitive to magnitude. Both are functions of the definite integrals of time valued functions for a given output. These factors only take into account information from the experimental mean (i.e. no information on the experimental variance is used).

The cumulative standard deviation or CSD, introduced by Rhule et al. (Rhule, et al. 2002) is the second OE method used. Unlike the S&G values, it does take into the account the spread of the experimental data by normalizing the sum of squared difference between a model and an experimental mean by the experimental variance. Since the CSD is the square root of that ratio, it can be interpreted as the number of standard deviations the simulated response is from the mean of the experimental data (Rhule, et al. 2002).

The final method used in the comparisons of OE methods is a suite of comparison metrics known as CORA (Gehre, et al. 2009). This is a set of algorithms that takes into account corridor fit, phase shift, size and shape differences. Among these, only the corridor evaluation takes into account experimental variance. However the method acknowledges that there are a number of different relevant criteria that are required to make a comprehensive assessment of the signal alignment. CORA v. 3.5 was used in this study. All defaults were used for parameters that control the evaluation except the phase range. The range for interpolation between perfect (1) and poor (0) phase match is suggested to be 3 to 12% of the time span of the signal. This was changed to 5 to 15% for this analysis (i.e. less than 5% time shift of the signal scored a 1 whereas greater than 15% time shift scored a 0). For the corridor analysis, the inner corridors were set at one standard deviation, and the outer corridors were set at two standard deviations.

The kinematic and kinetic results of the model simulation were run through each of the OE methods identified above (n = 7 metrics). A total of 53 time valued signals were extracted from the simulation. For each of these signals, corresponding experimental data from the literature (Shaw, et al. 2009) were available for comparison. The S&G Magnitude and Phase factors, as well as the CSD factor by Rhule et al. were programmed in Matlab v. 11 (The Mathworks, Natick, MA). The values from CORA were obtained from release 3.5 of the CORA software.

The results of this phase of the study were 7, 53x1 vectors with the coefficients of the OE methods. Each of these was then cross-plotted to determine if there was a linear correlation between the results. Table 2 below provides a schematic of the cross plots that were conducted. No comparisons along the diagonal of the test matrix were conducted as they would yield a perfect correlation, and only the upper off-diagonal terms were considered as the lower terms would be equivalent. Linear regressions were conducted in Matlab v. 11. The coefficient of determination, R^2 , was used to evaluate regressions. The p-value for all regressions was also determined from the F-test and a significance value of $\alpha = 0.01$ was used to assess significance due to the relatively large sample size.

	Sprague and Geers		Rhule et al.	Gehre et al.			
	SGM	SGP	CSD	C _{cor}	C _{phase}	C _{size}	C _{shape}
SGM		✓	✓	\checkmark	✓	✓	✓
SGP			✓	\checkmark	✓	✓	✓
CSD				\checkmark	✓	✓	✓
C _{cor}					✓	✓	✓
C _{phase}						\checkmark	✓
C _{size}							\checkmark
C _{shape}							

Table 2. Cross plot matrix for comparison study.

RESULTS

The frontal sled event was conducted in two separate simulations. A 90 ms settling event was simulated and required 16 hours to run on 48 cores. The full body sled test was then simulated using output from the settling run to determine initial nodal locations. The simulation of this 150 ms event required 29 hours on 48 cores. A time sequence of the sled event modeled is shown in Figure 1, with an oblique view of the model, a lateral view of the spine and posterior view of the spine. The model showed good robustness with hourglass energy remaining below 12.4% of the sum of kinetic and potential energy in the model (including the buck). The peak of this hourglass energy ratio occurred at 127 ms, which closely matched the maximum forward excursion of the model, which occurred at approximately 130 ms.



Figure 1. Time lapse images showing the kinematics of the GHBMC M50 model. The top row indicates overall body motion with the second and third rows showing spine kinematics from the side and back, respectively.

Following simulation of the event, 53 time history traces were extracted and compared to the experimental data. The results of these comparisons were OE metrics for each of the three methods tested. Cross plots and linear regressions of the metrics resulted in the correlations summarized in Table 3. The four coefficients of determination shown with dark gray backgrounds were found to be statistically significant at the selected significance level of $\alpha = 0.01$. To summarize, the study's findings indicate that the following metrics were correlated. SGM was correlated to CORA Size ($R^2 = 0.73$), SGP was related to CORA Shape ($R^2 = 0.82$), and CSD was correlated to CORA Corridor ($R^2 = 0.59$). Additionally, statistically significant relationships, though with mild correlations, were found between SGP and CORA Phase ($R^2 = 0.31$) and CORA Shape and CORA Phase ($R^2 = 0.21$). Coefficients in bold demonstrated R^2 values greater than 0.5, the linear regressions of which are plotted below in Figure 2.

