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

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Abstract: 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 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). Commonly, structural monitoring is a task that maps high-dimensional input data on low-dimensional output data (feature extraction of information), e.g., in the simplest case a Boolean output variable “Damaged”. Machine Learning (ML), e.g., supervised learning, can be used to derive such a mapping function. But quality and performance depends strongly on feature selection, too. Therefore, adaptive and reliable input data reduction (feature selection) is required at the first layer of an automatic structural monitoring system. Assuming some kind of one- or two-dimensional sensor data (or n-dimensional in general), image segmentation can be used to identify ROIs. Major difficulties in image segmentation are noise and the differing homogeneity of regions, complicating the definition of suitable threshold conditions for the edge detection or region splitting/clustering. Many traditional image segmentation algorithms are constrained by this issue. In this work, autonomous agents are used as an adaptive and self-organizing software architecture solving the feature selection problem. Agents are operating on dynamically bounded data from different regions of a signal or an image (i.e., distributed with simulated mobility), adapted to the locality, being reliable and less sensitive to noisy sensor data. Finally, adaptive feature extraction (information of structural state and damage) is performed by numerical algorithms and Machine Learning based on ultrasonic measurements of hybrid probes with impact damages.

Keywords: Adaptive Image Segmentation, Feature extraction, Autonomous Agents, Self-organizing systems, Machine Learning and Clustering

1. INTRODUCTION

Monitoring of mechanical structures is a Big Data challenge that addresses Structural Health Monitoring (SHM) as well as Non-destructive Testing (NDT) methods. Trends poses the integration of sensor networks towards the design of self-aware structures, increasing the sensor density significantly and increasing the complexity of applications **[1]**. The sensor data produced by common measuring techniques, e.g., guided wave propagation analysis, is characterized by a high dimensionality of data in the temporal and spatial domain. There are off- and on-line methods applied at maintenance- or run-time, respectively. Online methods (SHM) usually are constrained by low-resource processing platforms, sensor noise, unreliability, and real-time operation requiring advanced and efficient sensor data processing **[5]**. Commonly, structural monitoring is a task that maps high-dimensional input data on low-dimensional output data (information, that is feature extraction), e.g., in the simplest case a Boolean output variable “Damaged”. Machine Learning (ML), e.g., supervised learning, can be used to derive such a mapping function, and reinforcement learning or unsupervised learning (clustering) can be used to improve information extraction. The development of hybrid and composite materials leads to new challenges in component testing and damage diagnostics. In contrast to mono materials, hybrids suffer from well known and complete models. With a combined effect of several factors on guided wave propagation in hybrids and laminates (e.g., fibre metal laminates), there is no clear determination of the cause of a change in wave propagation to the reference state is possible because the effects interfere. Commonly the effect of damages on the signals of detected guided waves are known effecting the signal processing.

The signal processing methodology shown in this work is the basis for the damage characterization and the description of the damage behavior of fiber composite metal laminates with different hybrid transition structures and in different states under quasi-static and cyclic loading conditions **[15]**.

Numerical analysis of measuring data as well as ML quality and performance depends strongly on the input data size and feature variable selection (quality). Therefore, adaptive and reliable input data reduction (that is feature selection) is required on the first layer of an automatic NDT or structural monitoring system (regardless if it applied at run- or maintenance time).

Assuming some kind of one- or two-dimensional sensor data (or n-dimensional data in general), image segmentation can be used to identify Regions of Interest (ROI), e.g., of wave propagation signals and fields. A ROI is characterized by its relevance for further data processing, and can be recognized by specific patterns or by heuristic knowledge (e.g., the third wave of a recorded ultrasonic signal delivers information about a damage that is demonstrated in the experimental section). Wave propagation in materials underlie reflections that must be distinguished, especially in hybrid materials (e.g., combining metal and fibre-plastic composites) there are complex wave propagation fields. The image segmentation is one of the most crucial part of image processing **[3]**. Commonly used approaches are edge detection by finding abrupt changes in the signal field suffering from a high sensitivity to noise and inhomogenities **[2]**.

