Comparing Methods for Damage Localization in Active Structural Health Monitoring Using Piezoelectric Sensors

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- Introduction
- System design
- System status
- Comparative analysis – damage location

Project background

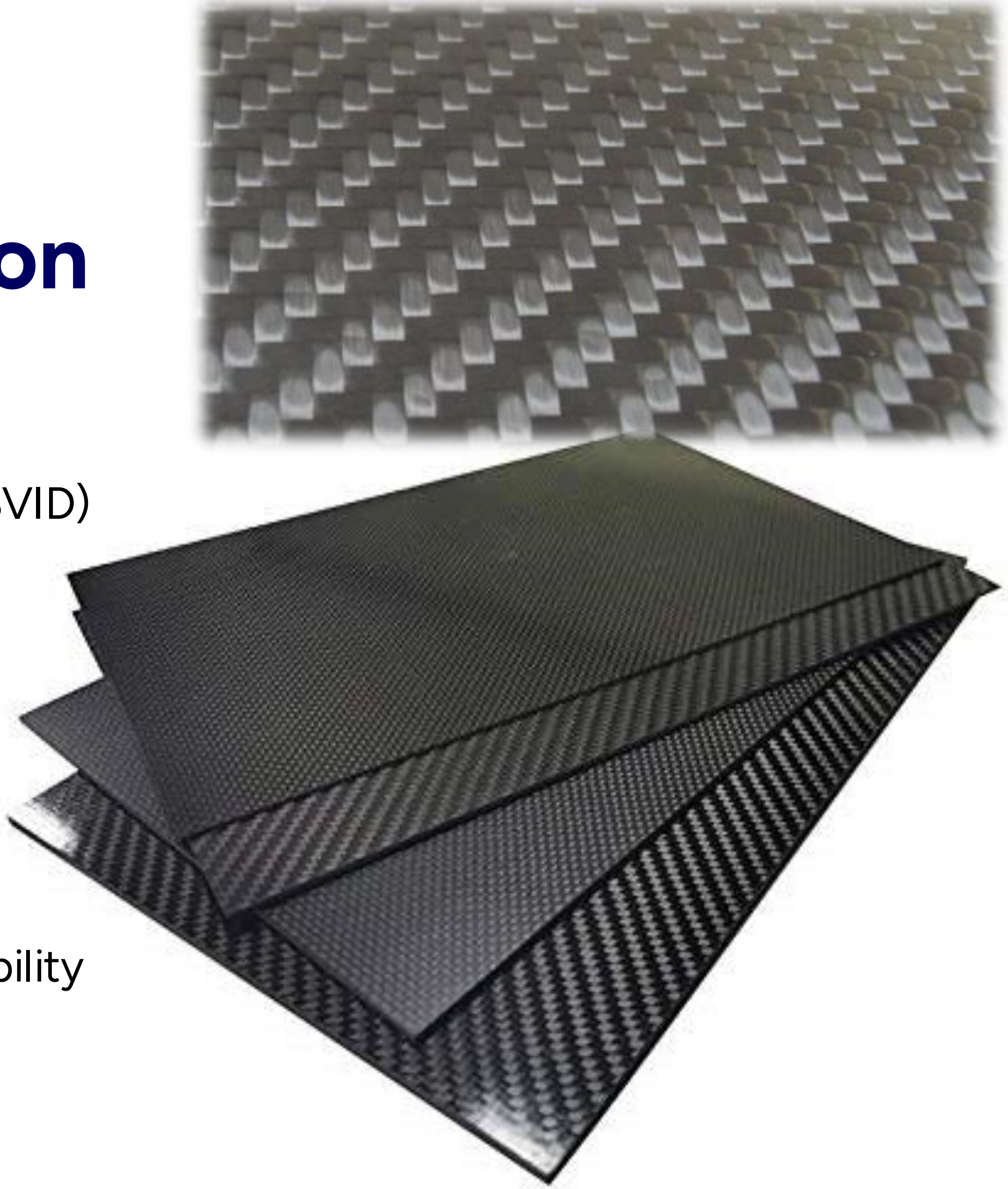
- Offset Indirect Program in 2020 – transfer of technology between Sweden-Brazil
  - Brazil bought 40 Gripen fighter aircrafts from Saab - Sweden.
  - “Scalable Hardware Solutions for Machine Learning”: 3rd study case in my PhD research
- 2025: postdoc research related to development of smart systems for SHM
  - In collaboration with Saab and BAE Systems

Saab JAS 39 Gripen

Introduction

Application + Methods + Technologies

Introduction: system application



- Composite structures in aerospace
    - Lightweight, high strength, corrosion resistant
    - Susceptible to complex failures (delamination, cracks, BVID)
- Limitations of traditional inspections
    - Visual and NDT require downtime & manual effort
    - Risk of missing hidden or in-between damages
- Structural Health Monitoring (SHM)
    - Enables continuous or on-demand monitoring
    - Supports condition-based maintenance
    - Improves safety, reduces costs, increases aircraft availability

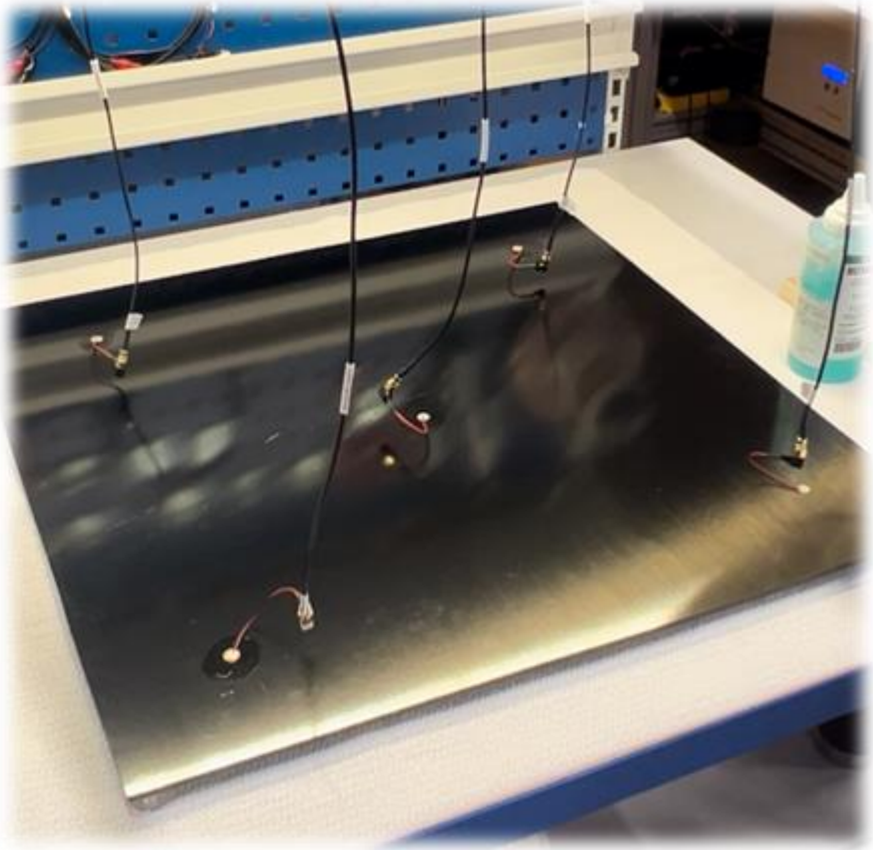
Introduction: system's methods and technologies

LAMB WAVES

- Guided waves that propagate long distances in thin plates
- Sensitive to a wide range of defect types (internal & surface)
- Provide time-of-flight (TOF) and amplitude changes for damage localization
- Well-suited for composites due to multi-mode propagation (A0, S0 modes)

