

A Comprehensive Validation Method with Surface-Surface Comparison for Vehicle Safety Applications

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ABSTRACT

Computer Aided Engineering (CAE) models have proven themselves to be efficient surrogates of real-world systems in automotive industries and academia. To successfully integrate the CAE models into analysis process, model validation is necessarily required to assess the models' predictive capabilities regarding their intended usage. In the context of model validation, quantitative comparison which considers specific measurements in real-world systems and corresponding simulations serves as a principal step in the assessment process. For applications such as side impact analysis, surface deformation is frequently regarded as a critical factor to be measured for the validation of CAE models. However, recent approaches for such application are commonly based on graphical comparison, while researches on the quantitative metric for surface-surface comparison are rarely found. To deal with this problem, a validation metric, which combines the discrepancies measurements in magnitude and shape, is proposed to evaluate the inconsistency between two deformed surfaces. For magnitude error, an exploited 2-Dimensional Dynamic Time Warping (2D-DTW) method is applied to address the mismatch in surface features between two surfaces. Geometric features, say mean curvatures of surfaces, are extracted for shape comparison. For decision making, the original assessments are then transformed into scores through a linear regression method. An analytical case is employed to verify the employed algorithms in the proposed method. Furthermore, the method is implemented on a real-world case involving surface comparison to show its potential in vehicle safety applications.

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INTRODUCTION

With the ever growing concerns about occupant protection, automotive manufacturers have to meet several increasingly strict vehicle safety regulations and laws, such as the mandatory Federal Motor Vehicle Safety Standards FMVSS and the market-driven New Car Assessment Program (NCAP). Traditional approach to assess whether these requirements are satisfied is commonly based on costly and time-consuming physical tests. To shorten the development time, Computer Aided Engineering (CAE) models based virtual prototype tests to evaluate the vehicle crashworthiness are on the rise. To maximize the use of these models, the validity and predictive capabilities of these models need to be assessed objectively and quantitatively. This calls for the process of CAE model validation.

The fundamental concept of model validation has been introduced mainly by several professional societies and institutions, including the U.S. Department of Energy (DOE), the American Institute of Aeronautics and Astronautics (AIAA), the U.S. Department of Defense (DOD), and the American Society of Mechanical Engineers Standards Committee (ASME). It is commonly defined as the process of determining the degree to which a model is an accurate representation of the real world from the perspective of its intended uses.

As a crucial step in validation activity, metric development for quantitative comparison between test and corresponding simulation needs to consider various features of responses. For vehicle safety applications, considerable researchers have paid their efforts to develop numerous potential metrics with various case studies. Cheng [2] utilized a wavelet decomposition based method to extract the features of crash pulses, and introduced a metric in the form of rating score. Yang [3] reviewed several popular metrics in safety applications, and proposed a metric to address the bias introduced by Subject Matter Expert and quantitative metric itself. More recently, Xi et al. [4] and Xu et al. [5] paid efforts on the metrics development involving uncertainty consideration. Moreover, several previously introduced metrics, say CORA [6], EARTH [7] and EEARTH [8] become the foundations of the published ISO standards "Road vehicles - Objective rating metrics for dynamic systems". Though great progress has been achieved in the field of curve-curve comparison based validation, the development of quantitative metric for surface-surface comparison has not been well studied.

For many vehicle safety applications, surface deformation is frequently regarded as a critical factor to be measured for validating the CAE models. For instance, to ensure occupant protection, besides

time histories responses, modeler would also concern the deformed door surfaces of vehicle in side impact test and accident. Currently, validation methods for these applications are commonly based on graphical comparison, which is neither objective nor accurate. Ideal metric should provide quantitative indication for the degree of agreement between computational and experimental data. For such purpose, a comprehensive validation metric for surface-surface comparison is proposed in this paper. The proposed metric for surface-surface comparison combines the measurements of errors in magnitude and shape. For magnitude error, a 2-Dimensional Dynamic Time Warping (2D-DTW) method is proposed to address the effect of shape features on magnitude. As for shape error, curvature based measurement is introduced to characterize the geometric features of surfaces. For convenient decision making, the two error measurements are transformed into scores through a linear regression method.

The rest of this paper is organized as follows. The proposed surface validation method is introduced in the following section. The third section demonstrates the validity of the techniques involved in this metric through an intuitive case. Then the proposed method is applied to a case to show its potential in real-world engineering application.

PROPOSED SURFACE-SURFACE VALIDATION METHOD

Let $\mathbf{D}^R = [\mathbf{x}^R, \mathbf{y}^R, \mathbf{z}^R]$ and $\mathbf{D}^C = [\mathbf{x}^C, \mathbf{y}^C, \mathbf{z}^C]$ be the coordinates of the nodes on real-world surface and corresponding CAE model based surface. For the convenience of formulation, the original coordinates data are projected onto respective principal planes, so that to represent the original data by the height information of the transformed nodes [9]. The other two dimensions are transformed as the mesh indexes of the surfaces. Therefore, the following validation activities are performed based on the projected and meshed CAE and test data, say $\mathbf{Z}^R$ and $\mathbf{Z}^C$, which are both $m \times n$ matrices.

