Robust and Adaptive Non Destructive Testing of Hybrids with Guided Waves and Learning Agents

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2. Non-destructive Testing (NDT) of Structures And Structural Health Monitoring (SHM)

2.1. Big Data Challenges

- **Monitoring** of mechanical structures is a **Big Data challenge** concerning **Structural Health Monitoring** and **Non-destructive Testing**
- The sensor data produced by common measuring techniques, e.g., guided wave propagation analysis, is characterized by a
  - **High dimensionality** in the **temporal domain**, and moreover
  - **High dimensionality** in the **spatial domain** using 2D scanning.

> *The quality of the results gathered from guided wave analysis depends strongly on the* ***pre-processing*** *of the raw sensor data and the* ***selection*** *of appropriate region of interest windows (ROI) for further processing (****Feature Selection****).*

2.2. Features

Some Definitions

Feature Selection

The task of feature selection separates relevant (information correlated) from irrelevant (information uncorrelated) data and performs the first significant data reduction of measuring sensor data.

- Feature selection is traditionally hand made by experts, sometimes using regression or curve fitting

Feature Extraction

The task of feature extraction derives meaningful information from the already pre-selected input data.

- Damages (class, localization, depth, ..)
- Fatigue
- Load changes
- Lifetime prediction

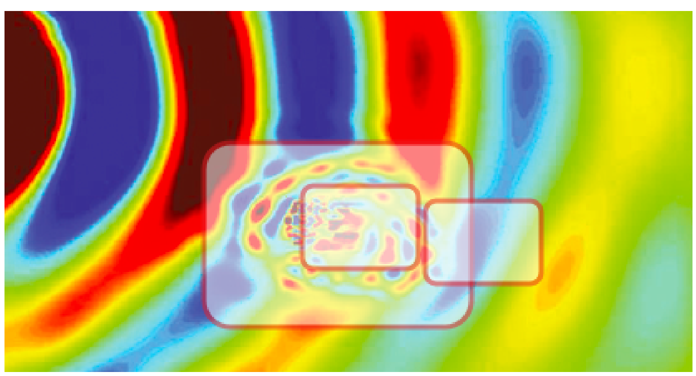
2.3. Measurement and Analysis Challenges

Noise and Models

- Noisy data makes feature selection difficult and unreliable
- Usually complex material compositions and unknown damage models increase the unreliability of the feature selection and extraction task

Automatic Feature Selection

- **Adaptive and reliable input data reduction** is required at the first layer of an automatic structural monitoring system.
- **Image segmentation** can be used to identify ROIs as one relevant feature selection technique



2.4. Non-destructive Testing

- NDT usually performs only a few point-to-point measurements to detect damages.

- The two-dimensional recording of the wave propagation and interaction of guided waves can be performed by using laser vibrometry or an air-borne ultrasonic testing technique → **Measuring time and big data are critical tasks**
- By adjusting the geometry of the actuator or its electrode configuration, the amplitudes of individual modes can be amplified or attenuated to emphasize specific wave interaction → **Parameter setting is critical task**
- The identification of damages is made by wave interactions, such as reflection, scattering, mode conversion and wave number changes, in wave propagation → **Feature Selection is critical task**
- A locally resolved scan of the wave propagation is required, producing wave propagation images with only a few regions of interest → **Segmentation is critical task**

2.5. Automatic Monitoring System

- Automated NDT system is proposed featuring:
  - Adaptive Segmentation & Feature Selection,
  - Machine Learning, Adaptive Filtering, and
  - SHM algorithms