PZT transducers for lamb waves

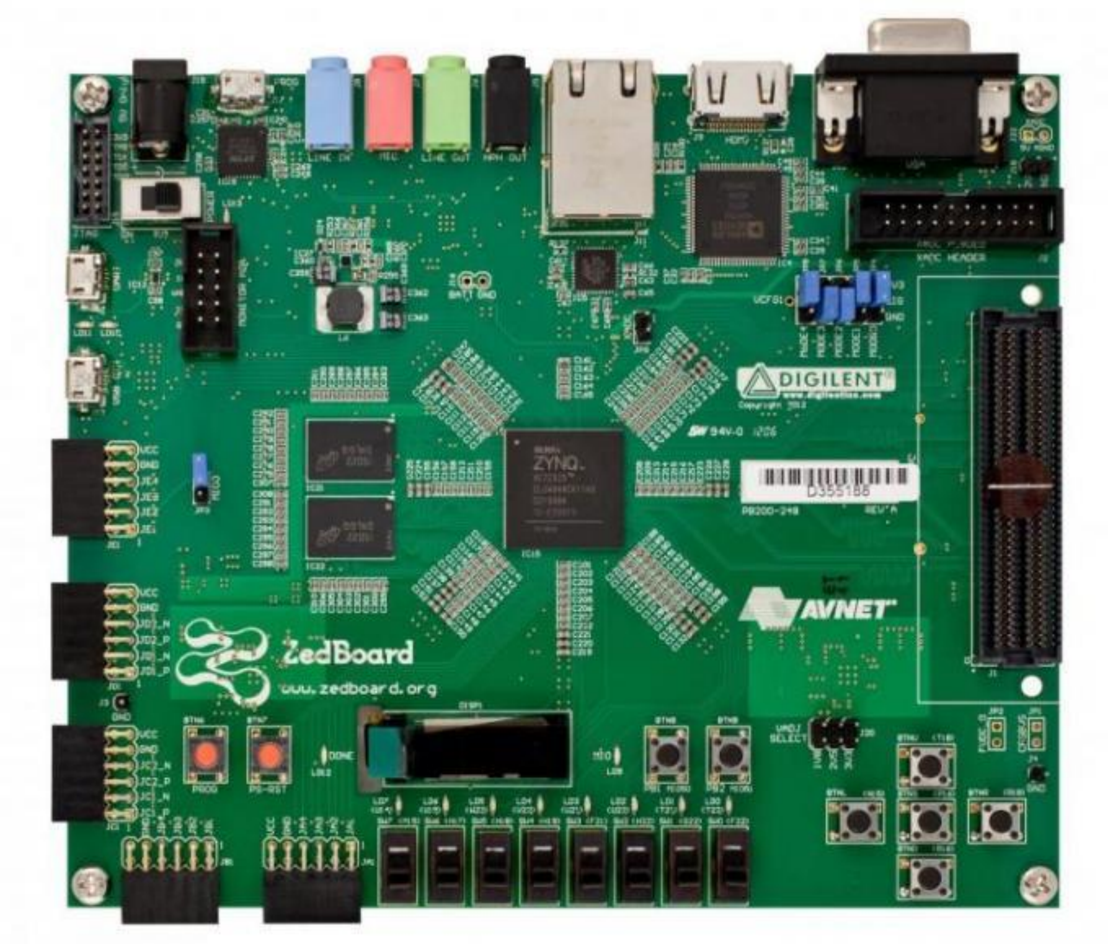
- Act as both transmitters (excitation) and receivers (sensing)
- Enable compact and scalable sensor networks for SHM



Introduction: system's methods and technologies

Field-Programmable Gate Array (FPGA)

- What it is
  - A reconfigurable integrated circuit
  - Hardware logic can be programmed after manufacturing
  - Combines parallelism of hardware with flexibility of software
- Why use FPGA for SHM
  - Handles large amounts of sensor data in real-time
  - Lower power consumption compared to CPUs/GPUs for same task
  - Deterministic execution → critical for safety-related aerospace systems
  - Flexible: hardware can be reprogrammed for different algorithms or upgrades