General difficulties in image segmentation are noise and the differing homogeneity (fuzziness and signal gradients) of regions, complicating the definition of suitable threshold conditions for the edge detection or region splitting/clustering. Many traditional image segmentation algorithms are constrained by this issue. Artificial Intelligence can aid to overcome this limitation by using autonomous agents as an adaptive and self-organizing software architecture, presented in this work. Using a collection of co-operating agents decomposes a large and complex problem in smaller and simpler problems with a Divide-and-Conquer approach. Related to the image segmentation scenario, agents are working mostly autonomous (de-coupled) on dynamic bounded data from different regions of an image (i.e., distributed with simulated mobility), adapted to the locality, being reliable and less sensitive to noisy sensor data. Agent-based approaches can be used to enhance classical edge-based approaches, e.g., applying edge regularization using Bayesian methods **[2]**. A review of agent-based image segmentation approaches can be found in **[3]**. Applying artificial intelligence approaches using autonomous agents and data marking to edge detection, clustering, and region growing was introduced in **[6]**, featuring reduced computational costs and a wide application field (due to its self-adaptation feature). Random behaviour can aid finding regions and clusters more accurately, efficiently, and faster **[4]**. This technique is applied in this work to (virtual) agent migration decisions.

In this work, a simple but powerful agent-based segmentation approach combined with Machine Learning (ML) is introduced and evaluated with measured high-dimensional data from piezo-electric acusto-ultrasonic sensors that recorded stimulated wave propagation in plate-like structures. Commonly, SHM deploys only a small set of sensors and actuators at static positions delivering only a few spatially resolved sensor signals (1D), but with high temporal resolution, whereas NDT methods additionally can use spatial scanning to create images of wave signals (2D). Both one-dimensional temporal and two-dimensional spatial segmentation is considered to find characteristic ROIs automatically.

2. NON-DESTRUCTIVE TESTING (NDT) OF STRUCTURES AND SHM

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 **[8]**, **[9]** or an airborne ultrasonic testing technique **[10]**. In order to be able to excite guided waves, an actuator, usually made of piezo-ceramic materials, must be applied to the structure. By adjusting the geometry of the actuator **[10]** or its electrode configuration **[7]**, the amplitudes of individual modes can be amplified or attenuated to emphasize specific wave interaction. The identification of damages is made by wave interactions, such as reflection, scattering, mode conversion and wave number changes, in wave propagation.

At delaminations or thicknesses these wave interactions can be determined using wave number spectroscopy (2D-FFT of the wave propagation) **[12]**. However, these methods require a locally resolved scan of the wave propagation, producing wave propagation images with only a few regions of interest. The entire measuring setup and the synopsis with this work performing feature selection and extraction is shown in Fig. **1**.

A locally resolved segmentation and clustering of sensors and their sensory data as a precursor of SHM and ML methods have so far only been inadequately addressed, but it is an important sensor fusion and feature selection instrument. Here we analyze the wave propagation and interaction using air-ultrasound technology and identify features to the damage interaction of different modes in the time and wave number domain.

Because of the risk of externally invisible damage in laminates (e.g., fibre metal laminates), integrated component monitoring (Structural Health Monitoring) also plays a key role for such hybrid materials. The goal of component monitoring is to answer the following questions: Is there a damage? Where is the damage? Of what kind is the damage and how big is its extent?

