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Feature-Based Model Validation

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Model Validation Using Quantities of Interest (QoIs)

- Model validation has historically been conducted by defining and comparing quantities-of-interest (QoIs)
- QoI must be calibrated for the specific application usually by expert opinion or correlation to damage/failure
- Actual failure mechanism may not be understood for a component or system (e.g., voltage dropout)
- System variability may have a large effect on damage potential and occurrence
- Lack of understanding and variability of response can make damage/failure an unreliable measure of model validation
- Input forcing functions are largely unquantified except in precision testing
- Extensive resources must be expended to calibrate a QoI for each application

Calibrating QoIs Using Expert Opinion

- Subject matter experts (SMEs) can identify the key "features" of the response characteristics based on extensive observation (similar to machine learning)
- Certain key features must agree (i.e., match) between the experimental and analytical results before validation can be concluded
- For a candidate QoI to be suitable, it must correlate with these essential features of the response
- It is difficult to encode expert judgment on an algorithmic basis due to many sources of spurious information (e.g., temporal shifting, frequency distortion, nonlinearities, noise, instrumentation error)

Eonverye taht can raed tihs rsaie yuor hnad..

- The word recognition model, which says that words are recognized as complete units, is the oldest model in the psychological literature
- The idea is that we see words as complete patterns, rather than the sum of letter parts

Feature-Based Image Analysis

- Feature-based image analysis is the process of identifying and comparing key features in a data set
- Typically, we think of the data set representing a visual image and a feature being a recognizable object
- A feature is defined as a characteristic shape or construct
- Segmentation is the process of extracting features from a data set
- Image understanding is the process of identifying features in a data set
- Matching is the process of correlating a specific feature to a data set

Medical Diagnostics Using Feature-Based Image Analysis

- We have all benefited from advances in the field of medical diagnostics that utilize feature-based image analysis technology
- Medical imaging can generate vast amounts of data that must be evaluated by qualified medical personnel
- Computer-based diagnostic routines sift through the data to limit further examination to a manageable level
- These diagnostic routines utilize known features of the disease (e.g., tumor shape, coloring) under investigation to pare down the search space
- The efficiency of medical diagnostic software is measured as the percentage of false positives

Proposed Approach for Model Validation

- Even if it is understood and well known (e.g., repeatable fatigue failure at a joint), damage or failure may have too much variability to use as a measure of model validation
- Calibrating a QoI using expert opinion is an indirect approach that requires extensive testing to define the QoI limits of correlation and applicability
- The proposed approach is to validate analytical models directly using the key response features identified by the SME
- Feature-based image analysis provides the technology for this new paradigm of model validation

Application of Feature-Based Image Analysis To Model Validation

- The disparity of results confounds any attempts at point-by-point comparisons of analytical and experimental solutions analogous to region-based image matching
- Feature matching replicates the SME process of model validation
- SME emphasizes certain key features while ignoring non-essential information
- Each problem class has its own set of essential features that must be carefully specified
- Implementation of existing segmentation and image understanding technology ensures a high chance of success

Application of Feature-Based Image Analysis To Model Validation (cont'd)

- Feature-based model validation implicity includes the structure and forcing function where frequency response functions and MAC only consider the structural response
- Work with SMEs to define features analogous to knowledge engineer in expert systems
- Degree of validation dependent on application
- If a feature can be identified then it can be matched (i.e., validated) in a data set
- Apply different weighting factors to the different features in a data set according to their importance

Identify Not Quantify

Example of Feature-Based Model Validation

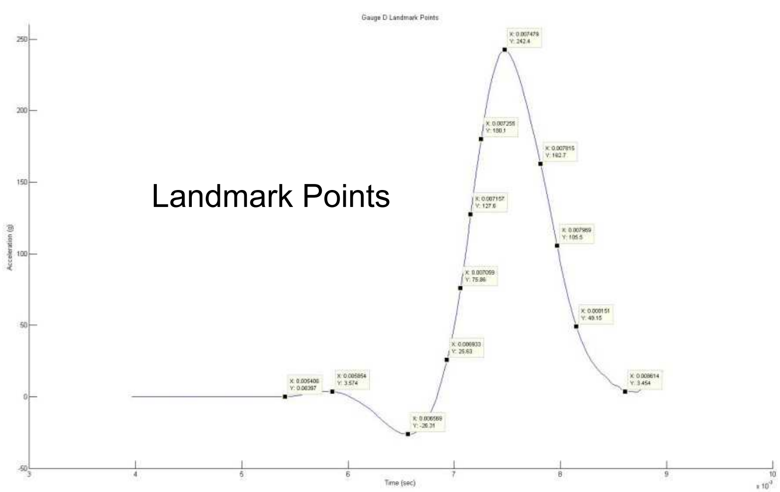
- **A standard data set has been identified consisting of a single barge shock test with measurements at eight locations**

