Data-driven and automated Damage Diagnostics from High-dimensional Data

Towards Learning Technical Systems and Sensor Data Science

PD Dr. rer. nat. Stefan Bosse

Overview

Self-organising and intelligent systems applied to sensor data.

Overview

Self-organising and intelligent systems applied to sensor data.

1. Introduction to complex and self-organising Systems
2. Material-integrates Intelligent Systems
3. Multi-agent Systems: From distributed computing to data-driven methods
4. **Internal Sensors**: Distributed Machine Learning for damage prediction and optimisation with Sensor Networks
5. **External Sensors**: Damage diagnostics with data from laboratory equipment and measurements

The story behind:

The **integration level and density of sensors** increased significantly in the last decades. The number of deployed sensors and the data volume increased exponentially.

The story behind:

The **integration level and density of sensors** increased significantly in the last decades. The number of deployed sensors and the data volume increased exponentially.

Integration of sensors, analogue and digital signal processing, and networking created a paradigm shift: From passive sensors to **active intelligent communicating and interacting sensor networks** and clouds.

The story behind:

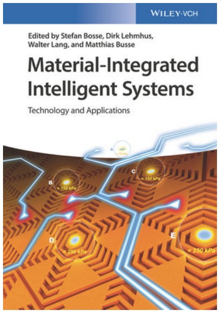
The **integration level and density of sensors** increased significantly in the last decades. The number of deployed sensors and the data volume increased exponentially.

Integration of sensors, analogue and digital signal processing, and networking created a paradigm shift: From passive sensors to **active intelligent communicating and interacting sensor networks** and clouds.

Sensors are now integrated in every thing and device. The next step: **Material-integrated sensing and actuation systems measuring and changing the physical state of structures and materials**.

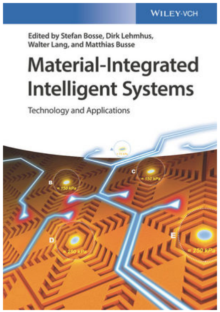
The book behind:

S. Bosse, D. Lehmhus, W. Lang, M. Busse (Ed. & Auth.), *Material-Integrated Intelligent Systems: Technology and Applications*, Wiley, ISBN: 978-3-527-33606-7 (2018)



The book behind:

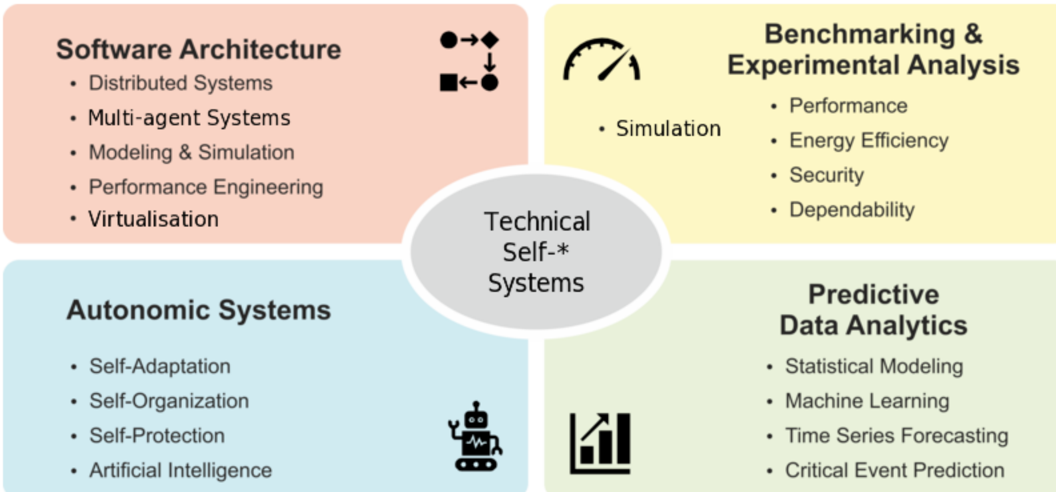
S. Bosse, D. Lehmhus, W. Lang, M. Busse (Ed. & Auth.), *Material-Integrated Intelligent Systems: Technology and Applications*, Wiley, ISBN: 978-3-527-33606-7 (2018)



Interdisciplinary Research

- Materials Science
- Computer Science
- Electrical Engineering and Electronics
- Fabrication and Integration
- Micro-system Technologies

Introduction



Complex Systems

Distributed Systems

- Sensor Networks: Phys. undirected graph of sensor nodes
- Sensor node: Core cell
- Communication: Messages (IP, IoT, Internet)
- Input: Local sensor data
- Output: Global state (e.g., in SHM)
- Data reduction (dimension, size)

Computational Systems

- High-volume data processing
- Virt. directed graphs of functions (functional graphs)
- Communication: Function arguments, shared memory
- Input: Global (sensor) data
- Output: Any target variables
- Data reduction (dimension, size)
- Organisation: Cellular Automata, Agents

Complex Systems

Complex systems pose a **behaviour** that is intrinsically **unpredictable and uncontrollable**, and that cannot be described in any complete or closed functional/analytical manner.

Complex Systems

Complex systems pose a **behaviour** that is intrinsically **unpredictable and uncontrollable**, and that cannot be described in any complete or closed functional/analytical manner.

Complex systems can be **composed of simple interacting cells**. The components of a complex system are commonly called agents or cells of a Cellular Automata.

Complex Systems

Complex systems pose a **behaviour** that is intrinsically **unpredictable and uncontrollable**, and that cannot be described in any complete or closed functional/analytical manner.

Complex systems can be **composed of simple interacting cells**. The components of a complex system are commonly called agents or cells of a Cellular Automata.

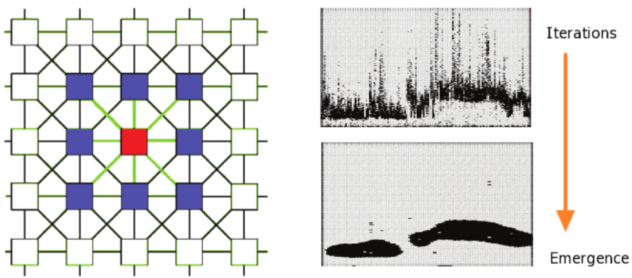
These are **individual systems** that act upon their environment in response to events they sense or experience. They **interact with each other** or the environment.