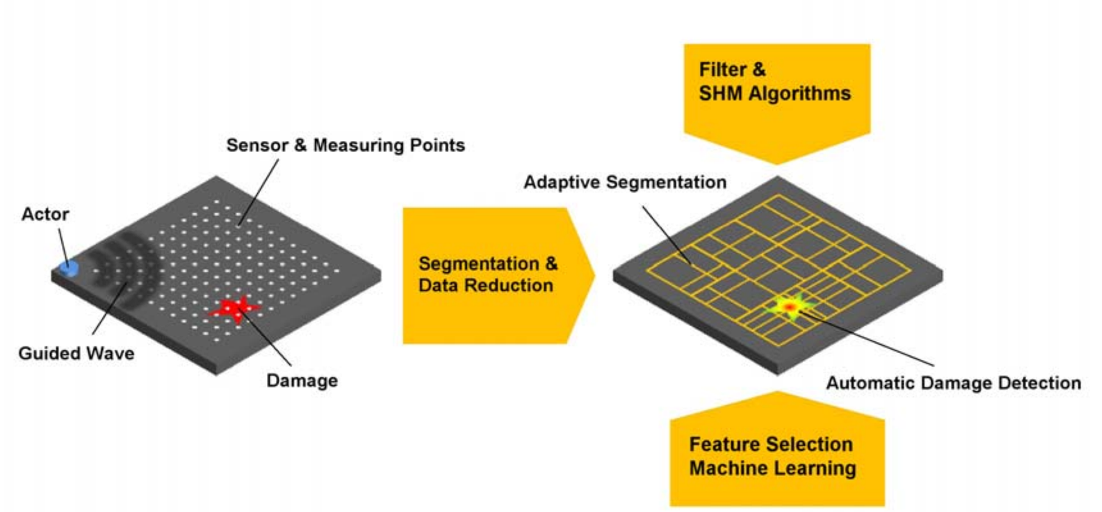

Figure 1. Automated, model-free damage detection with guided ultrasonic waves and 2D scanning

In particular, when detecting the type of damage and size of damage there is still considerable, fundamental issues for components made of layered materials with anisotropic layers and high impedance differences between the layers. The high impedance differences lead to previously unknown wave propagation behavior in laminates. This complicates the evaluation of measurement signals of guided waves for detecting damages.

The data processing methods introduced in this work address NDT and SHM, too.

3. HYBRID MATERIALS: THE CHALLENGE

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 the whole lightweight structure. Owing to their outstanding lightweight potential hybrid materials penetrate more and more into applications in transportation.

Since hybrid materials combine dissimilar materials, the structures made of such materials are characterized by complex, multiphase bonding zones whose strength depends to a great extent on their dimensional as well as material design, the applied production techniques and the resulting material and interface properties at local level.

Hence, the destructive analysis and evaluation of the failure behavior of these structures with the intention of deepening the understanding of their loading capacity in order to improve their design and production techniques, and to make their strength and survival probability predictable are extremely challenging compared to monolithic structures.

For instance, the failure mode of a failed structure is result of the failure mechanisms leading to a propagating degradation of the structure. The failure mechanisms themselves again are strongly depending on both the design and dimensioning of the structure, but particularly on the defects caused by the involved production techniques.

For example three different failure modes occurred in hybrid CFRP-Titanium-Aluminum transition structures are shown in Fig. **2** **[17]**.

Figure 2. Different failure modes occurring in hybrid CFRP-Titanium-Aluminum transition structures after failure (Top: CFRP; Middle: hybrid laminate; Bottom: Aluminum (width 15 mm))**[17]**

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.

Current research is focused on integrated structural health monitoring (SHM) systems that are capable of detecting structural damage via guided ultrasound waves.

To realize this, the effects on the propagation characteristics of piezo-induced guided waves have to be analyzed. In order to enable the identification of a specific failure the correlation of sensor response and the failure propagation is mandatory. This could be arranged by a systematic classification of the failure modes by means of materialographical analysis combined with clustering techniques of AI methods.

4. IMAGE AND SIGNAL 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). In a signal processing system this is the first important feature variable selection (considering each pixel of an image as variable), e.g., using this reduced variable set as an input vector for Machine Learning. In this work, one-dimensional vectors retrieved from time-resolved ultrasonic wave measurement are used for segmentation tasks. The goal is to automatically detect the relevant signal region (Region of Interest, ROI) used for further numerical damage detection and analysis under varying measuring conditions and without the requirement of manual scaling of signal records. The ROI extraction depends on the signal record, geometrical signal sender and receiver positions, signal quality (noise), and the probe geometry.

5. THE MULTI-AGENT SYSTEM WITH SELF-ORGANIZATION

The Multi-agent System (MAS) consists of simple agents with different behaviour. The signal segmentation algorithm bases on an event-based divide-and-conquer approach, shown in Fig. **3**. Details of the underlying agent behaviour and programming model can be found in **[5]**.The time-resolved signal vector $\boldsymbol{x}(t)$ is reduced to a segment vector $\boldsymbol{s}(n)$ by using a data filter algorithm (peak, arithmetic average, or exponential filter). Each data segment is handled by a segment agent, instantiated by a master agent. A segment agent can create explorer agents to investigate the segment neighbourhood within a given radius. Agents communicate with each other by using signals (lightweight messages). The segment and explorer agents perform the feature variable selection, and the master agent finally performs the feature information extraction delivering ROIs of the signal input vector.

