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OPPORTUNITIES AND CHALLENGES OF STRUCTURAL IDENTIFICATION

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Abstract

In the wake of development of enabling technologies in sensors and computer hardware, there are many opportunities to generate, store and transmit measurement data. Structural identification methodologies support data interpretation, thereby improving the quality of decision making for infrastructure management. Multiple model candidate identification is a method for systematically including the intrinsic ambiguity of inverse engineering tasks as well as measurement and modeling errors. The multiple model approach also leads to rational methodologies for designing sensor networks. Data mining methods assist in model interpretation and support the incremental measurement – interpretation cycles that are common in large scale civil-engineering structures. Damage scenario detection can be improved through inclusion of damage models. Engineer-specific interaction methodologies have the potential to provide the support that is necessary to extend the usefulness of performance based engineering. Challenges include avoiding the data interpretation bottleneck, appropriate management of errors, development of a comprehensive framework for sensor network design, and ensuring that engineers are not overwhelmed by the complexity of coping with multiple models.

INTRODUCTION

Developments in sensor technology and advanced computing methods are creating opportunities to benefit from the potential of structural identification. In addition, lower costs and more flexible hardware are increasing practical viability. Structural identification techniques are becoming kernel enabling methodologies for implementation of performance based engineering (maintenance as well as design) and this will lead to more economical management of infrastructure. In the longer term, there is potential for more efficient design, increased safety and innovative solutions as structures become self aware.

However, there is much work to do. For example, in conventional structural identification, a model is identified through matching measurement data with model predictions [1-4]. This involves identifying values of model parameters that minimize the difference between predictions and measurements. These methods are based on the assumption that the model that best fits observations is the right model. This assumption is flawed due to the following reasons: (1) system identification is an inverse problem and thus, several models can predict the same measurement data, and (2) errors in modeling and measurement [5-7] may compensate such that the model that best predicts the measurements is not the best model for diagnosis, evaluation and prediction.

This paper begins by highlighting key technologies that provide opportunities related to structural identification. Opportunities such as recently developed approaches in multiple model identification are then described and this leads to a description of new methods for sensor network configuration and definition of spaces of possible models. Such spaces are delimited by an error threshold that is determined from combined considerations of measurement and modeling errors. Challenges include an accurate definition of such thresholds, characterization of model spaces and optimal sensor-network configuration. Efforts to meet these challenges are providing engineers with methodologies to rationally design sensor networks and to interpret measurement data accurately for improved structural management.

ENABLING TECHNOLOGIES: MEASUREMENT SYSTEMS AND COMPUTING HARDWARE

Two barriers to more general use of structural identification methodologies, lack of useful measurements and expensive computer hardware, are falling. Over the last ten years, there has been a tremendous increase in the number of ways engineers are able to monitor structures. New embedded sensors, advances in photogrammetry, increased accuracy of global positioning system (GPS) measurements are just a few of many examples.

Perhaps the most important advances for structural health monitoring are the developments in optical measurement techniques [8]. Use of optical measurements avoids many difficulties associated with drift in electrical signals over time and damage during thunderstorms. This advantage has made feasible measurement of long-term phenomena such as creep and temperature induced deformation in full-scale structures. Values of measurements due to these effects often have the same order of magnitude of measurements due to short term effects. Adding to this advantage, long-gauge optical-fiber sensors make possible measurement of deformations in non-homogenous materials (such as reinforced concrete, fiber reinforced polymers and wood). These advantages have greatly increased the number of possibilities for measuring important aspects of the behavior of structures.

It is not enough to have high-tech equipment that accurately measures the behavior of full-scale structures in changing environments. Data needs to be stored and communicated. Increases in capacities of computers have made possible cheap storage and transmission of the gigabytes of data that are generated by continuous measurement systems on full-scale structures. Improvements in robustness of equipment have made storage and transmission more reliable. As flash memory chips replace hard drives, robustness will increase further. Finally costs of computing equipment continue to fall and with the introduction of wireless data acquisition, costs are decreasing further.