Complex Systems

Emergence: Simple interactions at the local level give rise to complex patterns at the global level with self-☆ capabilities.

Complex Systems

Emergence: Simple interactions at the local level give rise to complex patterns at the global level with self-☆ capabilities.



[Barszcz et al.,2013]

Fig. 1. Emergence in a Cellular Automaton with Moore Neighbourhood after an iterative run (Initialisation: Signal frequency spectrum) for detecting anomalies in sensor signals

Self-Organising Systems

"It is a system where a collection of interacting elements gives rise to **patterns of behaviour** that the individual elements are not capable of when they don't interact"

Self-Organising Systems

> "It is a system where a collection of interacting elements gives rise to **patterns of behaviour** that the individual elements are not capable of when they don't interact"

* A system which changes its basic structure as a function of its experience and environment [Farley and Clark, 1954]
    * **Emergence** and **Emergent properties**
    * Organization can be defined as **structure with function**: the components (agents) of the system are arranged in an orderly way (structure) so as to achieve a certain goal (function).
* Absence of external control (**autonomy**)
* **Decentralised** control
* **Dynamic** operation (evolution over time)
* Strongly related to the concept of agent-based systems
* **Resilience** (Failure of some elements do not effect system behaviour)

Self-organisation Concepts

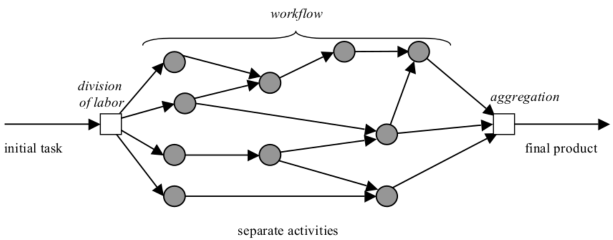
Self-organisation as a problem of coordination and communication

- Self-organization by **Alignment**
- Concept of **Division of Labor** - coordinates activities that happen simultaneously —in parallel.
- **Workflow** is its complement: it coordinates activities that take place one after the other—sequentially.
- **Aggregation**

Self-organisation Concepts

Self-organisation as a problem of coordination and communication

- Self-organization by **Alignment**
- Concept of **Division of Labor** - coordinates activities that happen simultaneously —in parallel.
- **Workflow** is its complement: it coordinates activities that take place one after the other—sequentially.
- **Aggregation**



[Francis Heylighen (Vrije Universiteit Brussel)]

Fig. 2. Flow in coordination with different concepts

Strong and Weak Self-Organising Systems

Strong self-organising systems are those systems where there is no explicit central control neither internal nor external.

Weak self-organising systems are those systems where, from an internal point of view, there is re-organisation maybe under an internal (central) or external control or planning.

Strong and Weak Self-Organising Systems

Strong self-organising systems are those systems where there is no explicit central control neither internal nor external.

Weak self-organising systems are those systems where, from an internal point of view, there is re-organisation maybe under an internal (central) or external control or planning.

Self-organisation in technical and digital systems is mostly data-driven.

Knowledge

> How can we derive knowledge from data and how can we understand data? What is the spatial and temporal context of data?

Knowledge

? How can we derive knowledge from data and how can we understand data? What is the spatial and temporal context of data?

Deductive Knowledge
: Semantic- and ontology-driven methods (semantic schemas).

Inductive Knowledge
: Data-driven methods like Statistical Modelling and Machine Learning.

Information Mapping
: Knowledge Graphs, e.g., can provide a relational mapping of data on knowledge and reasoning.

Knowledge

How can we derive knowledge from data and how can we understand data? What is the spatial and temporal context of data?

Deductive Knowledge
Semantic- and ontology-driven methods (semantic schemas).

Inductive Knowledge
Data-driven methods like Statistical Modelling and Machine Learning.

Information Mapping
Knowledge Graphs, e.g., can provide a relational mapping of data on knowledge and reasoning.

Machines do not have a-priori access to deductive knowledge!

Self-organisation in technical and digital systems

- **Dynamic Communication Structures** (Networks)
  - Mobile and ad-hoc network formations
  - Resilient network graphs
  - Load balancing

- **Distributed Sensor Fusion**
  - Local sensor processing
  - Virtual sensors: Aggregates

- **Distributed Sensor Networks**
  - Local interaction based on context
  - Damage Diagnostics
  - Structural Health Monitoring

Self-organisation in technical and digital systems

- **Dynamic Communication Structures** (Networks)
  - Mobile and ad-hoc network formations
  - Resilient network graphs
  - Load balancing
- **Distributed Sensor Fusion**
  - Local sensor processing
  - Virtual sensors: Aggregates
- **Distributed Sensor Networks**
  - Local interaction based on context
  - Damage Diagnostics
  - Structural Health Monitoring
- **Distributed Learning and Adaptivity**
  - Multi-model inference (Ensemble Learning)
  - Local models using local data
  - Global model fusion
  - Incremental Update Learning
  - Reinforcement Learning
  - Concept Drift compensation
- **Distributed Solving of Optimisation Problems**
  - Adaptive Robotic Structures
  - Energy Management
  - Manufacturing Processes

Applications and Research

In the next sections an overview of different applications and use-cases is given:

1. **Agent-based Pattern Recognition**
2. **Distributed Damage Diagnostics in Sensor Networks**
3. **Incremental Distributed Learning for SHM**
4. **Multi-domain simulation combining learning agents and multi-body physics**
5. **Data-driven Damage Diagnostics and Prediction**

Data-driven State Estimation

The aim of data-driven state estimation is to derive approximated model functions $m(s): s \rightarrow \sigma$ that map sensor data on mechanical or structural states (or probabilities) incl. damages.

Data-driven State Estimation

> The aim of data-driven state estimation is to derive approximated model functions $m(s): s \rightarrow \sigma$ that map sensor data on mechanical or structural states (or probabilities) incl. damages.

Examples of target states (attributes/properties) of materials and structures:

- Damage (class, position, propagation)
- Load (static, dynamic, cyclic)
- Vibration
- Bending and strain
- Fatigue, Breakage

Data-driven State Estimation

The aim of data-driven state estimation is to derive approximated model functions $m(s): s \rightarrow \sigma$ that map sensor data on mechanical or structural states (or probabilities) incl. damages.

Examples of target states (attributes/properties) of materials and structures:

- Damage (class, position, propagation)
- Load (static, dynamic, cyclic)
- Vibration
- Bending and strain
- Fatigue, Breakage

But data-driven methods in engineering suffer from low experimental data variance resulting in specialised rather than generalised state estimation models.