The summary of the behaviour of the different agents is listed below:

Master Agent

The master agent controls the divide-and-conquer process and instantiates segment agents (one for each signal data segment). 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 by sending a `LOAD` signal.
The master agent collect all markings from marked data cells and computes ROIs (by using its *gap* and *roiXX* parameters, see below).

Segment Worker Agent

Each segment agent is responsible for one data cell and performs a check for an data event if it got a `LOAD` signal, that means, if there is a significant change in its associated cell data value. 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. The segment agent communicates with its explorer child agents and with its master agent via signals.

Explorer Agent

The explorer agent has the goal to collect data from the current left and right side neighbourhood within a given radius. The neighbourhood data values are compared with the current associated data value (difference $|\boldsymbol{s}(i\pm\delta)-\boldsymbol{s}(i)|$ with $\delta=\{-r,..,-1,1,..,r\}$), and differences lying within a given interval Δ are counted. If the counter lies within another given interval $\{\eta_{min},..,\eta_{max}\}$, the explorer marks the cell and reproduces itself. The clone migrates virtually to another neighbour cell (left or right side). If the counter values is outside of the interval, it migrates (virtually) to another neighbour cell, performing the exploration again. If random walk is enabled, the diffusion and reproduction direction are chosen randomly, otherwise always one more agent is instantiated on diffusion (opposite direction) and two agents are reproduced (moving in opposite directions).

The explorer agent parameter set consists of the following variables: $\{i, \Delta, \eta_{min}, \eta_{max}, r, \textit{lifetime } \tau, \textit{decay } \delta, \textit{randomwalk } \rho\}$. The segment agent is parameterized by: $\{\textit{threshold } \zeta\}$. The master agent is parameterized by the set: {*gap*, *roiMin*, *roiMax*, *roiWeightMin*, *roiWeightMax*}.

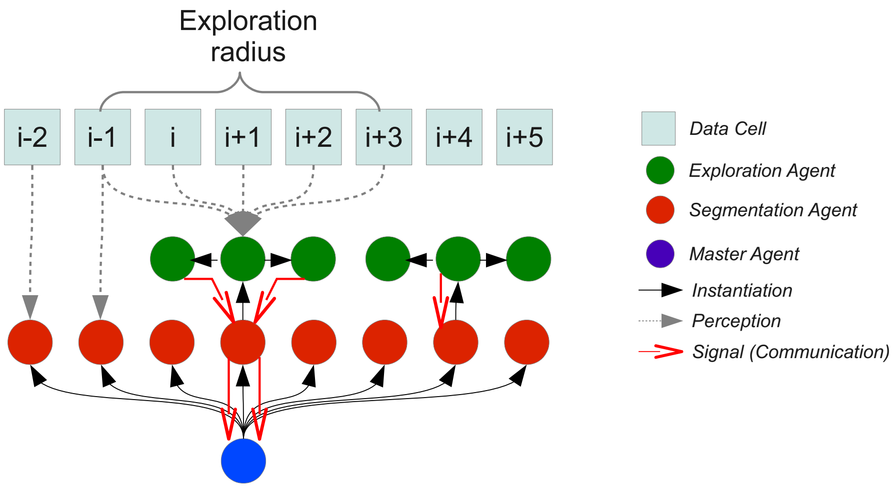

Figure 3. The MAS: Perception; Event-based instantiation of explorer agents; Diffusion and Reproduction; Communication via signals

A signal segmentation and ROI feature extraction delivers the following output variables (delivered by the master agent) enabling the calculation of a quality measure of the extraction: {*agentsTotal*, *markings*, *roi*, *roiWeight*}.

Initially there is a pre-defined table of parameter sets that must be mapped on different signal properties (i.e., sensitivity, noise, signal shape). The success of the ROI feature extraction is sensitive to the proper choice of a parameter set for a specific signal record. The selection of a suitable parameter set is performed by a machine learner introduced in the next section.

6. AUTOMATIC PARAMETER SELECTION

Signal records from acoustic measurements can differ significantly with respect to amplitudes, the frequency spectrum, and noise. The MAS introduced in the previous section used for signal segmentation and ROI extraction relies on parameter sets. Different signal records require different parameter sets for optimal ROI extraction and minimal computational costs. Among auto-adaptation of parameter sets by back-propagation and reinforcement learning based on on quality-of-service evaluation of the ROI extraction, supervised learning can be used to predict an optimal parameter set for a specific signal record to be processed, shown in Fig. **4**.