Introduction: system’s methods and technologies

Machine Learning for SHM

Role of ML in SHM

Extracts patterns from complex Lamb wave signals

Enables automatic classification of location

Reduces reliance on manual feature interpretation

Challenges in software-only ML

High computational demand for real-time SHM

Latency and energy inefficiency on CPU/MATLAB implementations

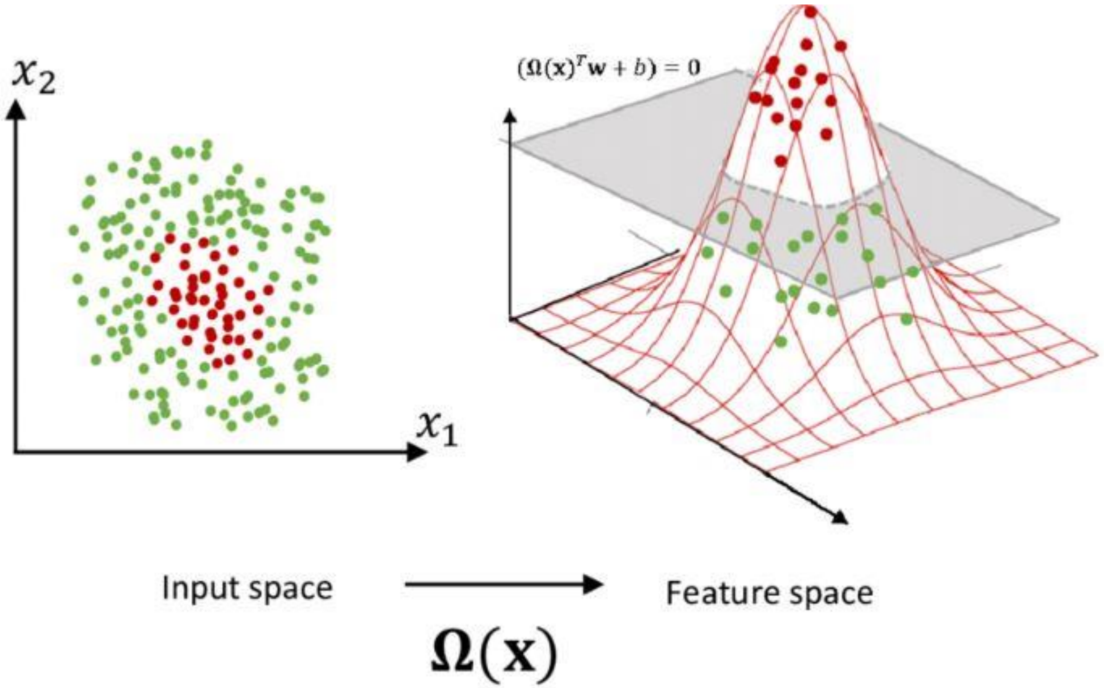
Why combine ML with FPGA

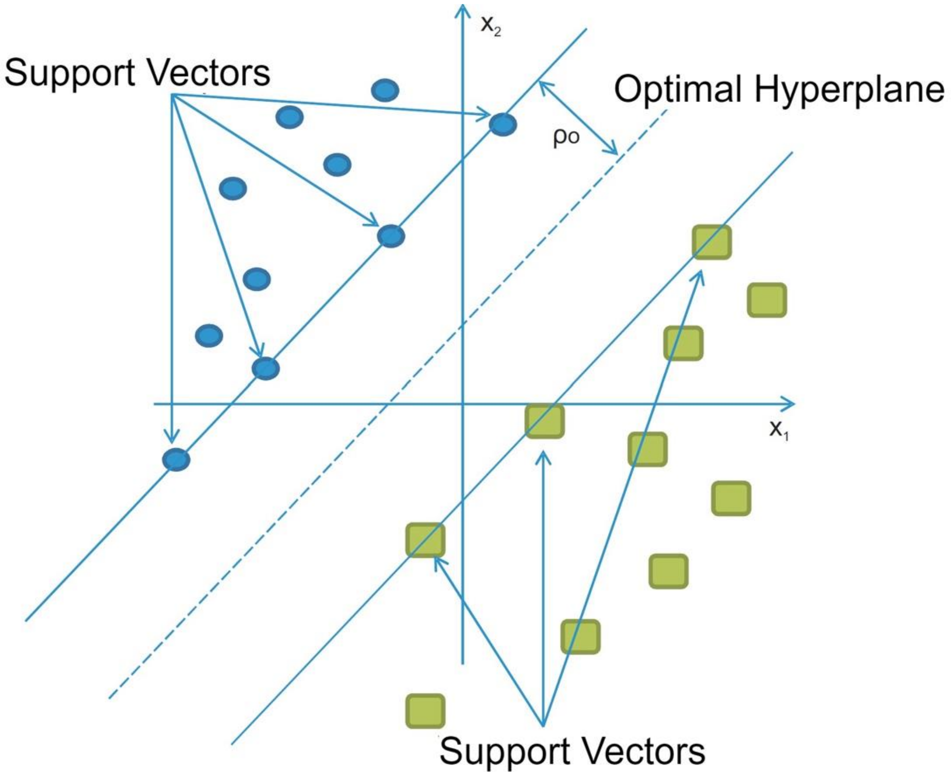
FPGA accelerates feature extraction (e.g., DWT) in real-time

Same classification accuracy as MATLAB version

Introduction: system's methods and technologies

Machine Learning algorithm: Support Vector Machine (SVM)

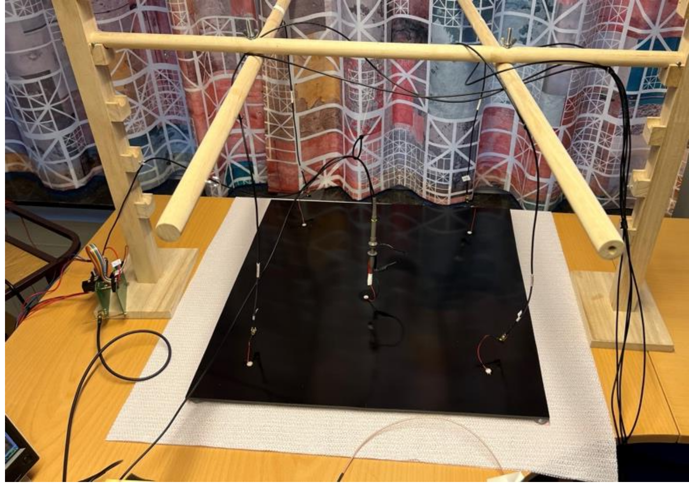




System design

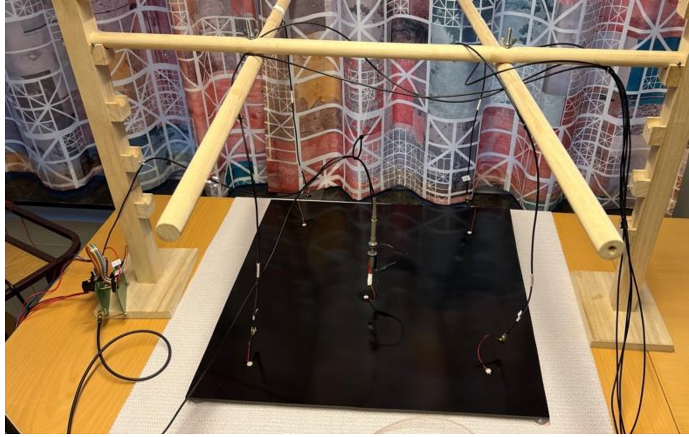
Data acquisition + Damage detection

System design: data acquisition



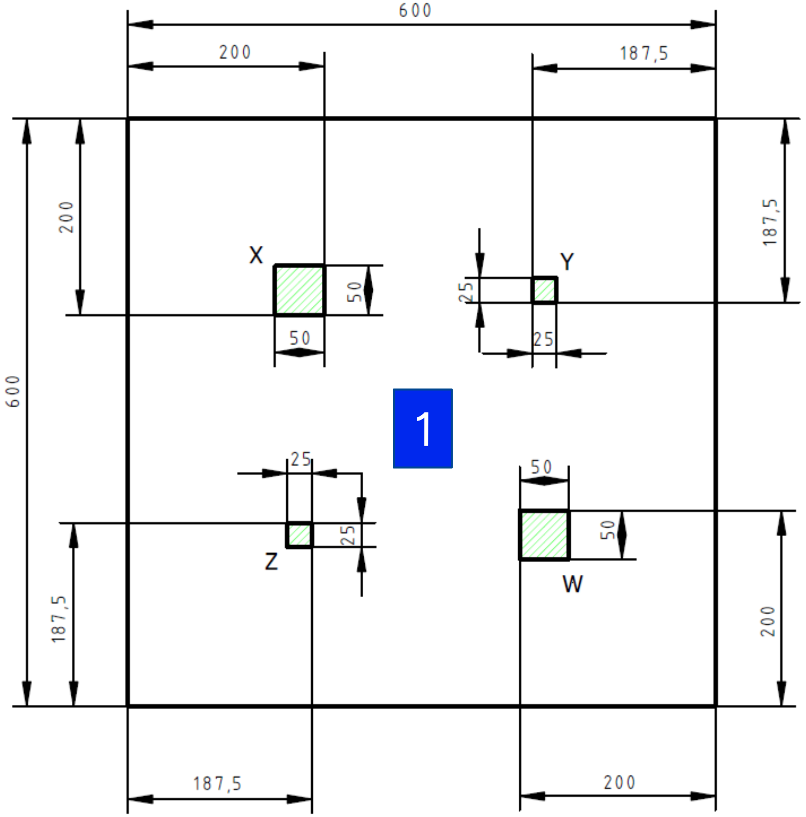
❖Specimens for the SHM testing

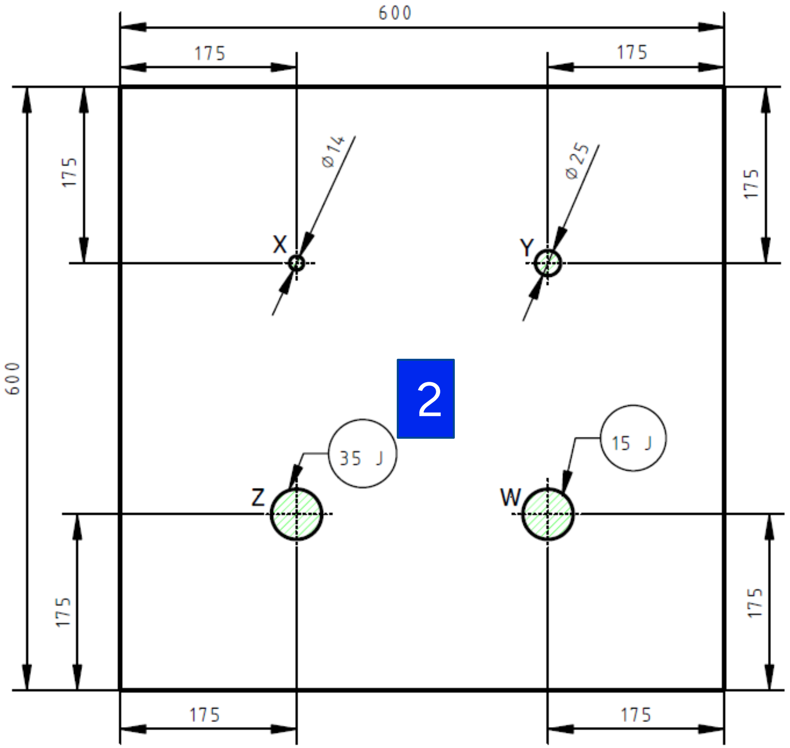
- Material & Manufacturing
  - Carbon fiber-reinforced polymer (CFRP) laminates
  - Fabricated at Saab AB Aeronautics, Sweden
  - Prepreg: Hexply 6376 epoxy, cured at 180 °C
  - Fiber: High Tenacity (HTS) unidirectional carbon fiber
  - Fiber volume content ≈ 57%
  - Quasi-isotropic layup $[0, 90, 45, -45]_5S$ → 40 plies, ~5.16 mm thickness
  - Panels trimmed with diamond blade (to avoid edge defects, fiber pull-out, delamination, or cracks)
- Dimensions
  – Two plates: 600 × 600 × 5 mm each