Material-integrated Sensor Networks

> Sensor data is processed locally by autonomous low-resource embedded systems (local state) and fusioned globally to relevant information (global state).

Material-integrated Sensor Networks

Sensor data is processed locally by autonomous low-resource embedded systems (local state) and fusioned globally to relevant information (global state).

The single networks nodes are simple and low-level, but their connection create complex high-level capabilities by self-organisation.

S. Bosse, D. Lehmhus, W. Lang, M. Busse (Ed.), Material-Integrated Intelligent Systems: Technology and Applications, Wiley, ISBN: 978-3-527-33606-7 (2018)

Concept of Material-integrated Intelligent Systems

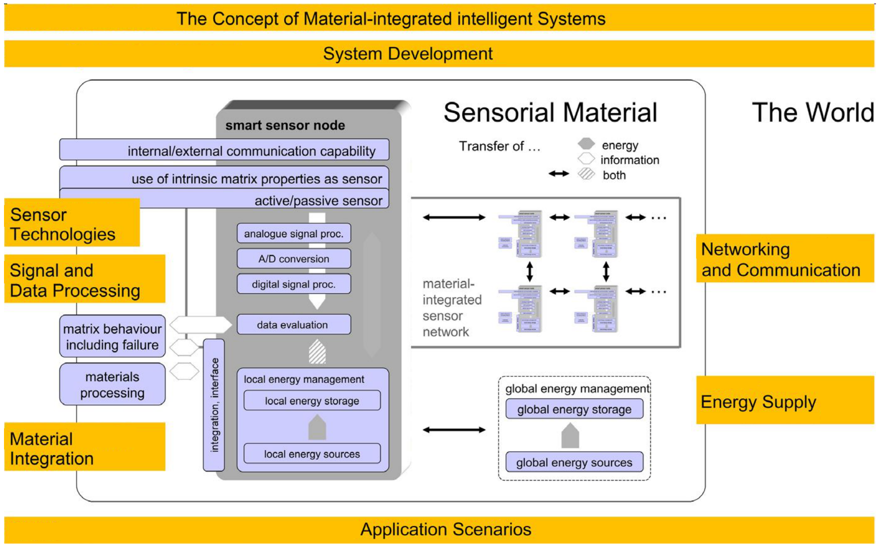


Fig. 3. The fundamental elements of a material-integrated intelligent system

Intelligent Objects

An intelligent object *O* is defined by its interaction with the environment and its state σ:
World ⇒ Sensing ⇒ $O{:}\sigma \rightarrow \sigma'$ ⇒ Actuation ⇒ World
World := { Environment, Machines, Devices, Humans, Data }.

- An intelligent object can be considered as an **agent** that is coupled loosely to its environment and poses self-☆ capabilities:
  - Self-adaptivity
  - Self-organisation
  - Self-connectivity
  - Self-learning
  - Self-mobility
  - Self-management
  - Self-improvement
  - Self-diagnosis and awareness

Intelligent Objects

> Self-☆ capabilities are considered as enablers for future computing systems that will have to deal with unprecedented complexity, heterogeneity, and dynamics.

- Self-☆ refers to the capability of a system to modify its own behaviour or structure without any external control in reaction to or even in anticipation of system dynamics.
- Intelligent objects are not limited to a sensing system - they are data analytic and mechatronic systems.

Structural Health Monitoring: Information Mining

Different integration levels: Sensors, full sensor nodes, full sensor networks

[Qing, Li, Wang, Sun, 2019; Chen et al. 2020]

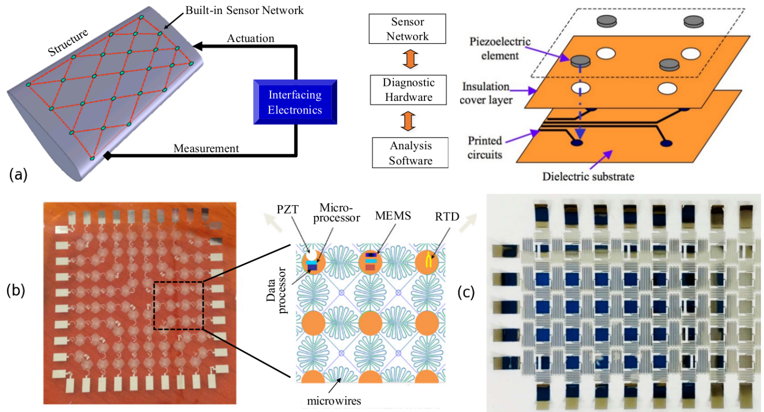
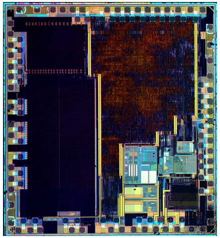


Fig. 4. (a) Ultrasonic sensors integrated in a wing (b) Expandable multifunctional SN (c) Multi-modal stretchable SN

Computers and Data Processing

- Even a square millimetre computer provides today enough capabilities to perform Machine Learning!

- About 100 MIPS/mm^2
- About 100 kbit/mm^2
- About 100 μW/mm^2
- About 100 kbit/s

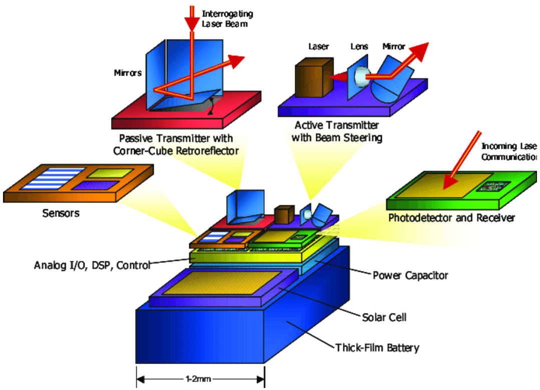


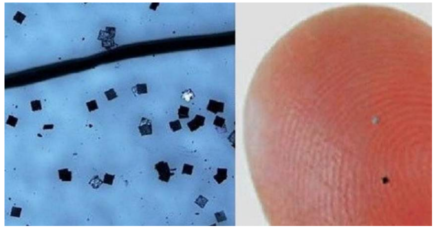
> Example: Arm Cortex M0(+): 1MIPS/MHz, 10-100μW/MHz, 8kB RAM, 32kB ROM, 0.01-0.1mm^2 (depends on silicon process)

Smart Dust: Large-scale Networks

Autonomous sensing and communication in a cubic millimeter

[Warneke et al, 2002; Hitachi]





(Left) Arm Cortex M0, 740kHz, 4kB RAM, S:Temperature+Light, C:900MHz+optical, P=70mW, V≈10mm ^{3}

(Right) read-only tracking, 128 Bit UID, S:∅, C:RFID/2.4GHz, V=0.0002mm ^{3}!