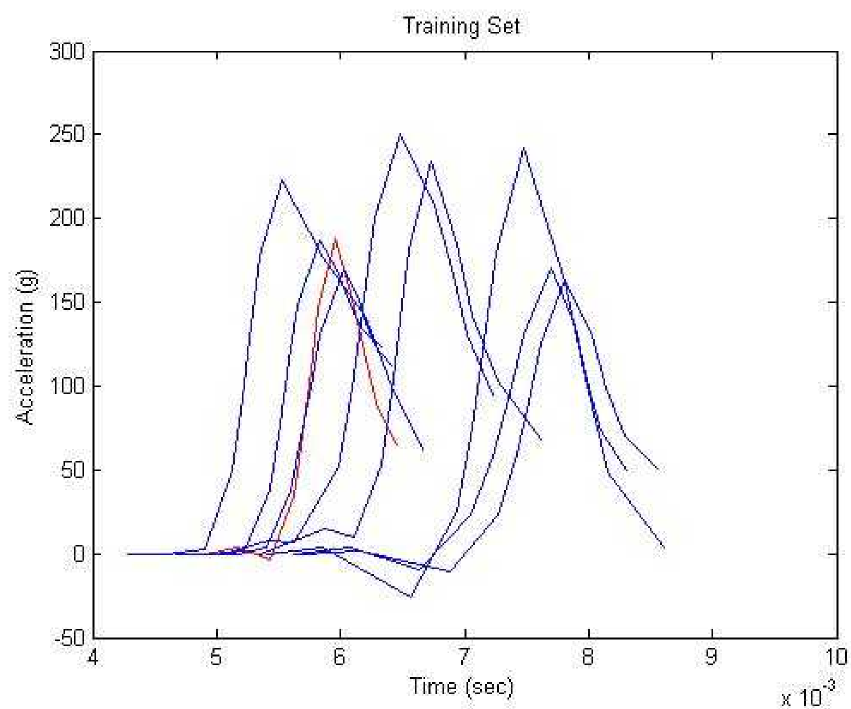
- **Navy uses the velocity change of the initial impulsive response as their QoI**
- **The two key features identified for this application include the initial impulsive response and windowed rms levels[1]**

[1] "Assessment of Validation Metrics for UNDEX Simulations," D. J. Manko and T. L. Paez, Presented at 2012 Shock and Vibration Symposium

Example of Feature-Based Model Validation (cont'd)

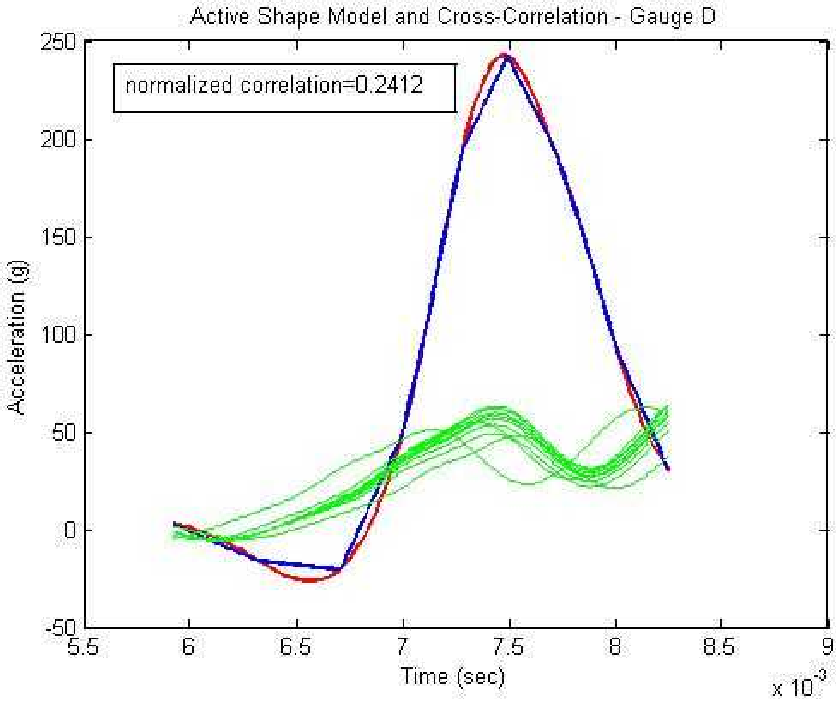
- Features are extracted from the data set using a Point Distribution Model (PDM) and training shapes are used to "educate" the software