System design: data acquisition

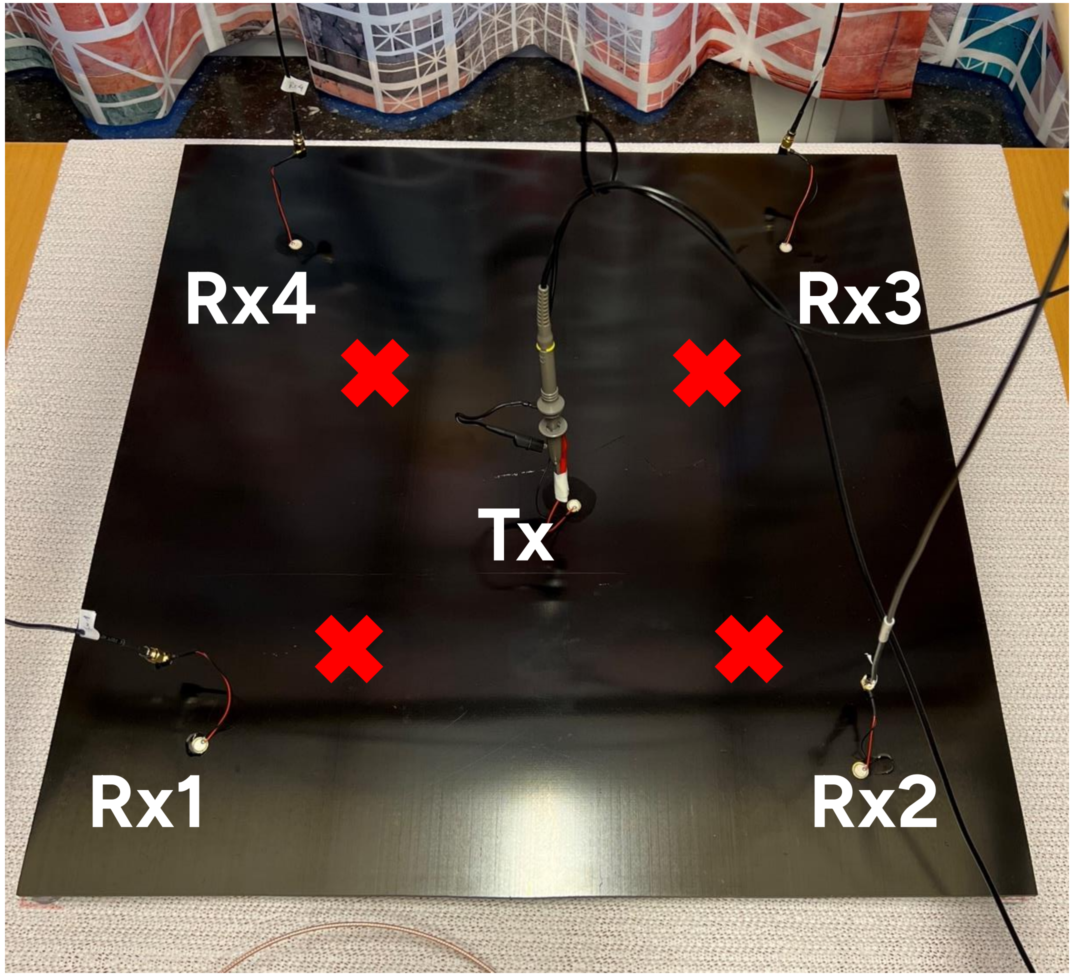
- **Specimen 1:** Internal Damage
  - Four embedded defects created with 3 layers of 2 mil FEP release film
  - Defect X: 50 × 50 mm, between layers 4–5
  - Defect Y: 25 × 25 mm, between layers 32–33
  - Defect Z: 25 × 25 mm, between layers 20–21
  - Defect W: 50 × 50 mm, between layers 32–33
- **Specimen 2:** Surface Damage
  - Two circular cutouts: Ø 25 mm and Ø 14 mm (top plies)
  - Two impact damages: 15 J and 35 J impact energies



