Combining Simulation and Machine-Learning for Real-Time Load Identification in Sensorial Materials

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Introduction

ISIS Sensorial Materials Scientific Centre

- ISIS:
  Integrated Solutions in Sensorial Structure Engineering
- Scientific centre at the University of Bremen, Germany
- Founded in Nov. 2008
- Approx. 60 members from
  - Production engineering,
  - Physics/electrical engineering,
  - Computer science, robotics, and
  - Biological/chemical engineering
Outline

In this presentation:

• Motivation: Sensorial Materials
• Vision: Monitoring Complex Structures with Intelligent Agents
• Our Machine-Learning Approach to Real-Time Load Identification
• Evaluation Scenario: A Simple Rubber Plate
• Conclusion and Outlook

Motivation

Structural Analysis vs. System Identification

• In classical structural analysis we calculate the system answer based on a predefined model e.g. for the material and the boundary conditions of the system.
  → system answer, e.g. displacements/strain
• In classical material science we apply sensors to verify our models (e.g. measuring displacements or strains).
  → material laws
• In classical system identification we perform a series of measures of system answers to derive the system properties (model).
  → system characteristics, e.g. stiffness
Motivation

Structural Analysis vs System Identification

• Basic approaches – different perspectives

System identification

Structural analysis

\[ K r = R \]

result of analysis

measurement

\[ K r = R \]

result of sequence of analysis

Motivation

Sensorial Material

• “Sensorisation” means to equip technical structures with an analogue of a nervous system by providing a network of sensors, communication facilities linking these and specific hardware as well as computational methods to derive meaning from their combined signals.

• Sensors detect if "overloading" occurs:
  – Strain is beyond the yield limit
  – A predefined number of load cycles was reached
  – …

Instead of designing once and testing event-based or in predefined intervals, the material is continuously monitoring itself by means of sensors.
Motivation

Increase Sensor Density of Sensorial Structures

Vision: A material that gathers information about itself and/or its physical surroundings, communicates them according to a specific protocol, and is homogeneous on the length scale of its macroscopic use.

Structure Monitoring With Intelligent Agents

Load R

FE substructure simulation based on mechanical model

Sensor element answering to applied loading

Sub-structuring with compatibility conditions
Our Approach Towards Sensorial Structures

Real Experiments

Real Experiments

DB

FEM Simulation of Load Case Library

Mechanical Effects Database

Data Reduction & Data Mining

Compact Dataset

Machine Learning Methods

Geometric Model & Load Case Definition

Real-Time Structural Health Monitoring

Self-Monitoring Structure

Chip Integration

Learned Model

Evaluation Setup

Simple Nitrile Rubber Plate Scenario

• Application of different load cases

  In our evaluation:
  – 150 different load positions
  – Three different masses (103 g, 207 g, 306 g)

• Can we infer properties of an unknown load case from only a few observed deformation effects?

  In our evaluation:
  – Can we infer load position, load mass, and displacement vectors – especially in-between sensor positions?
Sensor Input
Optical Surface Metrology Techniques

- Shearography / Fringe Projection to be used as reference to measure the real deformations that occurred.
- Naturally, the data obtained by these methods will not be free of noise either...

Load Inference Prototype
Simple Nitrile Rubber Plate Scenario

**ISIS Functional Mockup:**
- NBR-60 rubber plate 360 x 260 x 3 mm
- Fixed at all four edges
- Weights placed on top face
- Strain measurements on bottom face
- Camera records position and mass of loads
Load Inference Prototype
Simple Nitrile Rubber Plate Scenario

**ISIS Functional Mockup:**
- NBR-60 rubber plate 360 x 260 x 3 mm
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Load Inference Prototype
Realisation of a Robust Sensor Network

Vision: Intelligent agents can run on miniaturised sensor nodes

(Digital circuits currently miniaturisable to approx. 6 mm² per node / 1-2 cm² with analogue circuits)
Evaluation Setup

**ISIS Demonstrator**

1. Place one weight at a time on the rubber sheet.
2. Choose “Memorize Load Case”.
3. Repeat this procedure several times with different weights and positions.
4. Switch to “Query Mode” when done.

You are in Training Mode.  

| Memorize Load Case | Query Mode |

Machine Learning Methods

- **k-Nearest-Neighbour**
- **C4.5 Decision Trees**
- **Neural Networks**

Numerical Regression of Load Position, Mass, and Displacement Vectors

Mass Classification

Numerical Regression of Load Position and Mass
Experimental Results  

**k-NN Location Error**

Vector Difference Between Predicted and Actual Load Position for 103 g:

- Load Coordinate X (mm)
- Load Coordinate Y (mm)

**k=3**

Sensor Position  
Error Vector  
Actual Load Position

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Experimental Results  

**k-NN Location Error**

Vector Difference Between Predicted and Actual Load Position for 306 g:

- Load Coordinate X (mm)
- Load Coordinate Y (mm)

**k=3**

Sensor Position  
Error Vector  
Actual Load Position
Experimental Results  

**k-NN Location Error**

Vector Difference Between Predicted and Actual Load Position for 308 g:

- **k=3**

**Experimental Results  

**k-NN Displacement Error**

Median Relative Difference Between Predicted and Actual Displacement:

- **k=4**  
  overall median: 0.36
Experimental Results  k-NN Location Error

Difference Between Predicted and Actual Load Position (Length in mm):

\[ k=3 \text{ median: } 37 \text{ mm} \]

\[ k=3 \text{ median: } 23 \text{ mm} \]
Experimental Results  Perceptron Location Error

Difference Between Predicted and Actual Load Position (Length in mm):

MLP median: 82 mm

Experimental Results  k-NN Mass Error

Absolute Weight Difference Between Predicted and Actual Load (in g):

k=4 median: 25.5 g
Experimental Results  

C4.5 Classification Error

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<tr>
<th>Actual Load Coordinate X (mm)</th>
<th>Actual Load Coordinate Y (mm)</th>
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</tr>
</tbody>
</table>

C4.5 Decision Tree Classification Error by Actual Load Position:

- Correct Mass
- Too High Mass
- Too Low Mass
- Sensor Position

81.1% correct

Our Approach Towards Sensorial Structures

1. Real Experiments
2. Geometric Model & Load Case Definition
3. FEM Simulation of Load Case Library
4. Mechanical Effects Database
5. Data Reduction & Data Mining
6. Compact Dataset
7. Machine Learning Methods
8. Learned Model
9. Real-Time Structural Health Monitoring
10. Self-Monitoring Structure
11. Chip Integration
Structure Monitoring With Intelligent Agents

Achieved so far

- Implementation of a robust sensor network and conceptualization of a functional mockup system.
- Shown: Simple machine learning methods already yield acceptable results on noisy sensor data.
- The machine learning algorithms and learned models are simple and small enough to be integrated into a System-on-a-Chip.

Conclusion and Outlook

Next steps

- Further improvement of electric signal measurement components (e.g., reduction of noise).
- Utilization/development of more elaborate machine learning approaches with better noise tolerance.
- Examination of distributed Multi-Agent monitoring approaches (e.g., organisation, communication).