Therefore developments within fields of measurement technology and computer hardware are enabling the necessary conditions for increased importance of structural identification methodologies. Over the past twenty years, applicability of structural identification concepts has thus moved from restricted scopes, such as short-term measurements on steel laboratory structures, to general applicability in structural health monitoring for a wide range of structures.

MULTIPLE MODEL STRUCTURAL IDENTIFICATION

Since measurement, data storage and transmission are no longer barriers for implementation of structural-identification methodologies for structural management; an important contributing factor to the current “bottleneck” is data interpretation. If data cannot be interpreted properly so that good decisions can be made, the most hi-tech sensor that feeds into the most advanced data acquisition system is useless. When there is weak support for data interpretation, engineers take the risk of drowning in data. This can be worse than no data at all.

The key task when interpreting data involves identification of the structural behavior model that is best able to predict current and future performance. As mentioned in the introduction, this is an inverse engineering task and therefore, possible solutions are rarely unique. Errors in measurement and in modeling further increase the number of behavior models that could explain a set of measurements. Taking inspiration from over twenty years of research into model based diagnosis in other engineering fields, for example [9], there are good opportunities to recognize explicitly multiple models and reason within a model space in order to improve the accuracy of structural identification.

As a first approximation, engineers often use the behavior model that was used during the design stage. Uncertainties in the original model, such as values for E and I in concrete structures, are then used to explain differences between model predictions and measurements. Typically, such approaches conclude with back-calculated “effective values” for the uncertain variables.

Unfortunately, design models are usually not appropriate for making sense of measurements. Since they are formulated prior to erection, they often contain conservative assumptions related to aspects such as support conditions and connection behavior. Such conservatism is entirely acceptable during the design stage since the impact on cost and other design objectives is almost always low. However, the assumption that design models can be used for interpreting measurements, a task for which they were never intended, can be justified only on very simple structures.

Rather than choosing a single model and updating parameter values, recent proposals have studied generation and subsequent filtering of candidate models. Figure 1 is a framework for multiple model system identification [10]. The framework links four activities: (1) model generation, (2) data mining, (3) measurement system design and (4) engineer-computer interaction.

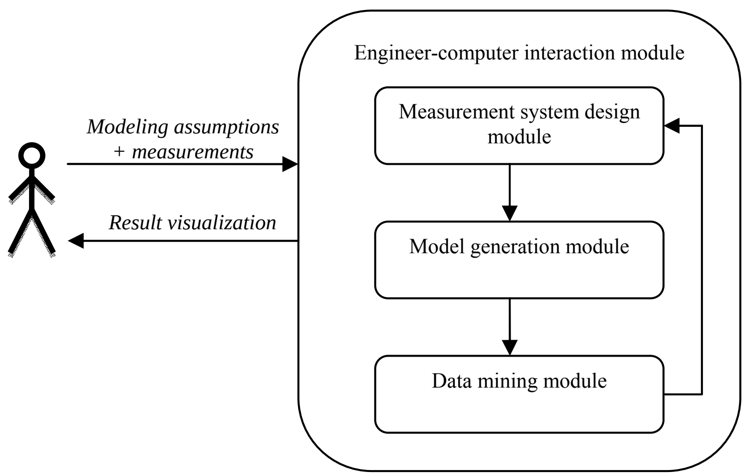

Figure 1. A framework for multiple model system identification, from [10].

Modeling assumptions and measurements are input starting data for the framework. With this information, the model generation module generates a candidate model sets using stochastic search [11] and this set is analyzed using data mining methods. Modeling assumptions define the parameters for the identification task. Model parameters may include parameters such as elastic constant, connection stiffness and moment of inertia. Each set of values for the model parameters corresponds to a model of the structure. The model generation module uses an objective function to evaluate the quality of candidate models. The objective function *E* is defined as follows [10].

$$E = \begin{cases} \varepsilon, & \text{if } \varepsilon > \tau \\ 0, & \text{if } \varepsilon \le \tau \end{cases} \qquad \text{and } \varepsilon = \sqrt{\sum (m_i - p_i)^2} \qquad (1)$$

ε is the error which is calculated as the difference between predictions p_i and measurements m_i. τ is a threshold value that is obtained from a probabilistic combination of measurement and modeling errors. The set of models that have $E = 0$ form the set of candidate models for the structure.