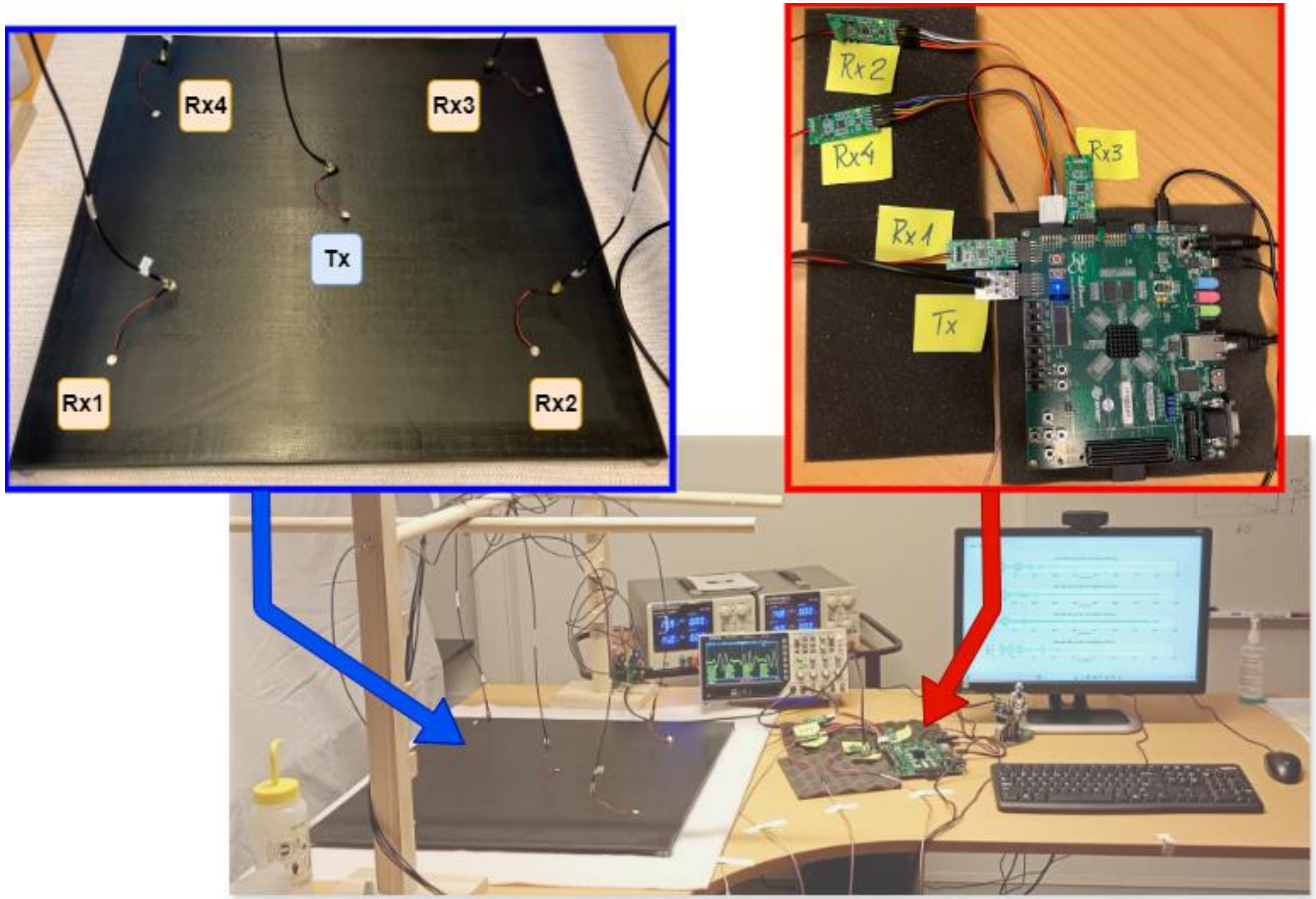


System design: data acquisition

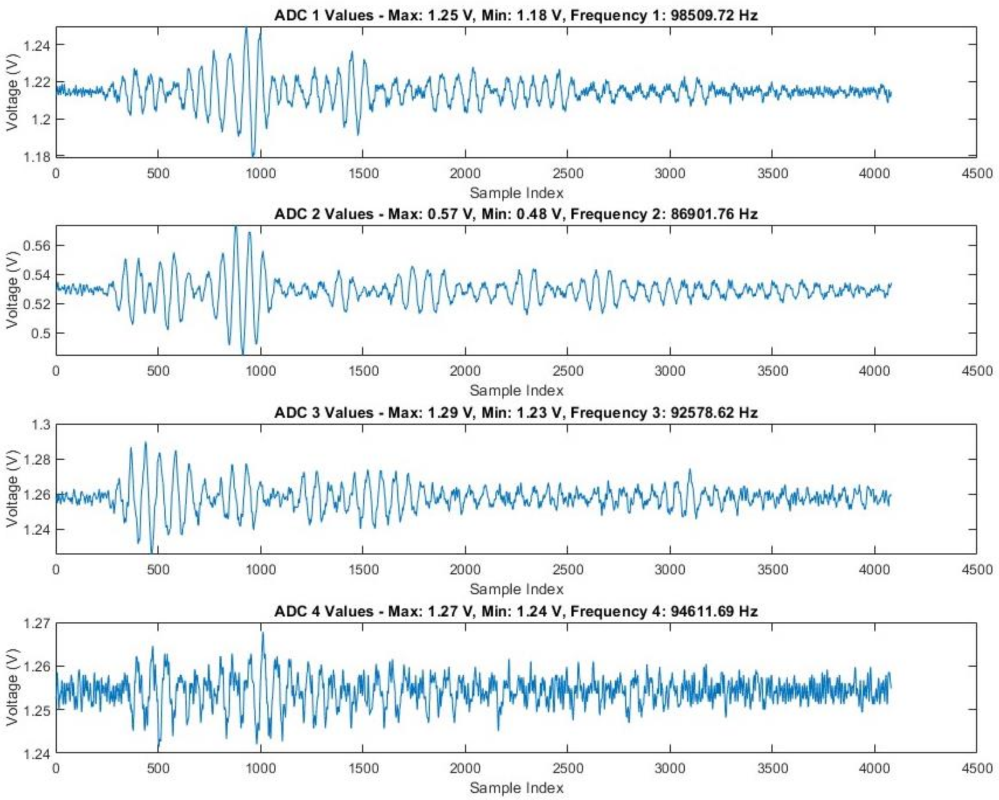
- Reason for defect choices
    - Circular cutouts → simulate material removal/delamination
    - Impact damage → assess tolerance to low-velocity impacts (ASTM D7136)
    - Embedded FEP films → simulate internal delaminations/voids
- Sensor Layout
    - 1 central PZT transmitter
    - 4 PZT receivers (10 mm patches) at corners, ~300 mm from edges (to avoid border effects) – **one for each defect**
    - Ultrasonic gel used for coupling, reapplied each session