The proposed surface-surface validation process contains two main parallel assessment procedures for magnitude error and shape error, respectively. For magnitude error, an exploited 2D-DTW method is applied to address the mismatch regarding surface features (i.e. peaks and valleys) between two surfaces. Then the pre-processed surfaces are submitted to the following Euclidean distance calculation. In terms of shape error, geometric feature, say mean curvatures of surfaces, are extracted for topology comparison. Since the ranges of two errors are quite different, the original assessments are transformed into scores through a linear regression method.

Magnitude Error Measurement

Given two surfaces data to be compared, the most direct way to assess the discrepancy is computing Euclidean distance, which forms the foundation of distance measure [10]. However, Euclidean distance is quite sensitive to even small mismatches between two data. For example, slightly misaligned phase of time histories or shifted shape features (i.e. peaks and valleys) of surfaces would lead

to unreasonably large Euclidean distance measurement [11]. To address such problem, a 2D-DTW is exploited to separate the interaction between the features of shape and magnitude.

2D-DTW based Euclidean distance measurement

Dynamic Time Warping (DTW) is originally an algorithm for measuring similarity between two temporal sequences which may vary in speed and was initially used in context with speech recognition [12, 13]. It shows remarkable potential in various applications, e.g., data mining [14], medical imaging [15], and geological monitoring [16]. The key idea of DTW is that any point of a time history can be (forward and/or backward) aligned with multiple points of the other time history that lie in different temporal positions, so as to compensate the temporal shifts [17]. With such advantage, DTW has also proven itself to be an exceptionally useful tool in the field of model validation to map the samples of two time history curves [18]. However, for surface-surface comparison, the matching process needs to be performed in a higher dimensionality space. For such purpose, a 2D-DTW method is developed to minimize the effect of mismatched surfaces features on the magnitude error measurement.

In the context of DTW for one dimensional problems, the warping path that minimize the cost to match two curves needs to be calculated. Similarly, the proposed 2D-DTW evaluates the warping paths in two dimensionalities, say horizontal $\bar{h}$ and vertical $\bar{v}$, as shown in Figure. 1.

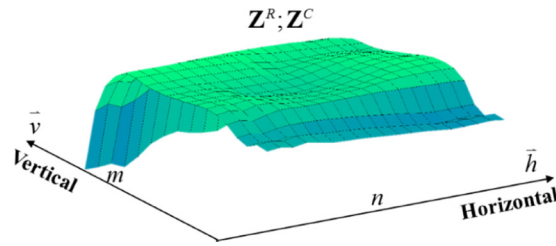


Figure 1. Dimensionalities definition for surfaces to be compared.

For the two directions, the distance matrices of the two surfaces are calculated as:

$$\mathbf{d}_h(i_h, j_h) = \|\mathbf{Z}_h^C(i_h) - \mathbf{Z}_h^R(j_h)\|_2, (i_h, j_h = 1 \text{ to } n);$$

$$\mathbf{d}_v(i_v, j_v) = \|\mathbf{Z}_v^C(i_v) - \mathbf{Z}_v^R(j_v)\|_2, (i_v, j_v = 1 \text{ to } m).$$

(1)

where $\|\cdot\|_2$ indicates L2-norm operation. $\mathbf{Z}_h^R$ and $\mathbf{Z}_h^C$ imply that the original matrices $\mathbf{Z}^R$ and $\mathbf{Z}^C$ are both sliced as n -column vectors, while $\mathbf{Z}_v^R$ and $\mathbf{Z}_v^C$ imply $\mathbf{Z}^R$ and $\mathbf{Z}^C$ are partitioned as m -row vectors. For each dimensionality, respective distance matrix can be obtained. The alignments of the two surfaces are optimized in the sense that it minimizes the cumulative distance. To optimize the warping paths “vertically” and “horizontally”, the matrices that minimize the

cumulative distances to match two surfaces are required to be calculated based on $\mathbf{d}_h$ and $\mathbf{d}_v$. For each warping step, the cumulative distance is expressed as:

$$\begin{aligned}\mathbf{D}_h(i_h, j_h) &= \mathbf{d}_h(i_h, j_h) + \min\{\mathbf{D}(i_h - 1, j_h), \mathbf{D}(i_h - 1, j_h - 1), \mathbf{D}(i_h, j_h - 1)\} \\ \mathbf{D}_v(i_v, j_v) &= \mathbf{d}_v(i_v, j_v) + \min\{\mathbf{D}(i_v - 1, j_v), \mathbf{D}(i_v - 1, j_v - 1), \mathbf{D}(i_v, j_v - 1)\}\end{aligned}\quad (2)$$

$\mathbf{D}_h$ and $\mathbf{D}_v$ indicate the cumulative distances regarding the two dimensionalities. The optimal warping paths to match the two surfaces can be determined based on $\mathbf{D}_h$ and $\mathbf{D}_v$.