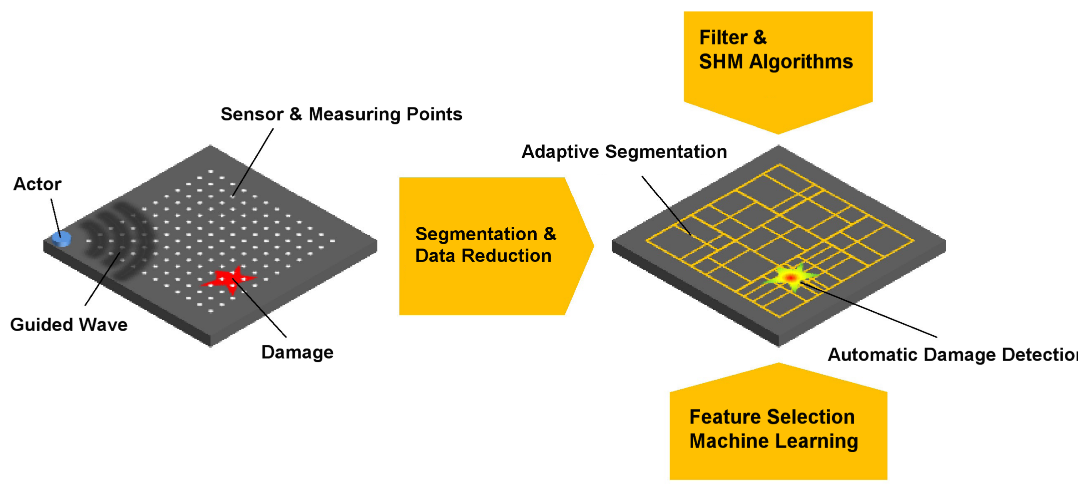


Fig. 1. Automated, model-free damage detection with guided ultrasonic waves and 2D scanning

3. Hybrid materials: The Challenge

3.1. Hybrid Materials

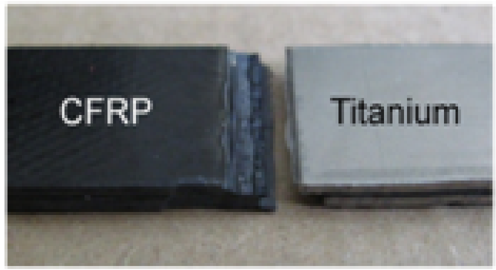
Hybrid materials combine dissimilar materials of different material classes in a way that the individual material-specific advantages become effective in an optimal manner within lightweight structures.

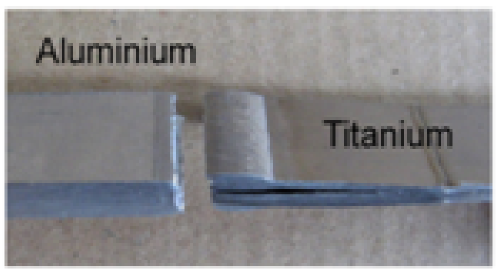
- ➤ Based on their outstanding lightweight potential hybrid materials penetrate more and more into applications in transportation.
  - ❏ But transportation is characterized by varying load situations
- ➤ Such materials are characterized by complex, multiphase bonding zones
  - ❏ Damages can be complex and very difficult to be modeled
- ➤ For example, the failure mode of a failed structure is a result of the failure mechanisms leading to a propagating degradation of the structure.

Different failure modes occurring in hybrid CFRP-Titanium-Aluminum transition structures after failure.

Hybrid Configuations

- ➤ (Top) CFRP
- ➤ (Middle) Hybrid laminate
- ➤ (Bottom) Aluminum with a width of 15 mm





3.2. Damage Detection and Classification

*In order to help identifying the failure mechanisms a **non-destructive detection** of the failure propagation in an early stage would significantly improve the understanding of the interrelation between failure mechanisms and failure modes.*

- To enable the identification of a specific failure the correlation of sensor response and the **failure propagation** must be determined.
- This could be arranged by a **systematic classification** of the failure modes by means of materialographical analysis combined with **clustering techniques** of AI methods

- **Clustering techniques** require a proper, stable, and robust **feture selction** and sensor pre-processing!

4. The Multi-Agent System with Self-organization

4.1. Image Segmentation

Image segmentation is a method to divide an image in different regions (clusters) to identify regions of interest, i.e., isolating regions for further processing (feature extraction).

- Image segmentation
  - is feature selection;
  - is suitable for divide and conquer approaches;
  - but is sensitive to intensity variations and noise!
- In this work, one-dimensional vectors retrieved from time-resolved ultrasonic wave measurement are used for segmentation tasks.