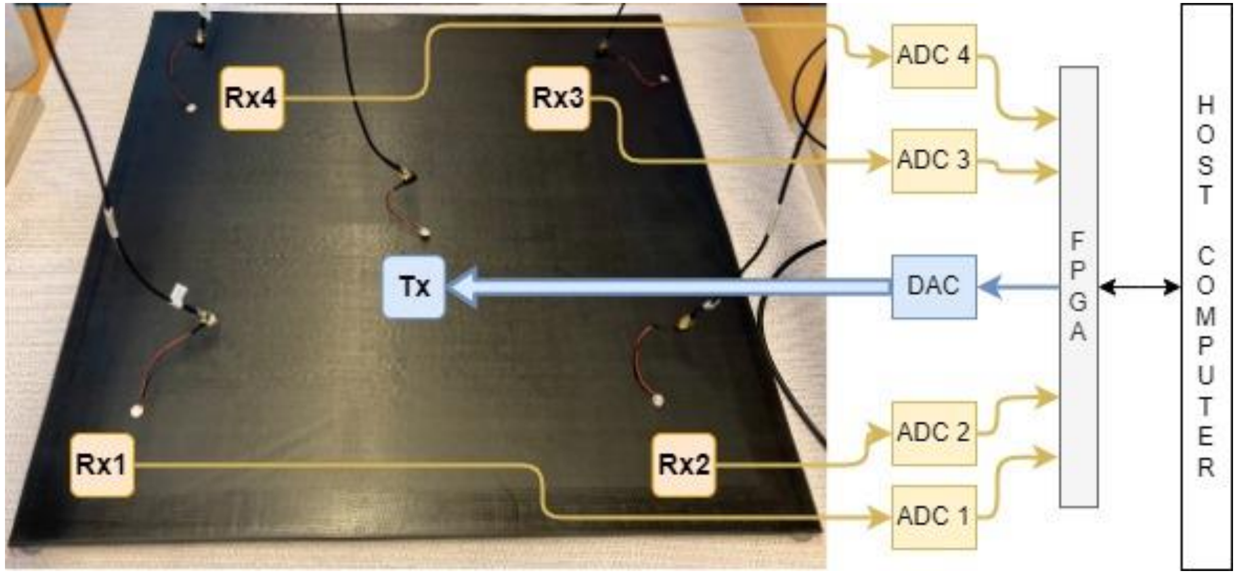


System design: data acquisition

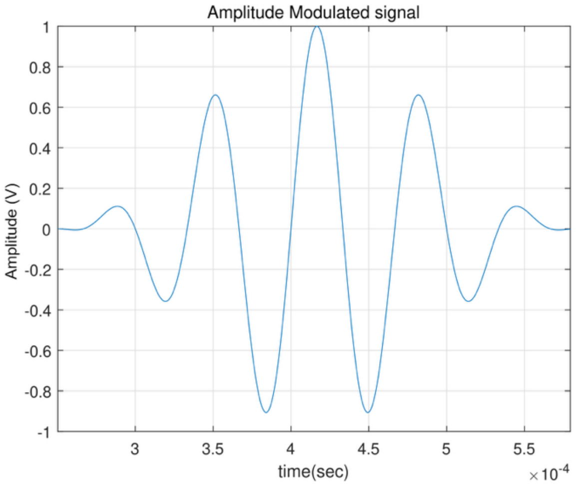


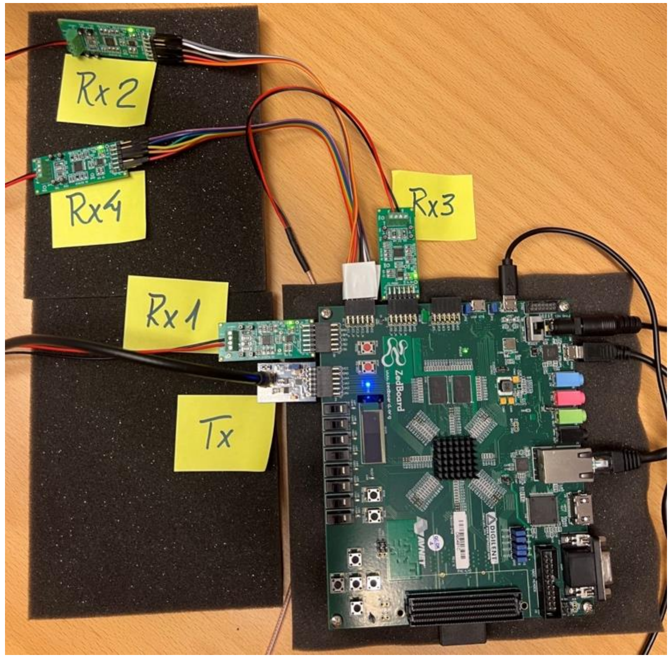
Receiver signals



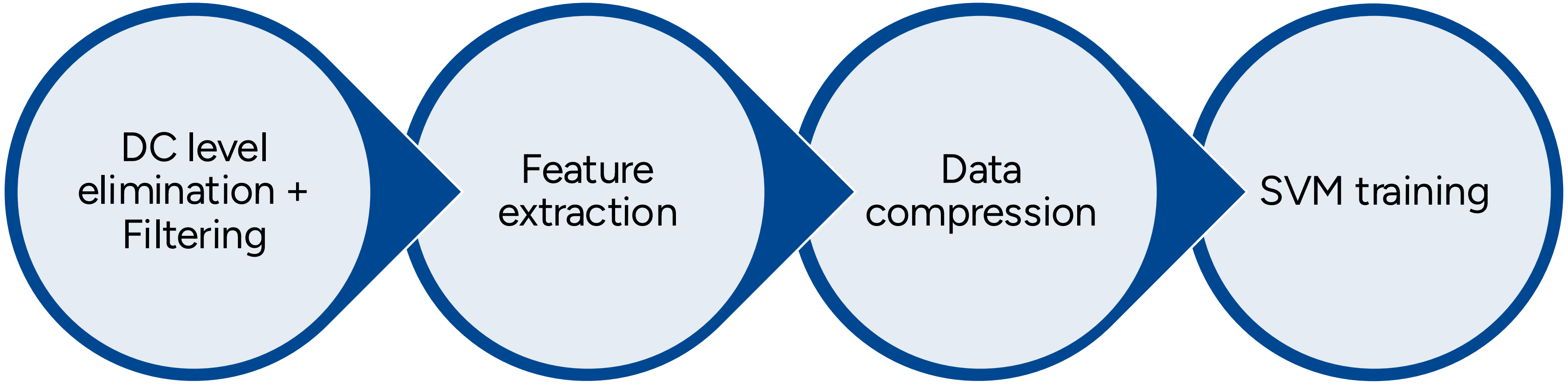


Transmitter signal





System design: dataflow



- 8176 samples
- 3-level DWT decomposition
- Daubechies wavelets – db4

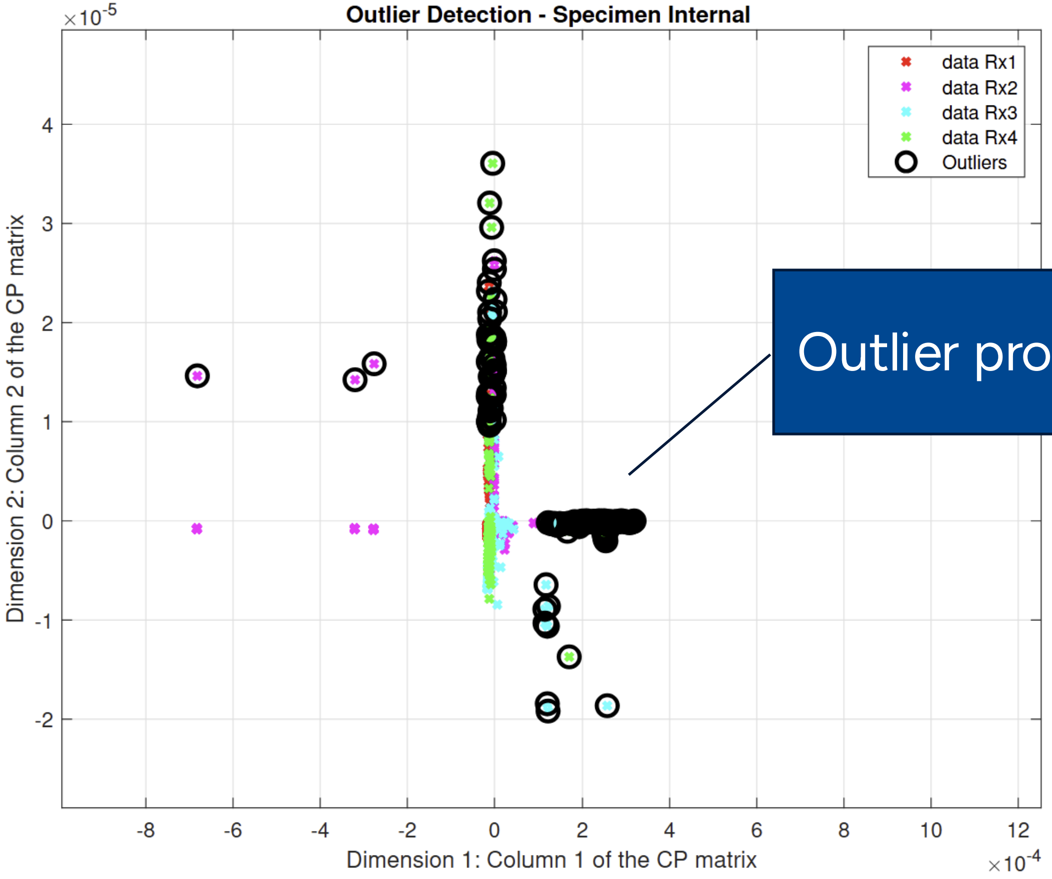
- Power spectral density (PSD)