Fig. 5. (Left) Conceptual diagram of a smart dust mote, one example of a tiny, autonomous, wireless sensor node / 2002 (Right) Hitachi "Smart Dust" / 2008

Multi-agent Systems and Cellular Automata

ABM. Agent-based Modelling

ABS. Agent-based Simulation

ABC. Agent-based Computation ① Mobile and autonomous computational processes ② Numerical Processes (Functions)

ABL. Agent-supported and Agent-based Learning

ABX. ABC+ABS/ABM

ABCA. Hybrid Agents + Cellular Automata

Agent-based Pattern Recognition

Self-organised Autonomy and Distributed Search // ABCA

Feature Marking in Images ⇒ Searching Regions-of-Interest (ROI) ⇒ Finding Anomalies

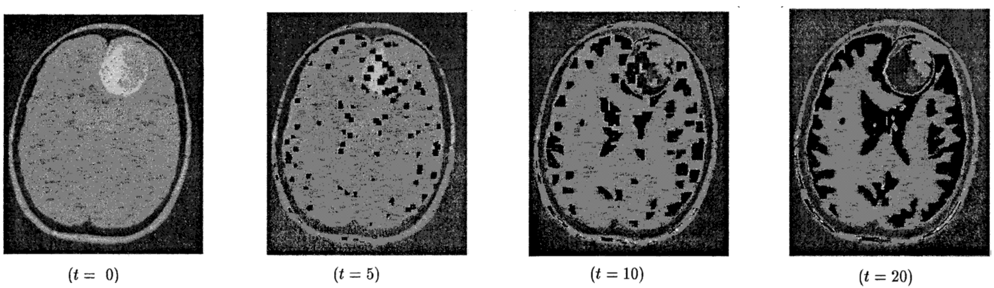


Fig. 6. Region growing and border feature detection for a brain-scan image [Liu,2001]

ROI Marking and Segmentation in Time Signals with Agents

Goal. Find ROI containing relevant damage feature information **without** knowing anything about damage (i.e., anomaly indeed).

System. Pure computational system applied to GUW time signals using functional agents ⇒ **Linear Cellular Automata**.

Methods & Algorithms. Time signal is segmented and discretised. ROI (start and end time point) is marked by agents searching local features (population density). Reproduction, diffusion, and termination of agents creating marking distributions.

ROI Marking and Segmentation in Time Signals with Agents

- The Multi-agent System consists of simple agents (just computational functions) with different behaviour:
  - Master agent
  - Segmentation agent partitioning signal in small segments
  - Explorer agents finding features by amplification

> Agent strategies: Self-organisation by reproduction and diffusion based on neighbourhood signal comparison (feature amplification and damping) delivering a feature estimation $\varphi \in [0,1] \Rightarrow$ Constrained by parameter set P

ROI Marking and Segmentation in Time Signals with Agents

Algorithm

- The signal segmentation algorithm bases on a divide-and-conquer approach:
  - The time-resolved signal vector $\vec{x}(t)$ is reduced to a segment set $\{s(n)\}$ by using a data filter algorithm (peak, arithmetic average, or exponential filter).
  - A segment agent can create explorer agents (at place i) to investigate the segment neighbourhood within a given radius (places $i \pm \delta \in r$).
  - Neighbouring agents communicate with each other by using signals ⇒ **Linear Cellular Automata**
  - The explorer agent $e(i)$ 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 ⇒ φ
  - *If* $\varphi \in [a,b] \Rightarrow$ *Reproduction+Marking else Diffusion* $(i \rightarrow i')$
  - *If* lifetime (number of iterations) is reached ⇒ *Terminate*.

ROI Marking and Segmentation in Time Signals with Agents

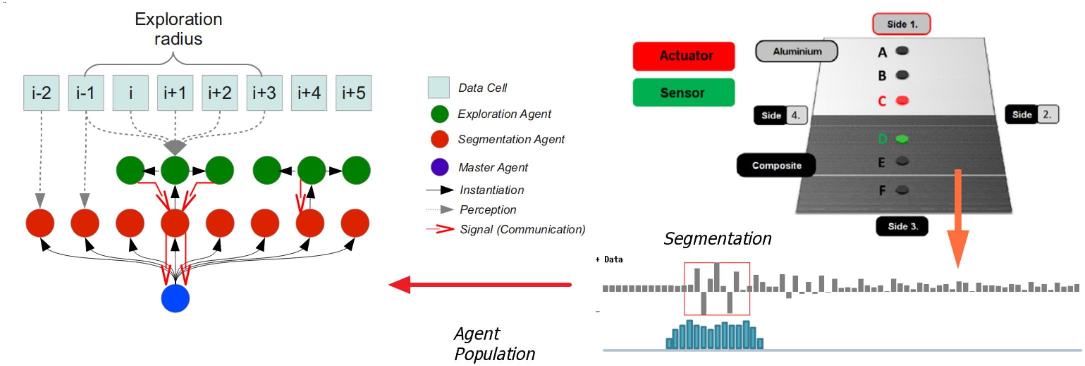


Fig. 7. The MAS: Perception; Event-based instantiation of explorer agents; Diffusion and Reproduction based on neighbourhood signal comparison; Communication via signals

S. Bosse, M. Koerdt, A. v. Hehl, Robust and Adaptive Non Destructive Testing of Hybrids with Guided Waves and Learning Agents, 3. Internationale Konferenz Hybrid Materials and Structures 2018

ROI Marking and Segmentation in Time Signals with Agents

- Signal records from acoustic measurements can differ significantly with respect to amplitudes, frequency spectrum, and noise
- MAS parameter set P cannot be chosen a-priori; selection based on evolutionary or data-driven prediction algorithms (ANN)
  - Hybrid approach combining ANN with MAS
  - ANN: $(s_0, s_1, f_1, ..) \rightarrow P$
  - MAS: $(\vec{x}(t), P) \rightarrow$ ROI $[i_a, i_b]$

> Automated data-driven parameter estimation and parameter space exploration is required!