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).

The signal record feature vector $\boldsymbol{sf}$=(s_0,s_1,s_2,s_3, f_1,f_2,f_3,f_4, h_1,h_2,h_3,h_4) is the input for a Decision Tree learner used to predict a suitable parameter set at run-time (see Fig. **4**). The learning task is performed with a known training data set with different signal records providing a relation between a specific measured signal record and the best matching parameter set for ROI feature extraction determined automatically. Initially an Interval Decision Tree Learner (DTL) providing noise stability was used **[14]**.

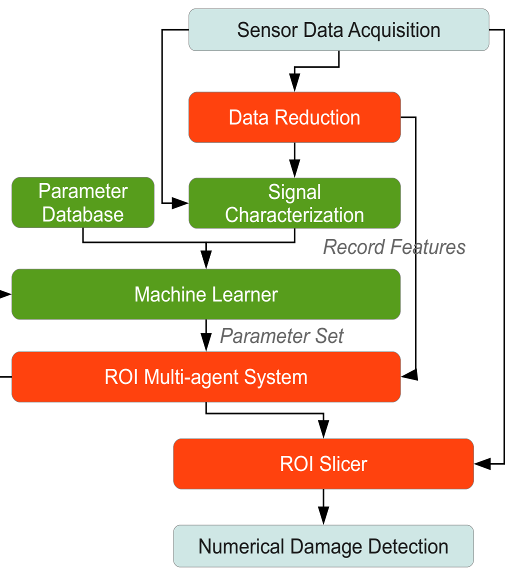

Figure 4. Sensor data pre-processing using a multi-level architecture and Machine Learning providing an automatic and adaptive MAS parameter selection..

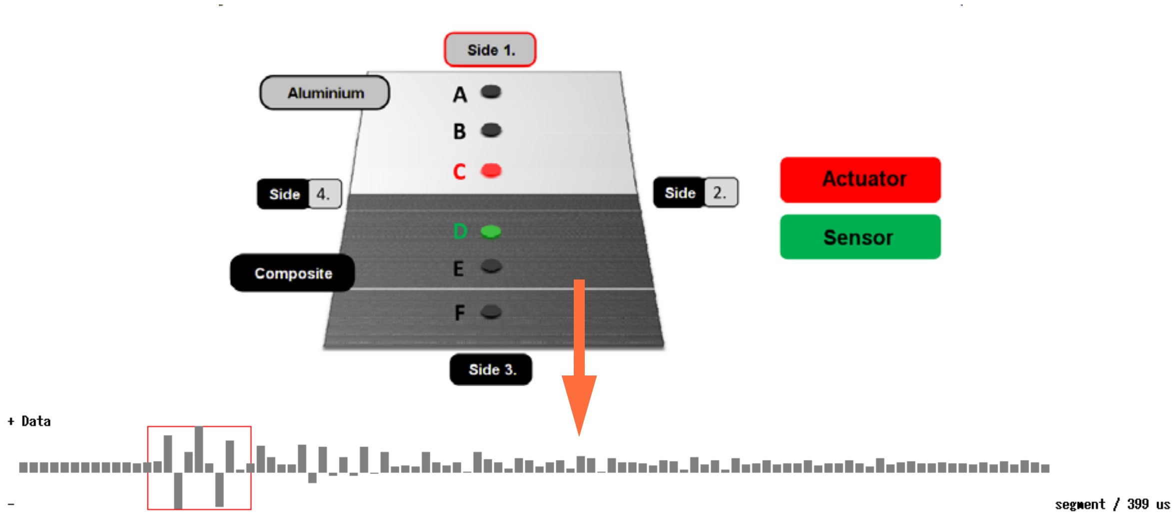

Figure 5. (Top) Experimental setup and placement of PWAS; in this case the transmitted signal from position C to position D is measured (Bottom) Down-sampled segmented signal record and result of the agent-based ROI feature extraction (red rectangle).