- Particle component analysis (PCA)
- Result: Compressed data matrices

- Gaussian kernel function
- Extraction of the training pattern data

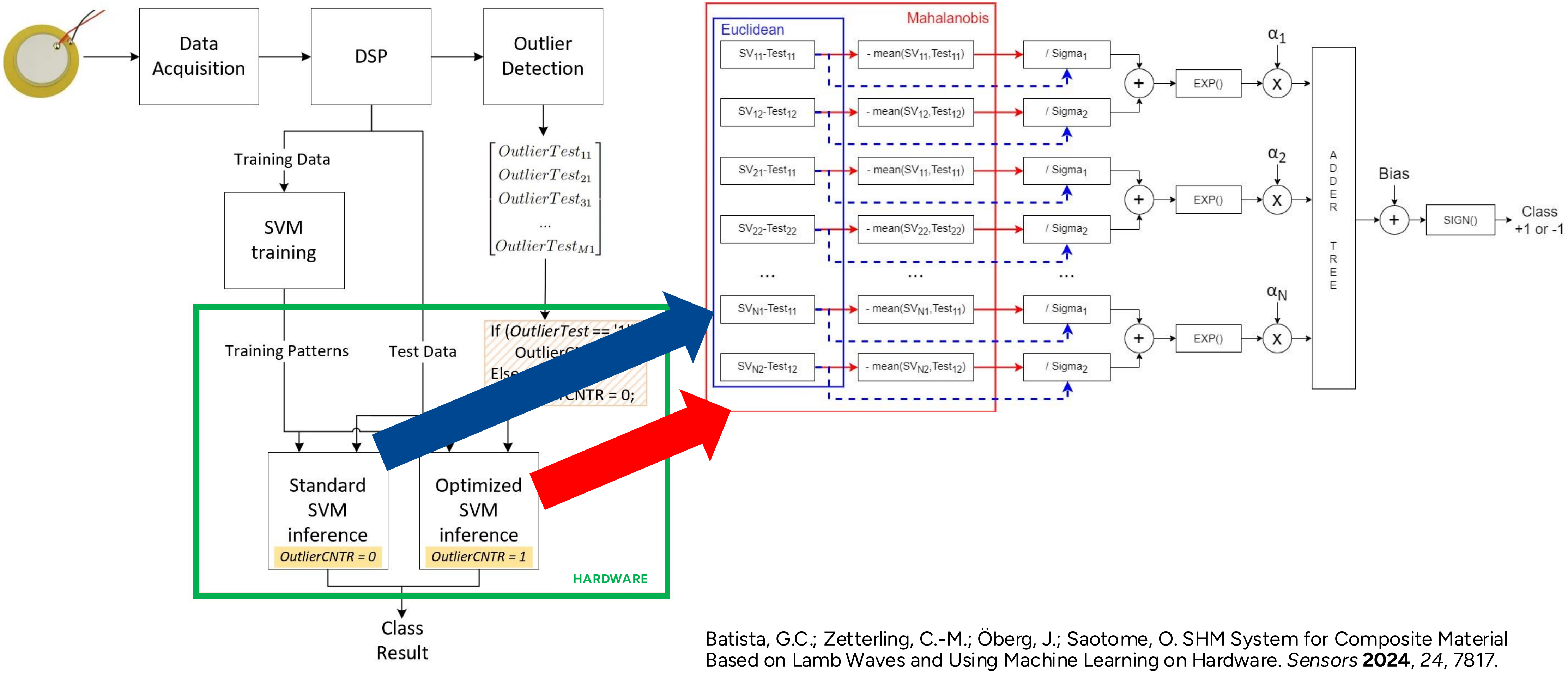
$$SV_{N\times 2} = \begin{bmatrix} SV_{11} & SV_{12} \\ SV_{21} & SV_{22} \\ SV_{31} & SV_{32} \\ \dots & \dots \\ SV_{N1} & SV_{N2} \end{bmatrix} \quad \alpha_{N\times 1} = \begin{bmatrix} \alpha_{11} \\ \alpha_{21} \\ \alpha_{31} \\ \dots \\ \alpha_{N1} \end{bmatrix} \quad Sigma_{1\times 2} = \begin{bmatrix} Sigma_{11} & Sigma_{12} \end{bmatrix} \quad Test_{M\times 2} = \begin{bmatrix} Test_{11} & Test_{12} \\ Test_{21} & Test_{22} \\ Test_{31} & Test_{32} \\ \dots & \dots \\ Test_{M1} & Test_{M2} \end{bmatrix} \quad Outliers_{M\times 1} = \begin{bmatrix} OutlierTest_{11} \\ OutlierTest_{21} \\ OutlierTest_{31} \\ \dots \\ OutlierTest_{M1} \end{bmatrix}$$

System design: challenges



Outlier problem

System design: damage detection

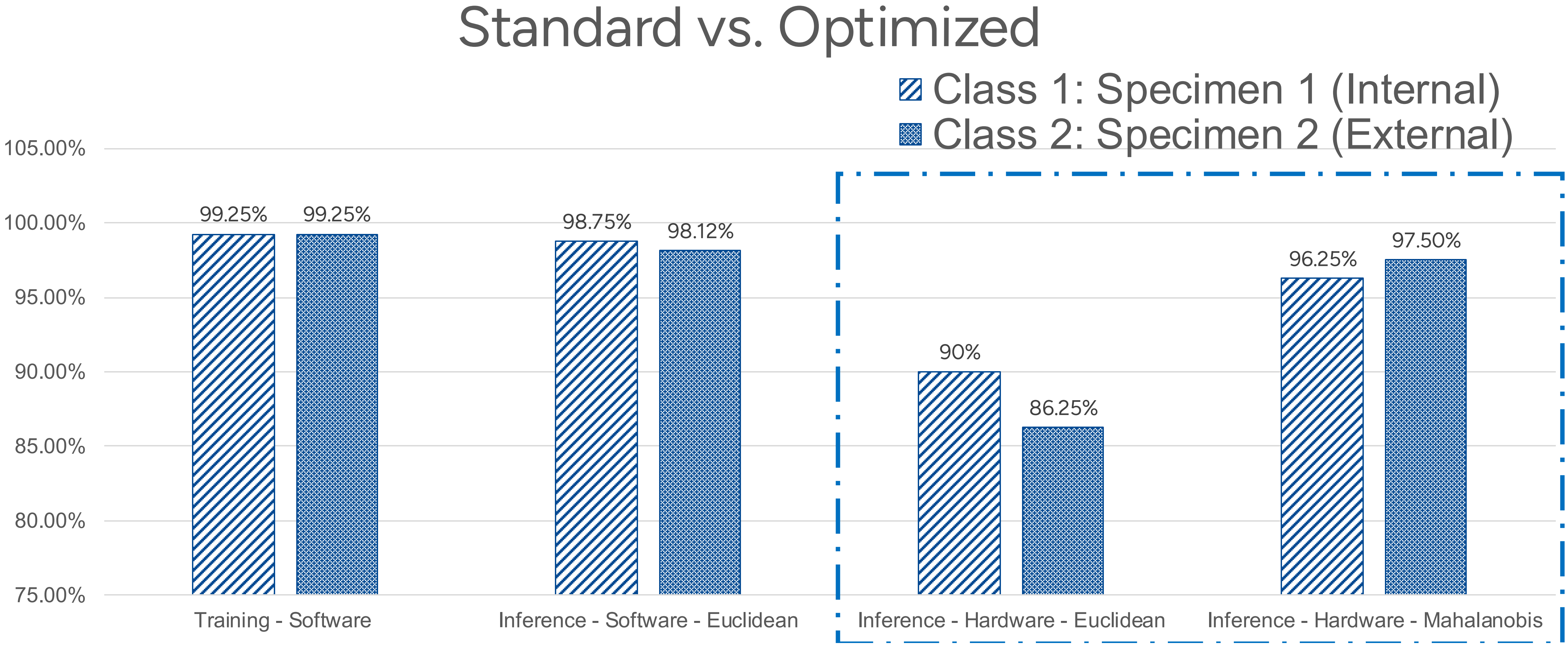


Batista, G.C.; Zetterling, C.-M.; Öberg, J.; Saotome, O. SHM System for Composite Material Based on Lamb Waves and Using Machine Learning on Hardware. *Sensors* **2024**, *24*, 7817.