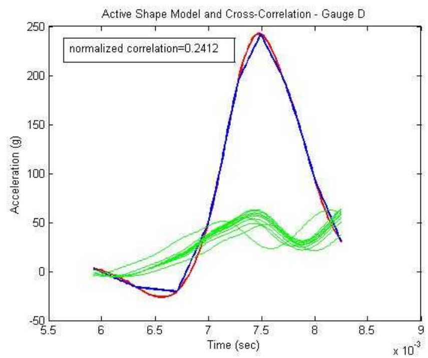


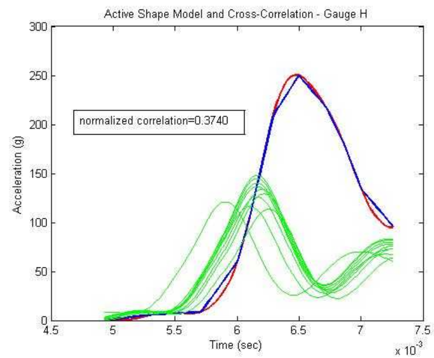
Example of Feature-Based Model Validation (cont'd)

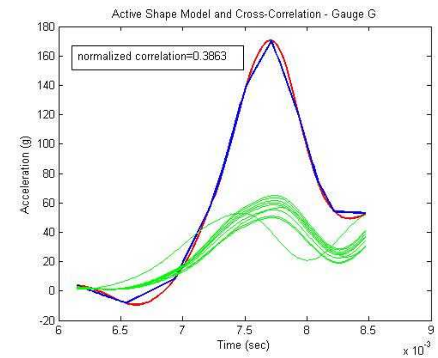
- The Active Shape Model (ASM) is used to identify the features in the data set
- Normalized cross correlation is used for feature matching

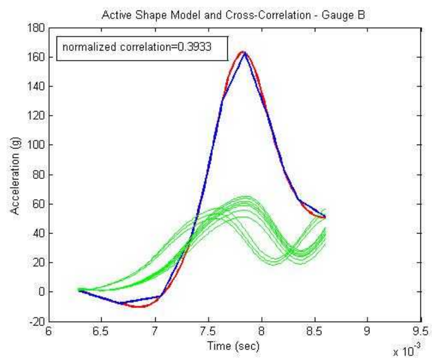


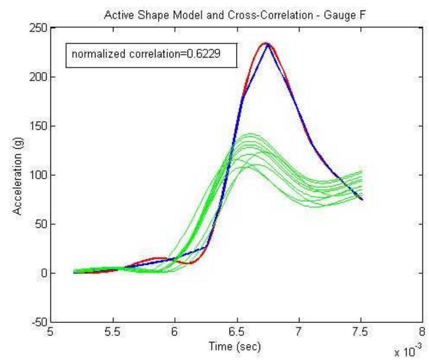
Example of Feature-Based Model Validation (cont'd)

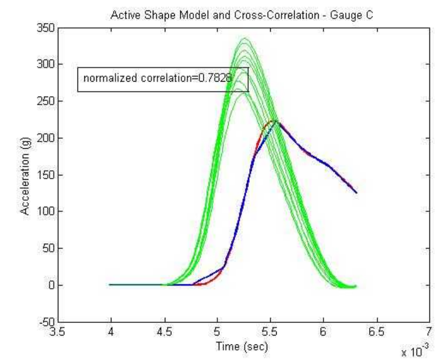


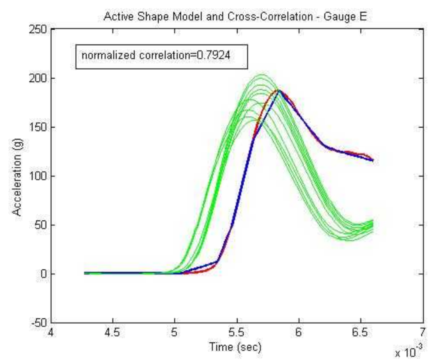


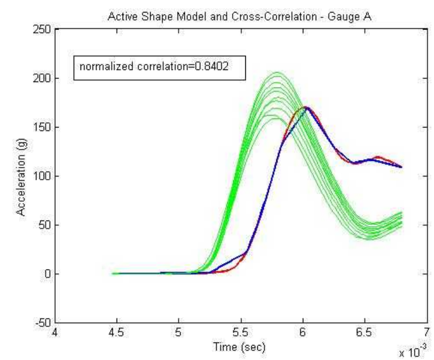












Example of Feature-Based Model Validation (cont'd)