Hybrid approach

- An adaptive multi-agent system is used to implement a self-organizing image segmentation
- Combined with Machine Learning to configure the agents
- The segmentation task splits irrelevant signal parts from relevant (ROI)

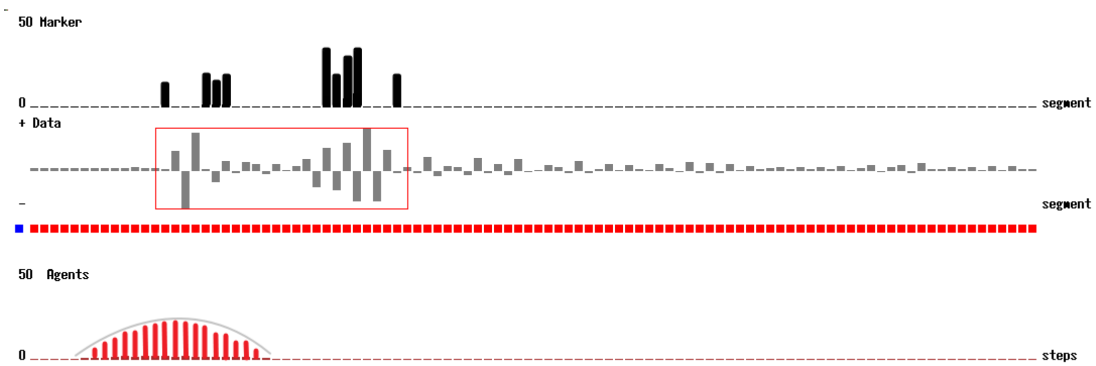


Fig. 2. (Top) Explorer Markings, (Middle) Signal and Segment Agents (Bottom) Agent population (time)

- The ROI extraction depends on the signal record, geometrical signal sender and receiver positions, signal quality (noise), and the probe geometry.

4.2. ROI Identification by MAS

- The Multi-agent System (MAS) consists of simple agents with different behaviour:

Master Agent

The master agent controls the divide-and-conquer process and instantiates segment agents.

- The master agent transforms the input signal vector to a segment vector of fixed length. Each time a new data set is loaded, the segment agents are notified.

Segment Agent

Each segment agent is responsible for one data cell and listen for data events.

- If an event was detected, an initial explorer agent is created.
- An explorer agent is created with a specific set of parameters, which can be adapted by the master agent and the segment agent.

Explorer Agent

The explorer agent has the *goal* to collect data from the current left and right side neighbourhood within a given radius to make a *feature decision*:

- The **neighbourhood data** values are compared with the current associated data value,i.e.:
  Difference $\delta=|s(\mathrm{i}\&\mathrm{pm};d)-s(i)|$ with $d=\{-r,..,-1,1,..,r\})$
- Differences lying within a given interval $\delta \in \Delta$ are **counted**.
- If the counter lies within another given interval set $\{h_{\min},..,h_{\max}\}$, the explorer **marks** the cell and reproduces itself $\rightarrow$ **reproduction** & **amplification**.
- If the **counter** values is **outside** of the interval, it migrates (virtually) to another neighbour cell, performing the exploration again $\rightarrow$ **diffusion**
- If **random walk** is enabled, the diffusion and reproduction direction are chosen randomly, otherwise one more agent is instantiated on diffusion (opposite direction) and two agents are reproduced (moving in opposite directions).