ROI Marking and Segmentation in Time Signals with Agents

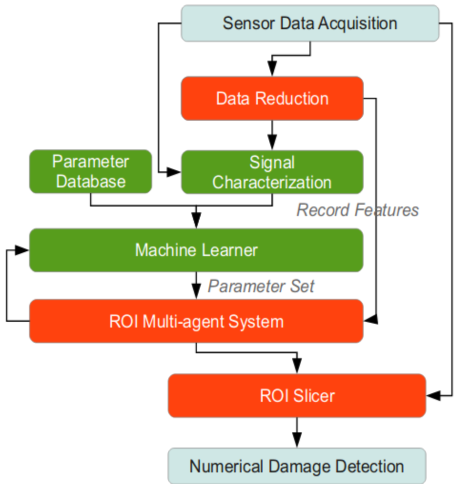


Fig. 8. Sensor data pre-processing using a multi-level architecture and Machine Learning providing an automatic and adaptive MAS parameter selection.

Distributed Machine Learning and Agents

DML

Multi-model ML with local inference and global fusion (global state estimation from local states)

STMP

Single-instance Training with Multi-instance Prediction (Training of one model with global data → Model replication → Prediction with local data)

MTMP

Multi-instance Training with Multi-instance Prediction (Training of multiple local models → Prediction with local data only,)

Distributed Damage Diagnostics in Sensor Networks

Goal. Robust detection of hidden damages in hybrid materials using guided ultrasonic waves (GUW) and a distributed sensor network.

System. Hybrid material plate with embedded or applied GUW sensors and actuators (transducers). Two set-ups: A) 12 discrete transducers B) one transducer and 2D air US scanning providing 250×250 virtual sensors $\Rightarrow$ time-dependent sensor signals.

Algorithms and Methods. Multi-model instance ensemble learning and model fusion. Global fusion: Negotiation, voting, point density clustering, centre of mass. Feature extraction: Discrete Wavelet Transformation (DWT), Predictor: sequential state-based LSTM ANN or parallel CNN.

S. Bosse, D. Weiss, D. Schmidt, Supervised Distributed Multi-Instance and Unsupervised Single-Instance Autoencoder Machine Learning for Damage Diagnostics ..., Computers 2021

Concept

Method: **Holonic** principle with decomposition of large complex problems in multiple simple problems (Divide&Conquer principle) **and** distributed local data processing.

Concept

Method: **Holonic** principle with decomposition of large complex problems in multiple simple problems (Divide&Conquer principle) **and** distributed local data processing.

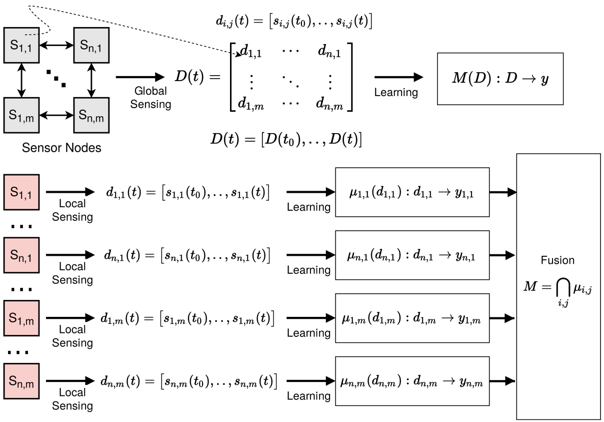


Fig. 9. From off-line and centralised single-model ML to distributed multi-model ML with global model fusion

Architecture & Results

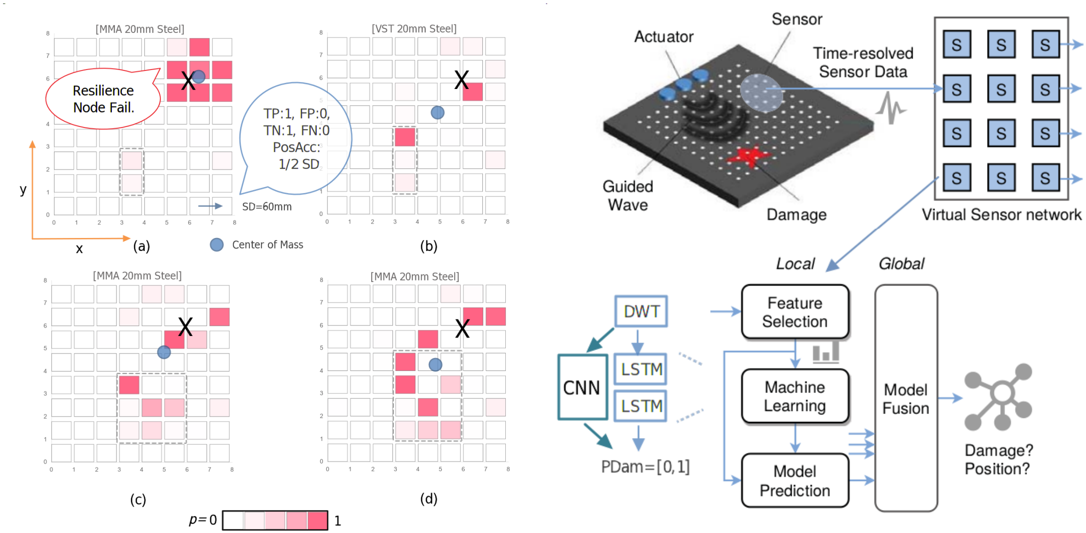


Fig. 10. Each sensor node performs damage prediction based on local sensor data (GUW) → Global fusion by density clustering and probabilistic filtering

Distributed Learning Agents and Simulation

Goal. Damage prediction and localisation with learning interacting agents with noisy and unreliable strain gauge sensor data (time series)

System. Multi-agent System with simple learning agents posing low complexity, network of virtual sensors from simulation.

Algorithms & Methods. Multi-domain simulation combining Multi-agent processing and Multi-body Physics (MBP) delivering virtual sensor data (JavaScript Agent Machine platform). Damage location computed by global fusion from local predictions.