Table 3. Results from the 21 regressions conducted with the statistically significant correlations highlighted. The three pairs with $R^2 > 0.5$ are shown in bold.

	Sprague and Geers		Rhule et al.	Gehre et al.			
	SGM	SGP	CSD	C _{cor}	C _{shape}	C _{size}	C _{phase}
SGM		0.00	0.09	0.06	0.02	0.73	0.01
SGP			0.00	0.00	0.82	0.03	0.31
CSD				0.59	0.01	0.09	0.01
C _{cor}					0.02	0.08	0.02
C _{shape}						0.04	0.21
C _{size}							0.01
C _{phase}							



Figure 2. Cross-plots of the three best correlated metric pairs.

DISCUSSION

Objective evaluation methods are becoming increasingly important in modeling. A comprehensive set of simulation results including seatbelt loads, reaction forces and kinematic data, were used to evaluate three common OE techniques. The findings of this study show which of these methods are correlated. They are also of use to researchers familiar with one of these techniques, as these results enable users of one technique to more accurately evaluate results in the literature that employ one of the other techniques tested. There are other intrinsic values to using OE methods not just in validation, but in the modeling process. These methods provide the most robust means of tracking model improvement during the model development process. A quantitative means of evaluating model performance also provides a means for comparing the results of two different FEA models that have been used to simulate the same event.

Three pairs of metrics were found to have statistically significant correlations and have R^2 values greater than 0.5; SGP and CORA Shape, SGM and CORA Size, and CSD and CORA Corridor. These relationships are consistent with the relationships between the mathematical formulations of the metrics. The correlations between SGP and CORA Phase and CORA Shape and CORA Phase were also found to be statistically significant, but with $R^2 = 0.31$ and $R^2 = 0.21$, respectively. It is clear from these coefficients of determination that no two metrics were identical. SGM and CORA Size, though related, encompass different ranges. SGM ranges from -1 to $+\infty$ while CORA Size ranges from 0 to 1. This difference is highlighted by Figure 3, in which the bar chart shows many of the SGM values were less than 0 while all of the CORA Size values were greater than 0. To reiterate from Table 1, a negative SGM indicates that the model response is, on average, smaller than the experimental mean. This is an advantage of the SGM, since the user can quickly evaluate whether the model is under predicting or over predicting the experiment. Because it does not carry the sign, the CORA Size metric does not offer this advantage. An additional difference between these metrics is that a perfect match between model and experiment would receive SGM = 0 and CORA Size values.



Figure 3. On Left: Bar chart showing that SGM can be less than zero while CORA Size is always positive. On Right: A) a case where SGM is negative since, on average, the model response is smaller than experimental mean. B) a case where both SGM and CORA Size are positive. Both the SGM and CORA Size factor do not consider the phase shift that is apparent in either A or B.

Other interesting differences exist in the correlated pairs of metrics, such as between CSD and CORA Corridor. Both values measure how well a model response fits within the corridors of experimental data. However, similar to the case of SGM and CORA Size, CSD can range from 0 to $+\infty$ while CORA Corridor can range from 0 to 1. This is illustrated in Figure 4 which shows a histogram of the CSD and CORA Corridor values obtained. Note that the range of the CSD value is much greater than the CORA value, since it is not normalized. The advantage to this range is that the value of CSD corresponds to the number of standard deviations the model results are (on average) from the mean experimental results, and is therefore more easily interpreted by the engineer. Of course, it should be noted that the choice of corridors strongly influences the rating that a model response receives. With respect to CSD, if the standard deviation is narrow (i.e. the data have a low coefficient of variation) a model response that is a number of standard deviations from the mean may not amount to a large relative difference. Conversely if the standard deviation is large, a better CSD value is to be expected. While CSD always uses the experimental standard deviation, CORA uses an inner and outer corridor. It is common to use a constant corridor width for both the inner and outer corridors (Gehre, et al. 2009), however an alternative to this is to use plus or minus one standard deviation for the inner corridor and plus or minus two standard deviations for the outer corridor. The latter approach was used in this study since standard deviation curves were readily available for the experimental data. Of course, the same issues related to the effect of tight or narrow standard deviations also apply to the CORA output.