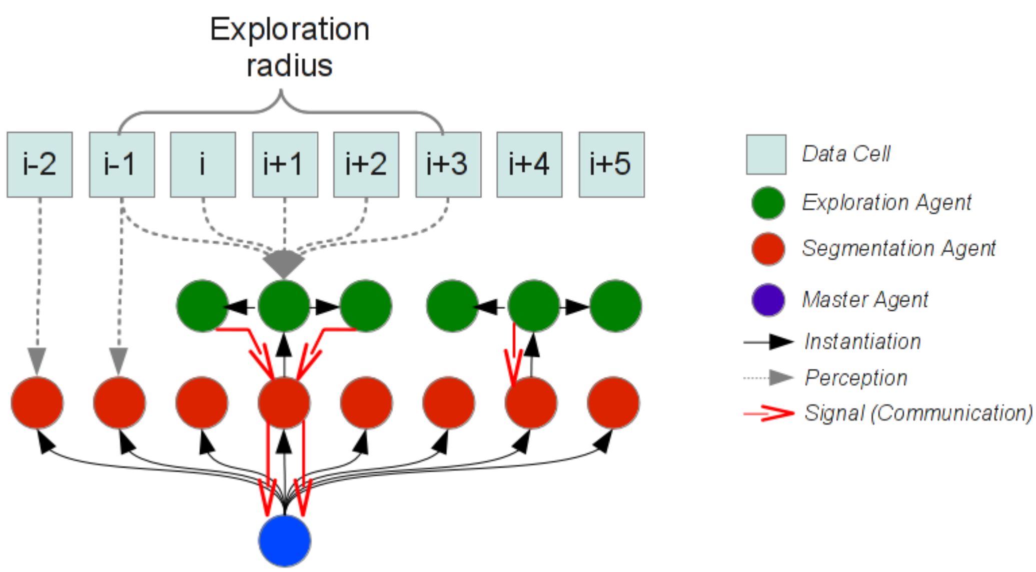


Fig. 3. The MAS: Perception; Event-based instantiation of explorer agents; Diffusion and Reproduction; Communication via signals

5. Automatic Parameter Selection

5.1. Parameter Sets

- Signal records from acoustic measurements can differ significantly with respect to *amplitudes, the frequency spectrum, and noise.*
- The feature selection MAS relies on *parameter sets*.
- **Different signal records require different parameter sets** for optimal ROI extraction and minimal computational costs.
- Machine Learning is used to select optimal parameter sets!

The initial high-dimensional sensor data record is down sampled. Relevant features are extracted from the original and down-sampled record to provide a signal characterization: Constant offset s_0 *(filtered mean value); Standard deviation* s_1*; Peak amplitude (positive & negative)* s_2,s_3*; Frequency distribution ranges (*f_1,f_2,f_3,f_4*); and the Histogram distribution (*h_1,h_2,h_3,h_4*).*

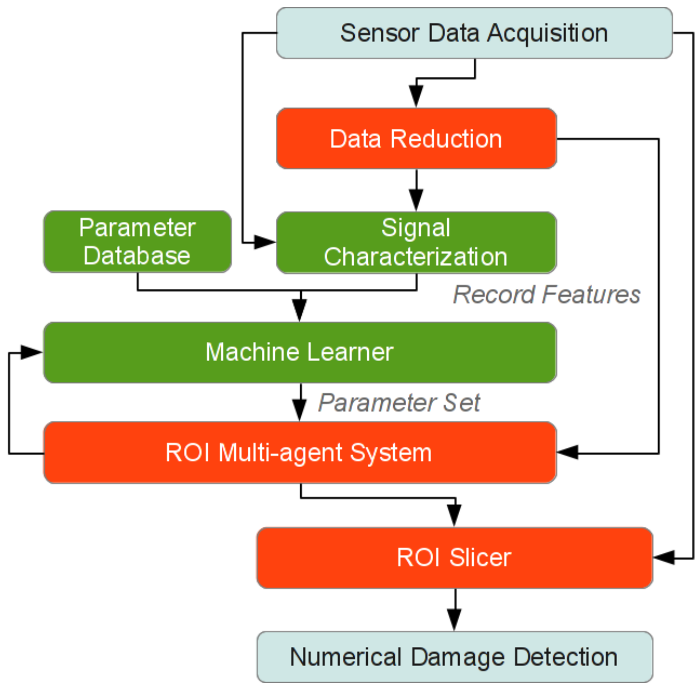
5.2. Automatic Parameter Selection

Sensor data pre-processing using

- A multi-level architecture
- Machine Learning providing an automatic and
- Adaptive MAS parameter selection.

Stages:

1. Data Reduction.
2. Signal Characterization
3. Machine Learner $\rightarrow$ Artificial Neural Network
4. ROI Feature Selection
5. ROI Slicer



6. Ultrasonic Measurement and Feature Selection

6.1. The experimental Setup

- Plate of Hybrid Material (Aluminum + Composite)
- Two sections with changeable gap between
- One Actuator, one sensor (placed on section A or B)
- Ultrasonic round piezoelectric wafer active sensors (PWAS)