But the training data delivers signal feature vectors very close to each other and the feature vector consists of different variable types (with respect to their value range and noise characteristics) preventing any suitable variable separation and leading to overall wrong predictions at run-time. Therefore, a simple Multi-layer Artificial Neural Network (ANN) classifier is used instead. The ANN implementing the classification function $f(\boldsymbol{sf})$: $\boldsymbol{sf} \rightarrow P$ requires a normalization of all input variables to the range [0,1] independently. Each parameter set is represented by one output node of the ANN. Hidden layers can be required to implement a proper classification function.

7. EXPERIMENTAL ULTRASONIC MEASUREMENT

The experimental setup for guided-wave propagation consists of a digital oscilloscope Tektronix DPO 5054 and an arbitrary signal generator Hewlett Packard HP 33120A connected to a wideband amplifier Falco Systems WMA-300. The input signal is a Hann-windowed 200 kHz sinusoidal burst of three counts.

Fig. **5** shows the principle experimental setup delivering the signal vectors used by the MAS and analyzed in Sec. **8.**. 512 values of the sensor responses with a time resolution of 8 ns are averaged for the signal vectors. The device under test (DUT) is a hybrid structure consisting of a metal (Aluminum) plate and a quasi-isotropic carbon fiber reinforced plastic (CFRP) composite plate. Each plate has a thickness of 4 mm and overall dimensions of 300 mm x 300 mm.

The plates are butt-coupled and an ultrasonic couplant gel is between the coupling edges of the plates. In this way the acoustic interface between the plates is realized by the ultrasonic couplant gel.

Along the vertical axis (side 1 - side 3) ultrasonic round piezoelectric wafer active sensors (PWAS) with a thickness of 0.2 mm and a diameter of 10 mm are placed at different positions A–F. The distance between the positions C and D is 150 mm. The distance between the positions C and B is 100 mm. The PWAS are bonded on the plate surface with Z70 cyanoacrylate adhesive. The piezoelectric material of the PWAS is the ceramic lead zirconate titanate (PZT) PIC255 from PI Ceramic GmbH with the notation PRYY+0412.

In the measurements the PWAS at position C is used as an actuator (and for some experiments at position D). As a sensor for the reflected ultrasonic signal at the interface the PWAS at position B is used. Finally, as a sensor for the transmitted ultrasonic signal through the interface the PWAS at position D is used. In order to simulate and create definite damages in the interface the ultrasonic couplant gel is removed over definite lengths and positions.

The signals recorded under different settings (transmission or reflection measurement) differ significantly with respect to their dynamic range, base-line offset, and noise.

8. SIMULATION AND ANALYSIS

The sensor data recorded in the experiments from Sec. **7.**.was used to simulate and evaluate the hybrid approach consisting of the SoS MAS and ML and using the JavaScript Agent Machine (JAM) platform (details can be found in **[13]**). Monte carlos simulation was used in all MAS/ML experiments applying 10% noise to each signal record. Each experiment was repeated ten times to get an average result.

An example ROI marking using the MAS is shown in Fig. **5**. Experiments are made with different DUT configurations: (105) Aluminum only without coupling layer; (108) Hybrid structure with actuator pos.

C; (110) Hybrid structure with actuator pos. D (details are shown in **[16]**). Furthermore, different MAS parameter sets were investigated (P1-P10, details are shown in **[16]**). Using random walk behaviour reduces the number of required (and created) agents on the order of a decade compared with the non-random walk behaviour.

The master agent observes the number of created agents (*agentsTotal*), the number of found ROIs (defined by the markers set by the explorer agents and a gap parameter), and the ROI weight (i.e., the mean width of the ROIs) to compute a quality measure of the self-organizing ROI detection. The higher the number of created explorer agents is, the higher is the number of markings (under the assumption there is the condition satisfied required to detect a region boundary).

The quality Q of the ROI detection computed by the master agent is given by Eq. 1.

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

with *#roi* as the number of detected ROIs (must be one), *roiw* as the ROI weight (width, i.e., roi_1-roi_0), roi_0 and roi_1 are the start and end time of the detected ROI, and c_0 is the expected center position of the ROI (based on export knowledge), and k is an error weight factor in the range k=[5,50]. The last term $|roi_0+roi_1|/2-c_0$ is only used for the evaluation of these ROI detection approach in this work, but not used for the on-line quality estimation at run-time (the expected center point of the ROI c_0 is unknown).