Multi-body Physics Model

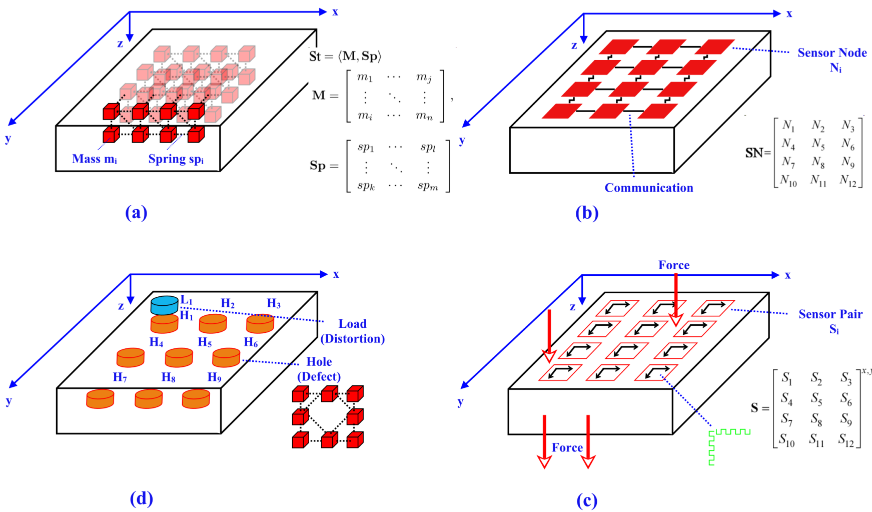


Fig. 11. (a) Mass-spring model of structure (b) Sensor Node Network (c) Strain Sensors (d) Virtual defects and disturbing loads

Concept

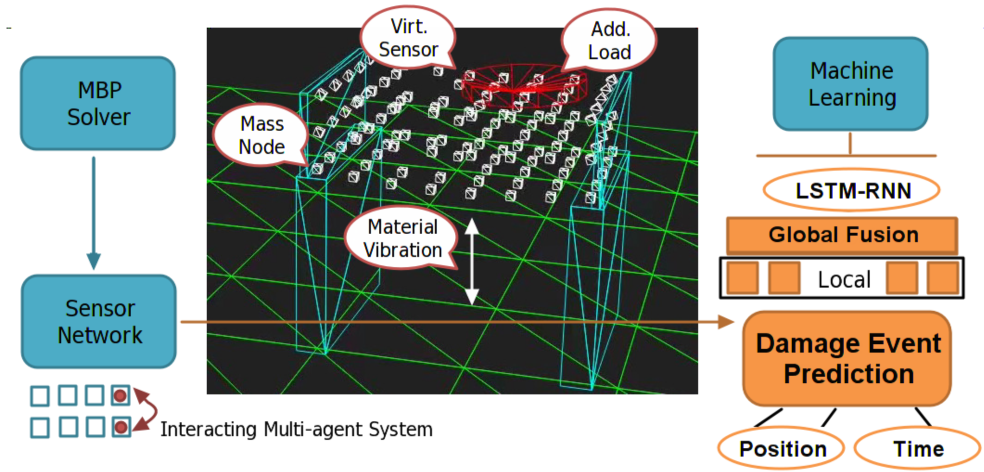


Fig. 12. The sensor processing and damage prediction concept: Local sensor processing, learning, inference ⇒ Global fusion and prediction of position and time of damage event

Training Data Variance

- One major issue in training of machine learned models is **specialisation of the model**!
- Broad variance of training data samples are required for **generalised models**!
- Experimental collection of large sensor data bases with **high variance** is difficult to achieve!
- **Simulation** can overcome this limitation:
  - Using **Monte Carlo methods** applied to sensor signals and experimental parameters create a broad variance of data samples!

Algorithmic Scaling

How to fit in embedded systems? Main principles:

1. **Decomposition and Distribution**: Localised sensor data processing → distributed information inference → hierarchical architectures.
2. **Down Scaling**: Data complexity, data accuracy, algorithmic complexity, algorithmic substitution, approximation.
3. **Model-driven** approaches: Feature selection, model fusion, model-reduction, model-substitution.
4. **Accelerators**: HW(SW) co-processors, HL synthesis of algorithms/SW → HW (RTL)

Algorithmic Scaling

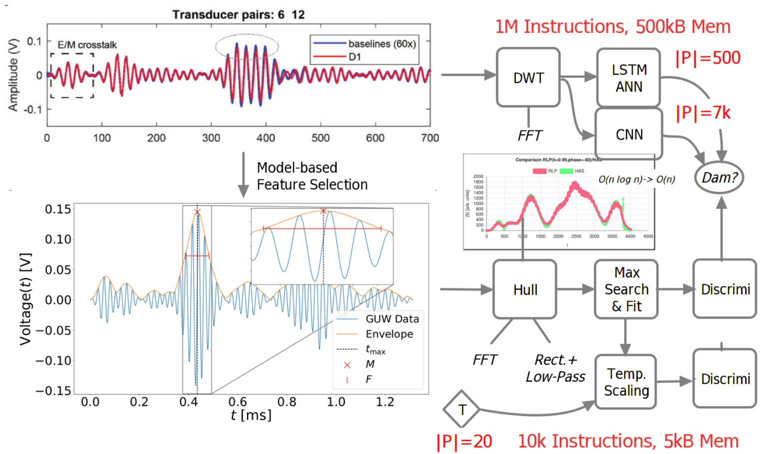


Fig. 13. (Left) **Data-driven** complex time-series prediction on GUW signal with DWT features using LSTM networks [Bosse, Schmidt, Weiss: Sensors 2019] and CNN (Right) **Model-based** feature extraction and simple numerical damage prediction [Polle, Bosse: SysInt 2022]

Damage Diagnostics with Laboratory Equipment

Non-destructive Testing

X-ray or US computer tomography for damage and material characterisation

Destructive Testing

Tensile tests for material characterisation; Micrographs for damage and material characterisation

Data Series Prediction in Tensile Tests

Goal. ① Predict material breakage by early data recorded in the linear and pre-non-linear material data ② Predict material curves by data series prediction

System. Tensile test equipment, data series recording.

Methods. Feedforward ANN, Recurrent and state-based ANN.