Figure 4. Histogram comparing the range of CSD to the range of CORA Corridor

It was found that Sprague and Geers Phase was more highly correlated to CORA Shape than to CORA Phase. While both correlations were found to be statistically significant, the correlation to CORA Shape was more than twice that of the correlation to CORA Phase. The small correlation between CORA Shape and CORA Phase combined with a strong correlation between SGP and CORA Shape is the likely cause of the mild correlation between SGP and CORA Phase. This stands to reason considering the method to calculate CORA Phase. This metric reflects the amount of time shift needed to align the signal to the experiment. It also "caps" the value of the time shift by allowing the user to input a minimum and maximum shift. If the calculated shift is less than the minimum, the Phase rating is automatically set to 1, if it is larger than the maximum; it is automatically set to 0. This artificial cap likely decreases the correlation with other techniques whose results are continuous functions of the time series data. SGP and CORA Shape, on the other hand, both use more complex calculations involving a cross-correlation of the signals. As evidenced from this result, the names of these metrics can lead to incorrect assumptions and the mathematical formulae should be familiar to the user.

Relative strengths and weaknesses of each method were examined to determine the most comprehensive of the three. The Sprague and Geers method is able to distinguish between magnitude and phase contributions to the model's error from the experimentally determined responses. Separating these contributions can be helpful in determining how model response can be improved. However, this method does not consider experimental variance, which can play a substantial role in injury biomechanics data due to human variation. A main part of the Rhule et al. BioRank method is calculating the Cumulative Standard Deviation (CSD), which represents how many standard deviations the model is from the experimental data, on average. The variance of the experimental data is clearly taken into account using this calculation. But, if the model response is simply out of phase, and would otherwise be a good match, it results in a poor CSD value because only a point-by-point comparison is made and no phase shift is incorporated. The methods of Gehre et al., known as CORrelation and Analysis (CORA), provide size, phase, shape, and corridor ratings. This method is the most comprehensive of the three examined in this study. Significant correlations were found between each of the metrics in the two other studies and the metrics of CORA. Furthermore, no strong correlations were found between the four metrics within the CORA approach, indicating that each metric provides independent data regarding the model to experiment comparison. While the correlation between CORA shape and CORA phase was statistically significant, an $R^2 = 0.21$ does not indicate a strong correlation.

All three of these methods rely on average experimental data and two methods require data on the experimental variance. How the average and standard deviations from the experiments are determined is important and has obvious implications on the data reported in this study. While this is a limitation of the analysis, it is considered beyond the scope of this study since the same data were used for all three comparison methods. The topic of averaging biomechanics data is an area of much research as well (Hsu, et al. 2005; Irwin, et al. 2005; Maltese, et al. 2002; Nusholtz, et al. 2009). Additionally, while only one study was used to conduct this comparison, it was chosen for a number of reasons. First, there was a large amount of data collected (53 data channels used in the comparison), second the breadth of the results cover kinematics and kinetics of the PMHS and finally, the subjects were reasonably close to the anthropometry of a 50th percentile male. A further limitation of the work is that standards from the ISO/TC 22/SC 10/WG 4 have not been evaluated in this work. To the author's knowledge these standards are forthcoming and will be evaluated once they become available.

Regardless of which method is chosen, this analysis shows that it is useful to keep metrics separate rather than combining them into a single biofidelity score. While having one number associated with the validation of a model can be convenient, this can oversimplify the analysis. Each of the types of metrics that are calculated in the methods has different meanings. Much can be learned from investigating each metric separately and this can guide further model improvements. For example, a reaction force that shows the proper magnitude but a poor phase may indicate that the interaction of the model with the buck is the principal source for the discrepancy between model and experiment. But, combining these scores could result in the loss of that insight, and lead to counterproductive efforts to address problems that may not even exist in the model.

Future work in this area may include implementing and applying the Nusholtz et al. (Nusholtz, et al. 2007) cross-correlation method to this set of data. An advantage of this method is that it does not use a mean or corridor of the experimental data. Rather, it compares the inter-PMHS cross-correlations to the cross-correlations of the model to the individual tests. Scores are then assigned to magnitude, shape, and phase for each body region. Finally, there is a need to establish standards for regional weighting of OE metrics in full body model analysis so that the most pertinent data is given the greatest consideration.