In practice, backtracking is needed to identify the indexes for each step. Taking the horizontal warping process as example, backtracking along the minimum cumulative index pairs (i_h, j_h) starting from the top-right corner indexes (n, n) of $\mathbf{D}_h$ yields the DTW results. In case that the original sequences of matrices indexes are not optimal, certain sample indexes of $\mathbf{Z}_h^R$ and $\mathbf{Z}_h^C$ will be repeated for several times to make the two surfaces matched, which will results in the prolongation of the original matrix. Assume the obtained matrices be in the size of $m' \times n'$ ($m' \geq m$, $n' \geq n$), the following magnitude comparison is conducted based on the warped surfaces data $\mathbf{Z}^R$ and $\mathbf{Z}^C$. Then the discrepancy in magnitude can be calculated based on Euclidean distance, as shown in Equation (3).

$$\mathbf{D} = \|\mathbf{Z}^C - \mathbf{Z}^R\|_2 \quad (3)$$

Shape Error Measurement

In the context of differential geometry, curvature is a critical attribute to describe the shape of a surface [19]. In this study, mean curvature is employed to characterize the surfaces to be compared.

Geometric Features Extraction

At any point on a surface, its normal planes that contain the normal vector would certainly intersect with the surface. The intersection forms a curve called a normal section. Different normal sections correspond to different curvatures at the evaluated point, and the maximum and minimum values of these curvatures are called the principal curvatures k_1 and k_2 , respectively. As expressed in Equation (4), the mean curvature is defined as the average of the two principal curvatures:

$$M = (k_1 + k_2) / 2 \quad (4)$$

Mean curvature is employed in this study as it is a physically meaningful quantity. In the theory of differential geometry, the implication of M related to geometry is provided in Table 1.

Table 1. Implication of mean curvature related to geometry.

M	Geometric Feature
>0	Locally convex region
<0	Locally concave region

Let $\mathbf{S} (\mathbf{D}^R, \mathbf{D}^C \subseteq \mathbf{S})$, which belongs to 3-dimensional Euclidean space, represent the surface data to be evaluated, the mean curvature matrix of the surface can be calculated as:

$$\mathbf{M} = - \left(\frac{\nabla \mathbf{S} \cdot \mathbf{H}(\mathbf{S}) \cdot \nabla^T \mathbf{S} - \|\nabla \mathbf{S}\|^2 \cdot \text{Trace}(\mathbf{H})}{\|\nabla \mathbf{S}\|^3} \right) \quad (5)$$

where $\nabla \mathbf{S} = \left(\frac{\partial \mathbf{S}}{\partial x} \quad \frac{\partial \mathbf{S}}{\partial y} \quad \frac{\partial \mathbf{S}}{\partial z} \right)^T$ is the gradient of $\mathbf{S}$, while

$$\mathbf{H}(\mathbf{S}) = \nabla(\nabla \mathbf{S}) = \begin{pmatrix} \frac{\partial^2 \mathbf{S}}{\partial x \partial x} & \frac{\partial^2 \mathbf{S}}{\partial x \partial y} & \frac{\partial^2 \mathbf{S}}{\partial x \partial z} \\ \frac{\partial^2 \mathbf{S}}{\partial x \partial y} & \frac{\partial^2 \mathbf{S}}{\partial y \partial y} & \frac{\partial^2 \mathbf{S}}{\partial y \partial z} \\ \frac{\partial^2 \mathbf{S}}{\partial x \partial z} & \frac{\partial^2 \mathbf{S}}{\partial y \partial z} & \frac{\partial^2 \mathbf{S}}{\partial z \partial z} \end{pmatrix}$$

is the Hessian matrix of $\mathbf{S}$.

$\text{Trace}(\bullet)$ denotes the trace of the matrix correspondingly. Details can be referred to ref. [20, 21].

Regression Based Rating

As the ranges of these two errors, say $\mathbf{D}$ and $\mathbf{M}$, are nondeterministic and quite different, it is difficult for engineers to interpret how good or how bad a CAE model is based on these raw error data. To provide more intuitive rating based on the original measurements, a rating score method is employed (Zhan et al., 2011b). The regression based method translates the original errors into one score between 0 and 100%, so that it can provide an intuitive rating score. In this study, Equation (6) is used to calculate the magnitude score S_m ,

$$S_m = \begin{cases} 100\%, & D = 0, \\ 0, & D \geq D^*, k_m \in \{1, 2, 3, \dots\}, \\ [(D^* - D) / D^*]^{k_m}, & \text{otherwise.} \end{cases} \quad (6)$$

where D^* is the maximum allowable magnitude error, k_m defines the order of the regression. In this way, the best magnitude score is 100%. If the magnitude is equal to or greater than the maximum allowable threshold M^* , then the score is 0%. In between, the score is calculated by regression method. Equation (7) provides the similar rating rule for shape error.

$$S_s = \begin{cases} 100\%, & M = 0, \\ 0, & M \geq M^*, k_s \in \{1, 2, 3, \dots\}, \\ [(M^* - M) / M^*]^{k_s}, & \text{otherwise.} \end{cases} \quad (7)$$