- Feature matching results are exactly consistent with SME validation judgment
- Only shapes characterized by training set are permissible, therefore, the approach is tolerant of noise
- Uncertainty manifests as spread in eigenvalues plus additional principal components (possibly)
- Eigenvalues can be used as a statistical means of quantifying agreement
- Knowledge retention inherent in training set definition
- Sufficient data must be available to define training sets for all relevant features
- Separate training sets could be used to differentiate vertical versus lateral initial barge response

Image Matching Applied to QoIs

- QoI assessment produces vector(s) that must be compared to reference vector(s) to conclude validation
- Hypothesis testing has been used to compare QoI vectors but subjectivity is still part of the process
- Image matching provides a methodology to objectively compare vectors and produce a single quantified value of correlation
- Windowed RMS time signal was identified[1] as the QoI that best correlated with the barge shock test results discussed earlier
- Windowed RMS QoI was calculated for the post-impulse response using a 1.5 msec interval width with no overlap and ten equally spaced Gaussian windows[1]

[1] "Assessment of Validation Metrics for UNDEX Simulations," D. J. Manko and T. L. Paez, Presented at 2012 Shock and Vibration Symposium

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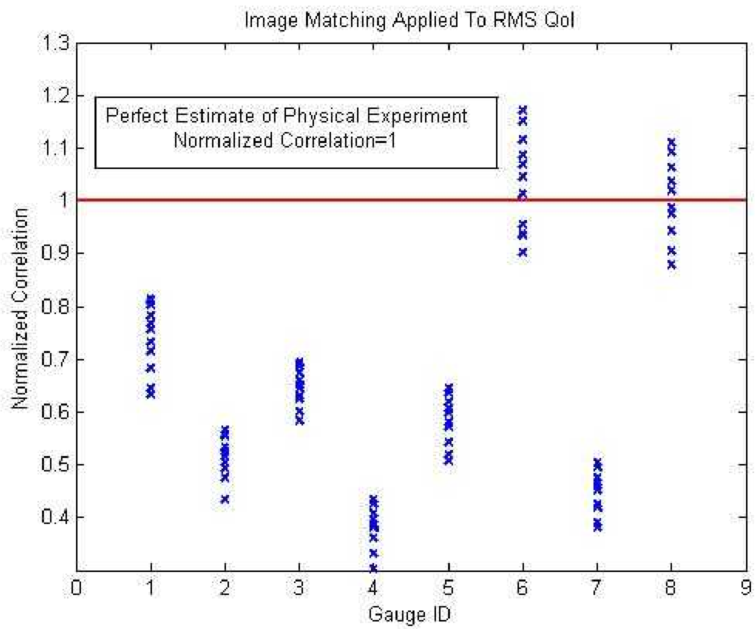
Image Matching Applied to QoIs (cont'd)

- **Normalized cross correlation used to quantitatively compare the experimental and analytical results for the eight gauge locations**



- **Rank ordering corresponds with visual assessment shown on next slide**

Image Matching Applied to QoIs (cont'd)