CONCLUSIONS

This study examined three methods commonly used to objectively compare model response to experimental data. A simulation of a full body frontal sled was conducted, from which 53 outputs were compared to experimental data using three methods of objective evaluation. It was found that the following three methods were both statistically significant and had an R^2 of greater than 0.5 – Sprague and Geers Phase and CORA Shape; Sprague and Geers Magnitude and CORA Size; and Rhule et al. Cumulative Standard Deviation and CORA Corridor. Based on the findings in this study, it is recommended to use an approach similar to CORA for full body model evaluation since it gives the most comprehensive evaluation of the results tested. The four metrics provided as part of the CORA analysis package were found not found to be correlated, indicating that each one provides independent data. Advantages for the other methods tested are reviewed as well. This work will additionally serve to clarify how these methods are related and facilitate comparisons between their results.

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REFERENCES

- ASH, J., SHAW, C.G., LESSLEY, D. AND CRANDALL, J. (2012). PMHS Restraint and Support Surface Forces in Simulated Frontal Crashes. 2012 JSAE Annual Congress (Spring). Pacifico Yokohama.
- BEILLAS, P. AND BERTHET, F. (2012). Performance of a 50th Percentile Abdominal Model for Impact: Effect of Size and Mass. European Society of Biomechanics Conference. Lisbon, Portugal.
- DEWIT, J.A. AND CRONIN, D.S. (2012). Cervical Spine Segment Finite Element Model for Traumatic Injury Prediction. Journal of the Mechanical Behavior of Biomedical Materials 10: 138-150.
- FICE, J.B., CRONIN, D.S. AND PANZER, M.B. (2011). Cervical Spine Model to Predict Capsular Ligament Response in Rear Impact. Annals of Biomedical Engineering 39: 2152-2162.
- GAYZIK, F.S., HAMILTON, C.A., TAN, J.C., MCNALLY, C., DUMA, S.M., KLINICH, K.D. AND STITZEL, J.D. (2009). A Multi-Modality Image Data Collection Protocol for Full Body Finite Element Analysis Model Development. SAE Technical Paper 2009-01-2261
- GAYZIK, F.S., MORENO, D.M., GEER, C.P., WUERTZER, S.D., MARTIN, R.S. AND STITZEL, J.D. (2011). Development of a Full Body CAD Dataset for Computational Modeling: A Multi-Modality Approach. Annals of Biomedical Engineering 39: 2568-2583.
- GAYZIK, F.S., MORENO, D.P., DANELSON, K.A., MCNALLY, C., KLINICH, K.D. AND STITZEL, J.D. (2012). External Landmark, Body Surface, and Volume Data of a Mid-Sized Male in Seated and Standing Postures. Annals of Biomedical Engineering 40: 2019-32.
- GAYZIK, F.S., MORENO, D.P., VAVALLE, N.A., RHYNE, A.C. AND STITZEL, J.D. (2012). Development and Validation of a Novel Full Human Body FE Model Utilizing a Multi-Modality Medical Imaging Protocol. International Crashworthiness Conference. Milan, Italy.
- GEHRE, C., GADES, H. AND WERNICKE, P. (2009). Objective Rating of Signals Using Test and Simulation Responses. The 21st ESV Conference. Stuttgart, Germany.
- GHBMC. (2011). GHBMC M50 Users Manual
- HSU, T.P. AND NUSHOLTZ, G.S. (2005). Considerations of Bio-Fidelity Corridors for Lateral Impacts. SAE Technical Paper 2005-01-0308