Most structures remain in service for decades. While deterioration and other time dependent phenomena may have an influence on the best behavior model, sudden collapses are rare. Typically engineers proceed iteratively in cycles of measurement and structural identification over a period of several years. This is analogous to a medical doctor who waits for the results of one set of tests before recommending more. Therefore, multiple model structural identification tasks usually start with large initial sets of candidate models. Models in these sets are then progressively filtered out using additional measurements until one of the following two conditions are met: i) the correct model is identified; ii) variations in the remaining set of models have no influence on the structural management decisions that are required.

DATA MINING

Data mining methods assist data interpretation through grouping together models that are similar and through indicating opportunities for further measurement. More specifically, data mining techniques are used to extract relationships between models and to identify clusters of similar models in multi-dimensional parameter spaces. For example, Principal component analyses (PCA) have been used to reveal clusters of similar models when no clusters were apparent using raw values of model parameters [12, 13].

Detection of clusters in data is not a trivial task when many parameters are under consideration. Recent work has employed the k-means algorithm [13]. Also a new score function is proposed to help determine the number of clusters in data [14]. This function is unique in so far as it is able to indicate the presence of a single cluster.

In spite of much progress in recent years, data mining often identifies spurious relationships between data and clusters that do not realistically separate data into meaningful groups. Therefore, data mining algorithms must be accompanied by advanced user interfaces so that engineers can visually interpret results and guide the process through introducing context specific information. More detail is given in the section after the next one.

SENSOR NETWORK DESIGN

Identification of multiple candidate models leads to opportunities for design of a sensor network in a structure. Three factors are of interest: sensor placement, the parameters being measured and sensor accuracy. Inspired from previous work [15], Robert-Nicoud et al proposed a greedy algorithm for sensor placement using Shanon's entropy function [16]. This was extended and compared with a global search algorithm [17]. Recently, Kripakaran et al. [18] investigated the inclusion of damage scenarios in the model sets.

Since sensor networks may be designed prior to construction, there are no measurement data to determine the initial set of candidate models. Instead, a model set is generated randomly from the total number of possible models. Users fix the number of models required to be in the set. These models are then used to predict values of potentially measured values at possible measurement locations. The best place for a sensor is proposed by [16] to be where the entropy is highest. Since entropy is a measure of information disorder, this is where knowledge of the measured parameter would be most effective in identifying the correct behavior model.

Two options are possible at this point. The first option involves incrementally placing a sensor at positions of highest entropy where the first location selected is not changed in subsequent iterations. This is called a greedy algorithm. The second option is where global search is used to fix sensor locations such that the total entropy is highest for a given number of sensors. In this option, the locations selected for n sensors may be different from the locations fixed for n+ 1 sensor. The second option is better for initial sensor configuration while the first option is most appropriate for incremental measurement – interpretation cycles on existing structures.

Damage scenarios can be included during initial sensor configuration through ensuring that the initial model set includes models of a damaged structure. The number of damage models included in the total model set relative to the number of other models depends on the importance of detecting damage and the likelihood of damage occurring. Alternatively, sensor configuration could be run two or more times using no-damage and damage scenarios to determine the union set of each run.

Development of decision support for sensor selection and sensor accuracy is underway at EPFL. Sensor accuracy is included in the width of the sensor location band as described in [16]. Initially, sensor selection involves maximum entropy comparisons with results from various sensor types. Global search using sensor type (measured parameter) as a variable and entropy in the objective function may be feasible for structures of medium complexity.