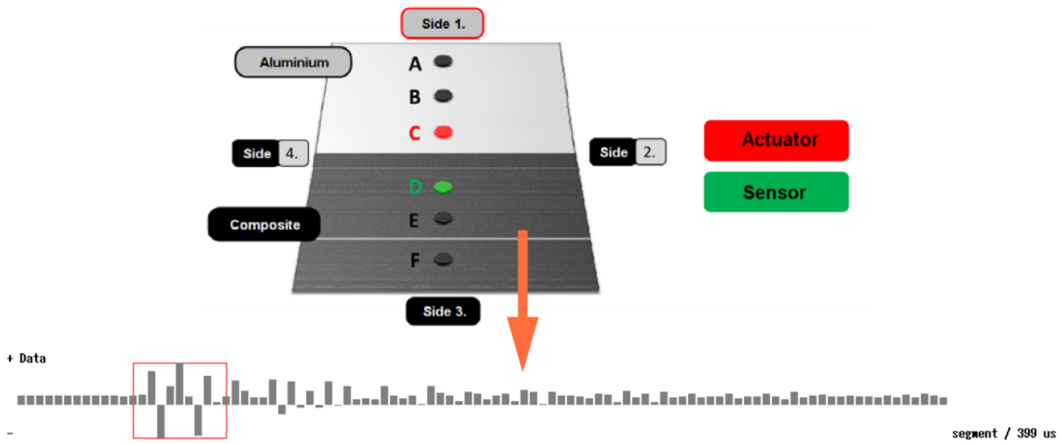


Fig. 4. (Top) Experimental setup and placement of PWAS; (Bottom) Example signal record

6.2. Measurement and Analysis

- Transmission and reflection signals were recorded and analyzed
- The quality of the automatic ROI extraction was evaluated with a quality parameter:

$$
\begin{aligned}
Q \quad = \quad & \left\{ \begin{array}{l} 0, \#roi \neq 1 \\ 1, \#roi = 1 \end{array} \right\} - \\
& \left| roiw - w_0 \right| / k - \\
& \left| (roi_0 + roi_1)/2 - c_0) \right| / k
\end{aligned}
$$

- with $\#roi$: Number of ROIs detected,
- $roiw$: weight of ROI, (width, i.e., roi_1-roi_0), roi_0 and roi_1 are the start and end time of the detected ROI (w_0: expected weight),
- k: error weight, c_0: expected center position

6.3. Analysis Results

- The ROI extraction of reflected signal records achieves mostly a high accuracy and quality $Q > 0.5$
- The ROI extraction of transmitted signal records is more difficult due to a much lower signal-to-noise ratio and reflections at the boundaries, but still most ROIs can be identified correctly with $Q > 0.5$.

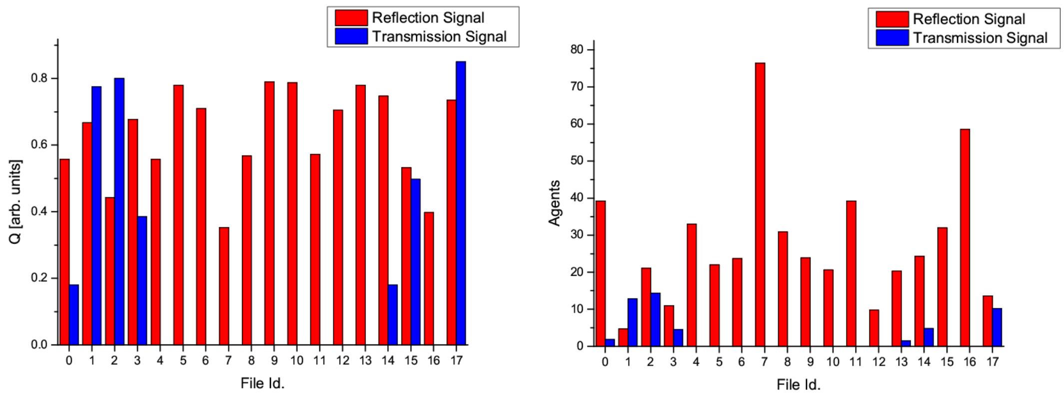


Fig. 5. Evaluation of ROI extraction results: (Left) Automatic ROI feature extraction quality for different signal records (Right) Required Explorer Agents

7. Conclusion

- **Monitoring** of mechanical structures is a **Big Data challenge** concerning **Structural Health Monitoring** and **Non-destructive Testing**
- Information mining (e.g. detection of damages) is two folded: **Feature Selection** and **Feature Extraction**
- Hybrid materials poses:
  - Complex models
  - Complicating damage detection and identification
- **Automatic and adptive Feature Selection** is required
- A hybrid approach using **self-organizing agents** and **machine learning** enables robust feature selection and damage detection

8. References

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