- IRWIN, A.L., SUTTERFIELD, A., HSU, T.P., KIM, A., MERTZ, H.J., ROUHANA, S.W. AND SCHERER, R. (2005). Side Impact Response Corridors for the Rigid Flat-Wall and Offset-Wall Side Impact Tests of NHTSA Using the ISO Method of Corridor Development. Stapp Car Crash J 49: 423-56.
- LI, Z., KINDIG, M.W., KERRIGAN, J.R., UNTAROIU, C.D., SUBIT, D., CRANDALL, J.R. AND KENT, R.W. (2010). Rib Fractures Under Anterior-Posterior Dynamic Loads: Experimental and Finite-Element Study. Journal of Biomechanics 43: 228.234.
- LI, Z., KINDIG, M.W., SUBIT, D. AND KENT, R.W. (2010). Influence of Mesh Density, Cortical Thickness and Material Properties on Human Rib Fracture Prediction. Medicine Engineering and Physics 32: 998-1008.
- MALTESE, M.R., EPPINGER, R.H., RHULE, H.H., DONNELLY, B.R., PINTAR, F.A. AND YOGANANDAN, N. (2002). Response Corridors of Human Surrogates in Lateral Impacts. Stapp Car Crash J 46: 321-51.
- MAO, H., ZHANG, L., JIANG, B., GENTHIKATTI, V.V., JIN, X., ZHU, F., MAKWANA, R., GILL, A., JANDIR, G., SINGH, A. AND YANG, K.H. (2012). Recent Advances in Developing Finite Element Head Model. International Crashworthiness Conference. Milan, Italy.
- NUSHOLTZ, G.S., HSU, T.P. AND BYERS, L.C. (2007). A Proposed Side Impact ATD Bio-Fidelity Evaluation Scheme Using Cross-Correlation Approach. The 20th ESV Conference. Lyon, France.
- NUSHOLTZ, G.S., HSU, T.P., SHI, Y., KOCHEKSERAII, S.B. AND LUNA, M.A.G. (2009). Creating Representative Curves from Multiple Time Histories of Vehicle, ATD, and Biomechanics Tests. The 21st ESV Conference. Stuttgart, Germany.
- RHULE, H.H., MALTESE, M.R., DONNELLY, B.R., EPPINGER, R.H., BRUNNER, J.K. AND BOLTE, J.H. (2002). Development of a New Biofidelity Ranking System for Anthropomorphic Test Devices. Stapp Car Crash J 46: 477-512.
- ROBIN, S. (2001). Human Model for Safety A joint effort towards the development of redefined humanlike car-occupant models. 17th International Conference for the Enhanced Safety of Vehicles. Amsterdam.
- RUAN, J., EL-JAWAHRI, R., CHAI, L., BARBAT, S. AND PRASAD, P. (2003). Prediction and analysis of human thoracic impact responses and injuries in cadaver impacts using a full human body finite element model. Stapp Car Crash J 47: 299-321.
- RUAN, J.S., EL-JAWAHRI, R., BARBAT, S. AND PRASAD, P. (2005). Biomechanical Analysis of Human Abdominal Impact Responses and Injuries through Finite Element Simulations of a Full Human Body Model. Stapp Car Crash J 49: 343-66.
- RUAN, J.S., R. EL-JAWAHRI, S.W. ROUHANA, S. BARBAT AND PRASAD, P. (2006). Analysis and Evaluation of the Biofidelity of the Human Body Finite Element Model According to ISO-TR9790 Procedures. Stapp Car Crash J. 50: 491-507.
- SHAW, G., PARENT, D., PURTSEZOV, S., LESSLEY, D., CRANDALL, J., KENT, R., GUILLEMOT, H., RIDELLA, S.A., TAKHOUNTS, E. AND MARTIN, P. (2009). Impact Response of Restrained PMHS in Frontal Sled Tests: Skeletal Deformation Patterns Under Seat Belt Loading. Stapp Car Crash J 53: 1-48.
- SHIGETA, K., KITAGAWA, Y. AND YASUKI, T. (2009). Development of Next Generation Human FE Model Capable of Organ Injury Prediction. The 21st ESV Conference. Stuttgart, Germany.
- SHIN, J., YUE, N. AND UNTAROIU, C.D. (2012). A Finite Element Model of the Foot and Ankle for Automotive Impact Applications. Annals of Biomedical Engineering
- SPRAGUE, M.A. AND GEERS, T.L. (2004). A Spectral-Element Method for Modelling Cavitation in Transient Fluid-Structure Interaction. Int J Numer Meth Engng 2467-2499.
- THOMPSON, A.B., GAYZIK, F.S., MORENO, D.P., RHYNE, A.C., VAVALLE, N.A. AND STITZEL, J.D. (2012). A Paradigm for Human Body Finite Element Model Integration from a Set of Regional Models. Biomed Sci Instrum 48: 423-30.
- VAVALLE, N.A., MORENO, D.P., RHYNE, A.C., STITZEL, J.D. AND GAYZIK, F.S. (2013). Lateral impact validation of a geometrically accurate full body finite element model for blunt injury prediction. Ann Biomed Eng 41: 497-512.
- YANG, K.H., HU, J., WHITE, N.A., KING, A.I., CHOU, C.C. AND PRASAD, P. (2006). Development of Numerical Models for Injury Biomechanics Research: A Review of 50 Years of Publications in the Stapp Car Crash Conference. Stapp Car Crash J 50: 429-90.
- YUE, N., SHIN, J. AND UNTAROIU, C.D. (2011). Development and Validation of an Occupant Lower Limb Finite Element Model. SAE Technical Paper 2011-01-1128