ENGINEER-COMPUTER INTERACTION

The model generation module, data mining module and sensor network design module require various amounts of engineer-computer interaction. For example, this module includes visualization tools for displaying results from the data mining module. Providing decision support for engineers requires special consideration since they work best when they see familiar representations. For example, each engineering field has developed special symbols that represent import ideas and concepts [19]. Perhaps the biggest challenge is providing support for reasoning in the context of multiple models that contain several parameters.

PERFORMANCE-BASED STRUCTURAL ENGINEERING

In structural engineering, much has been written about performance over the last decade. Ideas in performance-based structural engineering (PBSE) are not at all new. Structural engineers have always been concerned about performance and many historical developments in the field, such as plastic design and avoiding progressive collapse, have their roots in the desire to consider explicitly structural performance. Design and subsequent management concepts in other fields have also focused on performance and concepts such as “fitness for purpose”, “damage tolerance” and “fail safe engineering” reflect performance strategies.

Most recent work in structural engineering involves proposals for more explicit aspects of PBSE on the requirements side of the basic inequality that is used for both design and management. Ignoring load and resistance factors, this is:

$$\text{Effects of actions} \leq \text{Requirements (or performance criteria)} \qquad (2)$$

Since for many performance criteria, such as deflections and earthquake resistance, requirements have traditionally had weak scientific support, this work contains many valuable proposals. However, increasing the granularity of only one side of an inequality implicitly assumes that the other side (in this case, the effects of actions) is sufficiently well known.

In many situations, the influence of factors such as inaccurate design assumptions, corrosion, settlement of supports, cracking and changing conditions at joints mean that more specific performance criteria has no impact on the quality of decision making. The success of PBSE is, in such cases, dependent on accurate estimates of the effects of actions using realistic models. Measurements become unavoidable for accurate model identification. Therefore, the opportunities and challenges that are discussed in this paper are also valid for extending the applicability of PBSE concepts.

CONCLUSIONS

There are many opportunities and challenges associated with structural identification. Opportunities are:

- Every year, sensors become cheaper, more versatile, more robust and more present in structures.
- Computer storage capacities, processing power and communication possibilities are no longer a hindrance to the success of structural identification.
- Generation of multiple model instances provides predictions within tolerance limits to account for modeling and measurement errors in a systematic fashion.
- Data mining techniques are useful for grouping models into clusters thus providing information regarding possible model classes and good opportunities for subsequent measurement.
- Promising sensor placement methods are global stochastic search for initial placement design and clustering data for input into a greedy algorithm for additional measurements. Placement methods are evolving into methods that also assist in the selection of sensor type and accuracy.

- A multiple-model approach allows for damage identification when damage scenarios are included in sensor configuration.
- Engineer computer interaction (ECI) methodology has the potential for providing support to enhance the quality of decision making.
- More generally, there is much potential to extend the usefulness of concepts related to performance based structural engineering, thus improving structural management and eventually providing opportunities for innovative designs.

Challenges related to structural identifications are:

- Data management and interpretation (not sensor and computing technologies) have become the dominant causes of the structural-identification bottleneck.
- Measurement interpretation is an inverse engineering task that may have many possible solutions. While models used at the design stage are usually appropriate for design, they are rarely useful for interpreting measurements on existing structures.
- The presence of errors in modeling and in measurements further increases the number of possible solutions. Single value optimization methods, traditionally used in model updating strategies, are often inappropriate.
- Engineers lack a generally accepted and systematic methodology for selecting sensor type, quantity, accuracy and position
- When confronted with decision making related to interpreting and filtering multiple candidate models, engineers can be overwhelmed by the complexity of coping with multiple models.

Meeting these challenges requires cooperation between research groups who are active on an international scale so that all opportunities can be investigated in the widest possible range of civil engineering contexts. The Structural Identification Committee at ASCE is actively moving in this direction and as a result, much progress is expected over the next decade.

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