S. Bosse, E. Kalwait, Damage and Material-state Diagnostics with Predictor Functions using Data Series Prediction and Artificial Neural Networks, ECSA 2020 MDPI, 15.11 -30.11.2020, Basel, Switzerland

Methods

Three different methods were used to predict the material behaviour of a device under test (DUT) from tensile test data $\langle F,x \rangle$ (F:load force, x: strain length):

1. Feed-forward Artificial Neural Networks (FFNN) predicting the damage fracture point (breakage $x_{\text{dam}} \in x$, strain length) of DUT from the first data points $\boldsymbol{F}_0$ of a tensile test, i.e., with data series $\boldsymbol{F}$ of the load forces

$$\Gamma(\vec{F}_0, P) : \vec{F}_0 \rightarrow x_{dam},$$
$$\vec{F}_0 \subset \vec{F} = [F(x) | x = 0, \epsilon, 2\epsilon, .., n\epsilon]$$

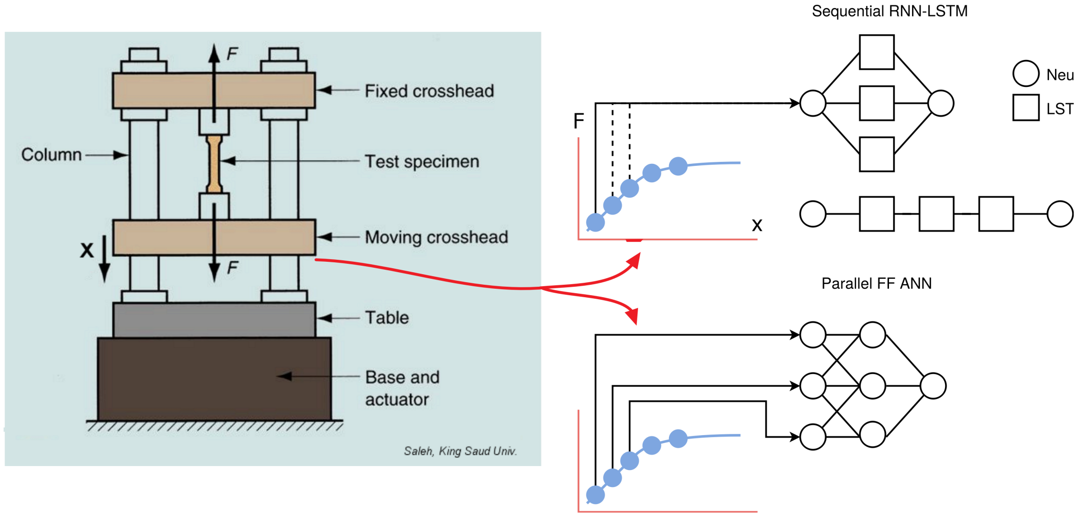
2. State-based Recurrent ANN (RNN) performing the same prediction of the damage strain length point by early tensile data.

3. State-based RNN performing data series prediction, i.e., the force-strain curves from tensile tests to predict the start of the inelastic range of the material:

$$\Gamma(F(\delta, \vec{F_{i0}}), P) : F_i \rightarrow F_{i+\delta},$$
$$\vec{F_{i0}} = [F_j | j < i]$$

> Γ is a parametrized (P) predictor function hypothesis derived from ML and training.

Experiments



Damage point Prediction

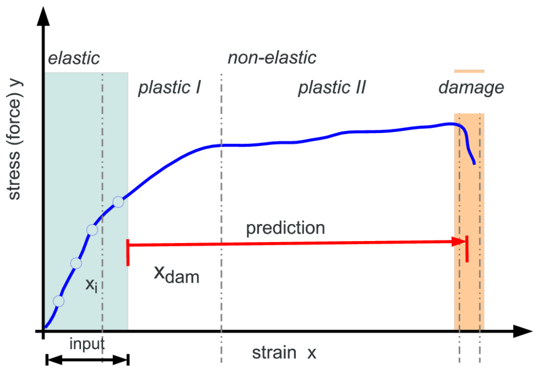


Fig. 14. Damage fracture point prediction (maximal strain length x_{dam} until damage) from measured data of the first segments of the strain-force diagram from tensile tests

Material State Prediction

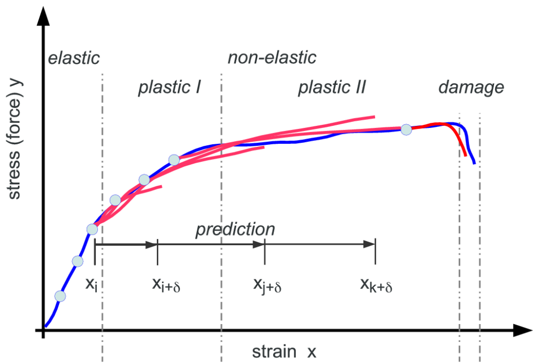


Fig. 15. A typical measured strain-force curve from a tensile test (blue line) and forward predictions (red line segments) $x_{i+\delta}$

ROI and Anomaly Detection in CT Data

Goal. Detect regions of interest in CT data volumes automatically. A ROI bases on anomaly detection and is a candidate for a damages: Breakage, impurity, delamination, cracks.

System. Micro X-ray CT devices providing different resolutions and X-ray energies, prepared composite plates (e.g., GLARE).

Methods and Algorithms. Edge detection using kernel filters and gradient algorithms, Z-profiling slicing the CT volume along z-axis (depth), anomaly marking by LSTM, CNN, and SOM, threshold discrimination.

Chirag Shah, Stefan Bosse, and Axel von Hehl. Taxonomy of Damage Patterns in Composite Materials, Measuring Signals, and Methods for Automated Damage Diagnostics, Materials 15 (MDPI), no. 13 (2022): 4645

Supervised CNN

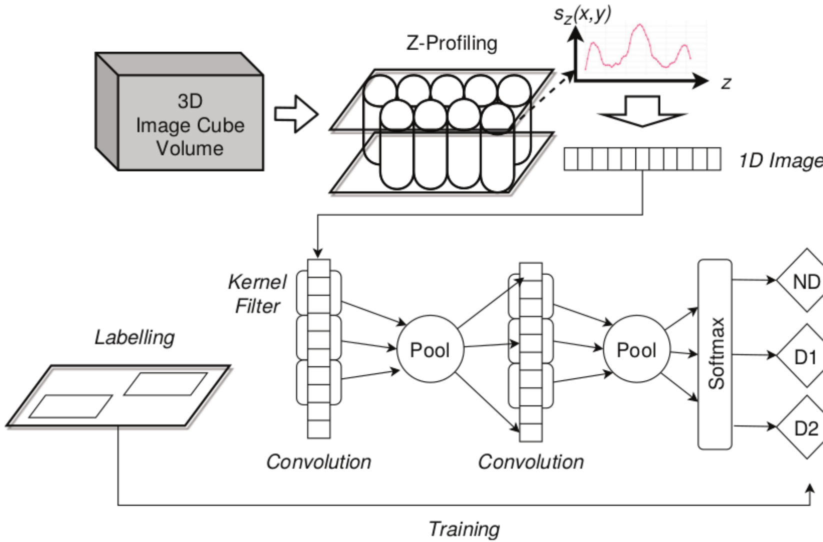


Fig. 16. Z-profile signals as 1D images as input for a CNN damage classifier (ND: No damage class, D1: Damage 1, D2: Damage 2, and so on)