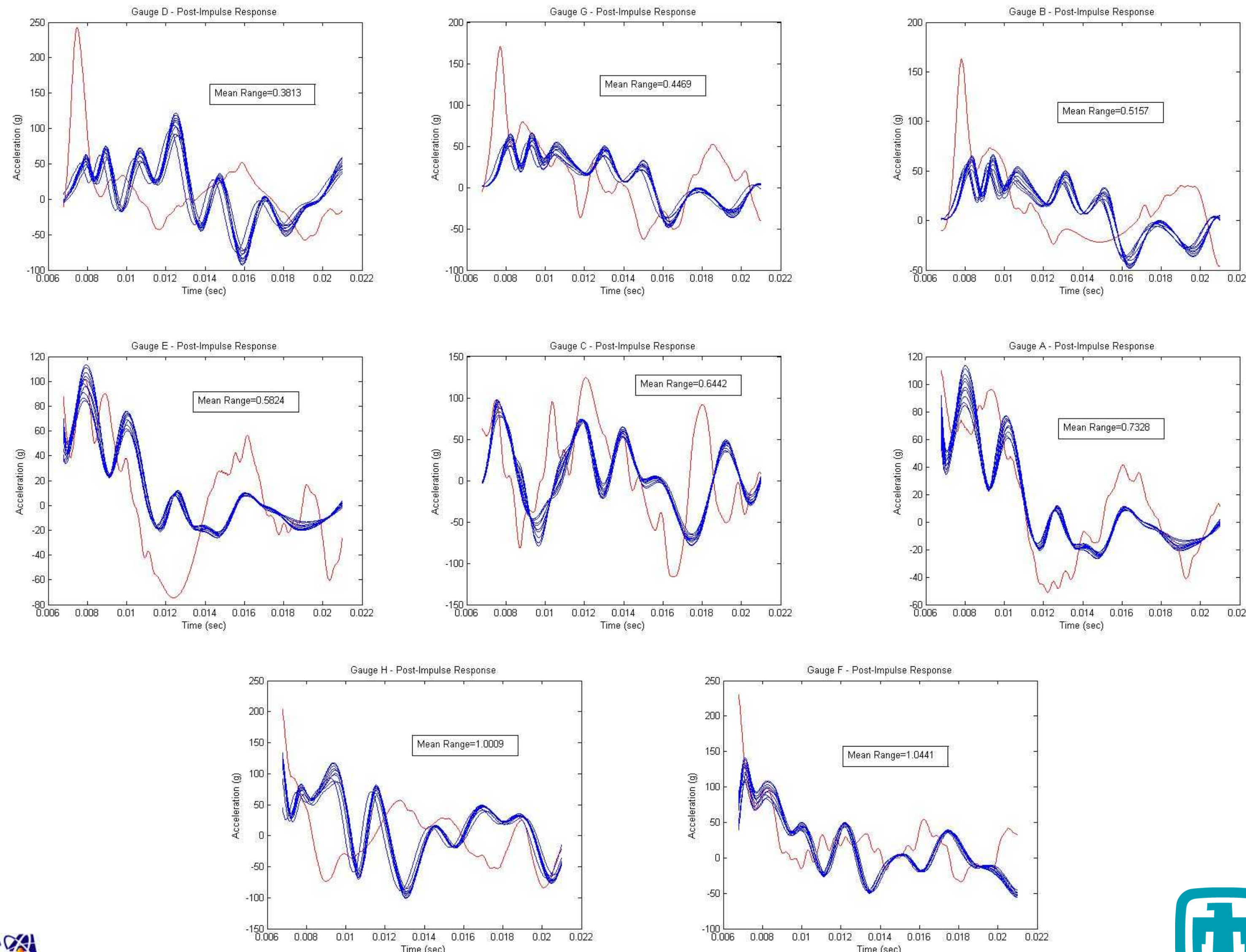


Image Matching Applied to QoIs (cont'd)

- The previous example was conducted for visual purposes only – it does not identify the best overall simulation
- Actual implementation would combine all gauge contributions using weighted correlation to determine the simulation that best corresponds with experimental results
- Weighted correlation enables emphasis of most important gauge responses
- Development required to determine best weighting function for a particular application
- Numerous algorithms are available to quantify correlation of data sets

Candidate Models for Feature-Based Validation

- Impact-deceleration
- Pyroshock
- Undex
- Blast panels – hole, no-hole, really dented
- Stresses – static (3-D), dynamic (time varying 3-D)
- Frequency response functions
- Modeshapes
- Power spectral densities
- Shock response spectra

Any Phenomenon With Identifiable Features

Possibilities

- Validity of experimental data can be assessed using feature-based methods
- Feature matching can be used for system identification such as nonlinear response characterization
- Define appropriate modeling approach by first conducting system identification analogous to medical screening
- Ultimately use machine learning to identify important features

Summary

- Feature-based model validation mimics SME approach to model validation
- Much simpler to identify features than accurately calculate response quantities
- Input forcing function does not require definition
- Expensive calibration of QoIs is avoided
- Any degree of validation accuracy can be specified to suit the specific application versus one-size-fits-all
- Most important features can be more heavily weighted
- Image matching provides a methodology to objectively quantify QoI comparisons thus supporting existing validation framework

Implementation of mature image processing technology ensures a high chance of success

Random Notes

- QMU isolation of unmodeled effects using machine learning
- Neural network based stock prediction
- Improve process by least-squares image matching and modified eigenvalue approach
- Mixed mode data description (time, g's) is an implementation issue
- Models exercise known parameters – use machine learning to quantify unknown uncertainties
- Sx and Sy versus S, and ty=0 examples of SME input
- Financial failure caused by unchecked machine learning
- Abstraction at multiple levels (e.g., rms levels) same as feature tracking, gaussian pyramid
- Filtering can be used for abstraction at multiple levels
- Undex example done blind, not knowing gauge locations, which affects physics and therefore, features