The first evaluation was performed with signals having a high signal-to-noise ratio (resulting from reflection signals). The DUT was the aforementioned Aluminum-Composite hybrid structure with an additional gap between the material boundaries. All parameter sets uses random walk behaviour that requires about 20 times fewer agents, but with comparable quality of the ROI detection in all evaluated data sets. Commonly only about 20-30 agents are required for a high-quality detection, shown in Fig. **6** (Bottom). The settings of these parameters depend on the overall signal strength and noise.

The second evaluation uses signals with a low signal-to-noise ratio making the ROI feature selection more difficult and unreliable (resulting from transmitted signals). The choice of appropriate parameter sets with signals having a high signal-to-noise ratio is less critical. Here the choice of an appropriate parameter set is crucial and parameter values must be chosen from narrow ranges for a specific signal. As more as the parameter set is unmatched to the signal as higher is the agent creation rate (or zero), though this primarily correlates with the delta Δ and threshold ζ parameter values.

In most cases the agents were able to find the relevant main ROI with a quality factor Q>0.5 based on a parameter set delivered by a previously trained ANN using the signals record feature vectors ***sf***, requiring typically less than 40 explorer agents (see Fig. **6**).

The configuration of the ANN is crucial. One hidden layer with 8 nodes was added to improve the prediction results (i.e., improvement of the separability of different input-output relations). The learning phase used 2000 iterations to train the perceptron nodes.

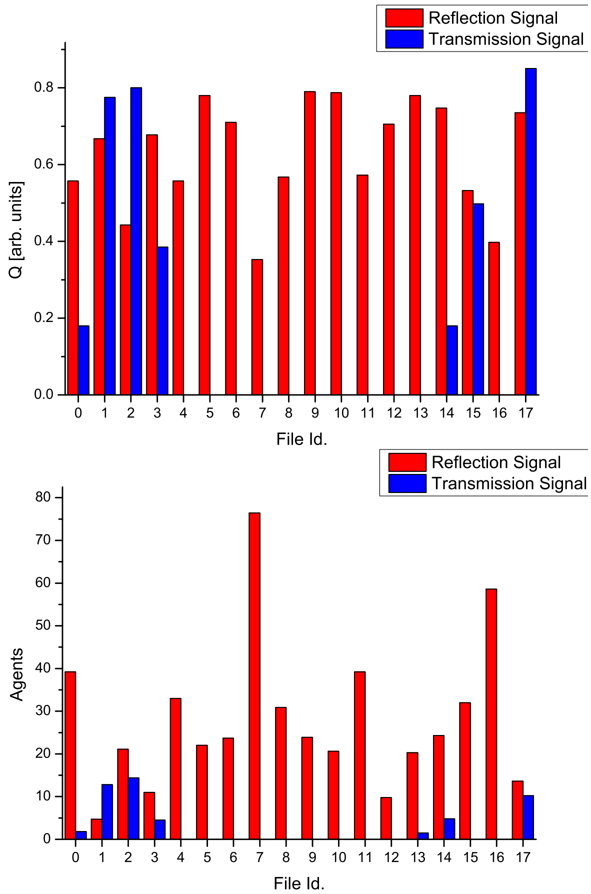

Figure 6. Evaluation of simulation results: (Top) Automatic ROI feature extraction quality for different signal records (Bottom) Required Explorer Agents

9. CONCLUSION

A self-organizing agent-based approach was used successfully to detect relevant regions in measured ultrasonic wave sensor signals performing a feature selection. With a suitable parameter set controlling the MAS a high quality ROI extraction can be achieved. The bounded regions are used for further processing in a numerical damage detection process (feature extraction). The MAS operates event-based and divides the input data vector in segments and is populated with agents operating regionally but cooperating to satisfy a global goal (the feature selection generating ROI markers). The self-organizing and parameterizable behaviour capabilities ensure robust feature extraction. In this work, a suitable parameter set for a specific signal record was automatically chosen by an ANN using a signal record feature vector. Most signal records can be processed properly this way. But the evaluation showed a weak correlation between the signal record feature vector and the right parameter set. Further work has to investigate more suitable feature variables able to separate and to identify signal record classes more robustly, eventually based on clustering.

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