Supervised CNN

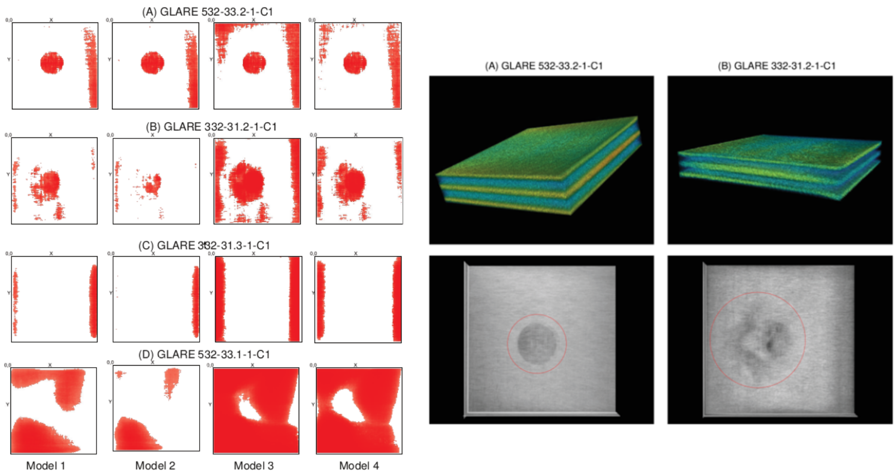


Fig. 17. (Left) Damage feature maps retrieved from four different CNN classifiers and for the specimen A (training and prediction), B, C, and D) (Right) CT image volume and selected x-y slice visualization (A-B) With centred resin defect in the PREG layer

Unsupervised SOM

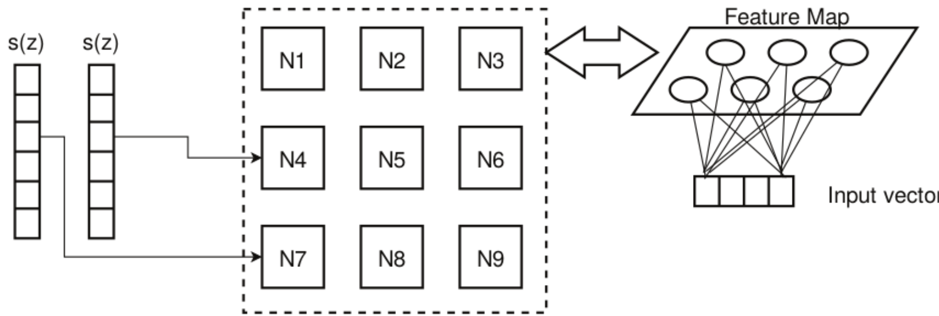


Fig. 18. Principle concept of Self-organising Maps (SOM). The neural node set {n} (squares, left side) represents a feature map {f} (circles, right side)

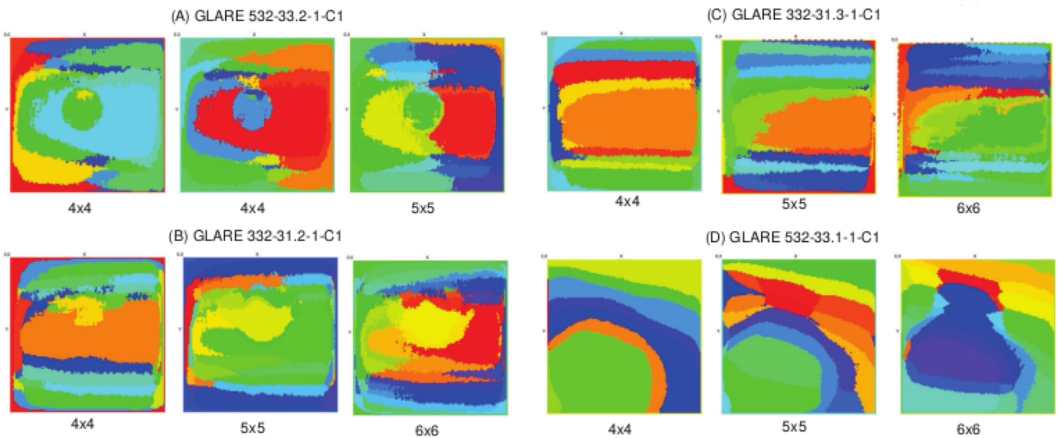


Fig. 19. SOM feature maps of the z-signal volumes for different specimen and with different SOM network sizes (rows × columns); Specimen A: Sharp resin washout, B: fuzzy resin washout; C: base-line; D: large area delamination

Conclusion

Data-driven state estimation (e.g., damages) from experimental data is a challenge.

Conclusion

Data-driven state estimation (e.g., damages) from experimental data is a challenge.

The measured sensor data space is sparse and lack of generalisation. Simulation can be beneficial.

Conclusion

- Data-driven state estimation (e.g., damages) from experimental data is a challenge.

- The measured sensor data space is sparse and lack of generalisation. Simulation can be beneficial.

- In addition to classical functional algorithms, agents, cellular automata, and maps posing self-organisation and self-adaptivity can be used to identify regions of interest in sensor data and to find anomaly regions.

Conclusion

- Data-driven state estimation (e.g., damages) from experimental data is a challenge.
- The measured sensor data space is sparse and lack of generalisation. Simulation can be beneficial.
- In addition to classical functional algorithms, agents, cellular automata, and maps posing self-organisation and self-adaptivity can be used to identify regions of interest in sensor data and to find anomaly regions.
- Distributed algorithms used in sensor networks process sensor data locally (including ML-based local state estimation) and derives a global state by fusion ⇒ Robustness (noise)!