System status

Optimization + Current results

System design: damage detection



System optimization: Digital Signal Processing

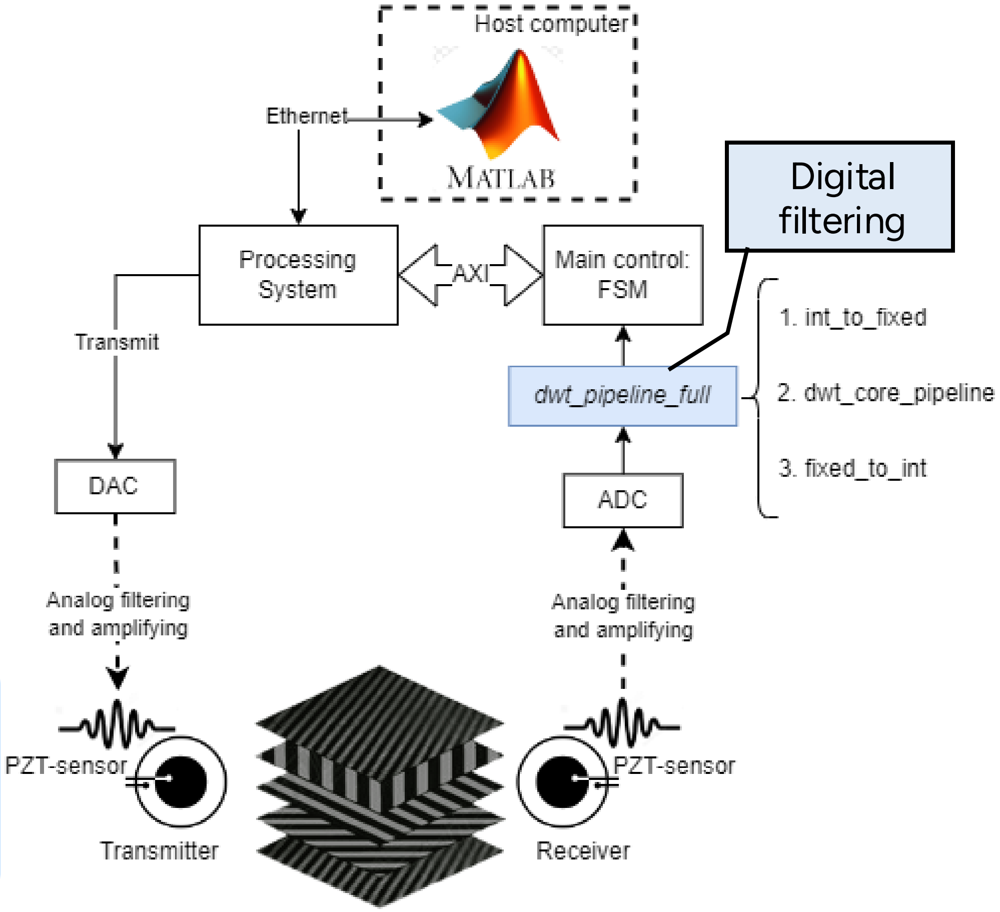
- **Goal:** enable embedded, real-time signal processing of Lamb wave data
- **Approach:** migrate MATLAB-based **Discrete Wavelet Transform (DWT) filtering** into FPGA hardware (Vitis HLS, C++)
- **Pipeline design:**
  - Three functional blocks
  - Parallel execution

Data format: fixed-point *ap_fixed<32,12>* (12 integer bits, 20 fractional bits)

  - Preserves precision of Daubechies-4 coefficients
  - Optimized for hardware resource balance

dwt_pipeline_full

  - int_to_fixed: converts ADC uint16_t input to fixed-point, applies DC offset correction (–2048)
  - dwt_core_pipeline: 3-level DWT with db4 filters (D1, D2, D3 outputs)
  - fixed_to_int: scales & converts outputs back to int16_t (AXI-compatible)



Before: hardware without DWT filtering

Resources	Values
LUT	5,275
LUTRAM	343
FF	8,283
BRAM	17.5
DSP	0

After: hardware with DWT filtering

Resources	Values	Overhead (%)
LUT	8,936	+69.4
LUTRAM	585	+70.5
FF	13,089	+58
BRAM	30	+71.4
DSP	16	-

Up to 20% usage of the FPGA total area

System status

Implementation	Processing Time	Latency	Throughput
MATLAB	1.43 s	-	
FPGA	5.68 µs	568 cycles @ 100 MHz	≈100 MS/s

- Software-based filtering on Matlab vs. Hardware-based filtering on FPGA

Comparative analysis

Damage location: triangulation vs. ML

TDOA Triangulation for damage location

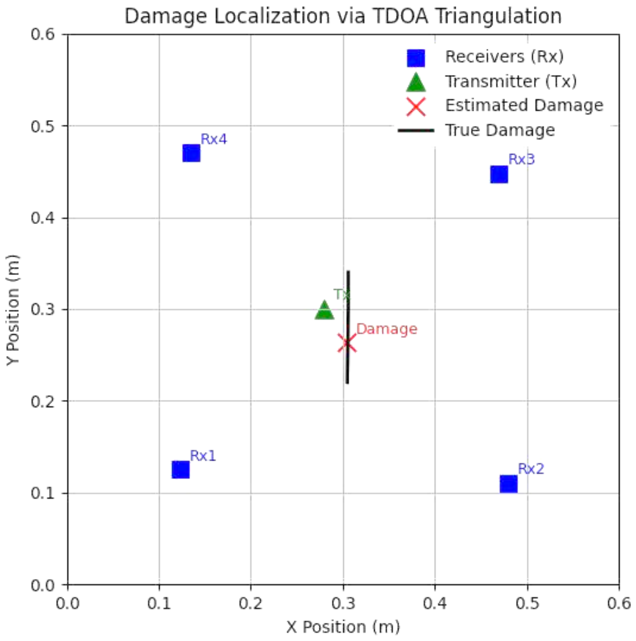
Advantages

✓ High accuracy for **single damage**

✓ Fast and fully deterministic (no training needed)

✓ Physically interpretable (geometry-based)

✓ Low computational load for hardware implementation



Limitations

✕ Assumes clean arrival times (TOAs)

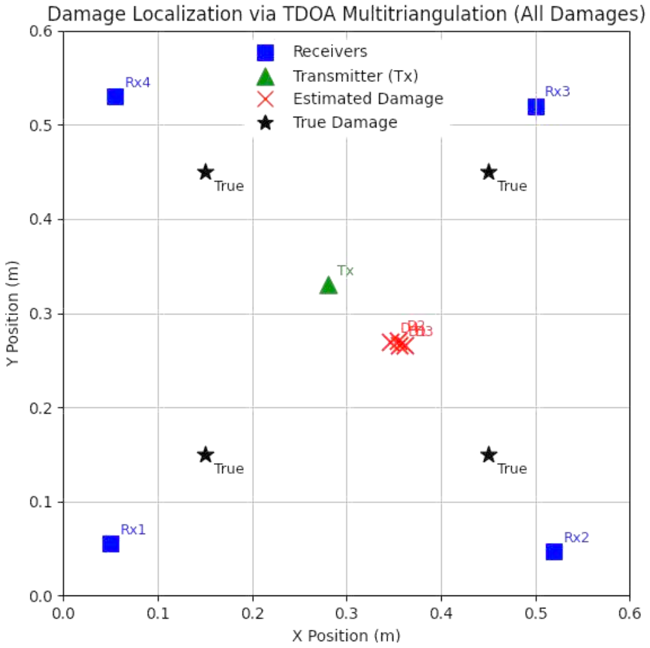
✕ Sensitive to noise and reflection overlap

✕ **Fails in multi-damage** scenarios due to:

→ Ambiguous peaks

→ Misgrouped TOAs

→ Interference between damages



Machine Learning for damage location

Advantages

✓ Handles **multi-damage** cases

✓ Learns complex wave patterns and propagation paths

✓ Robust to noise and overlapping signals

✓ More features/information from the receiver signals → damage characterization

Limitations

✕ Requires labeled training data

✕ Black-box (less interpretable)

✕ Performance depends on model quality and generalization

✕ High computational load for hardware implementation

TDOA Triangulation works well for **single damage** cases

- Accurate and physics-based
- Sensitive to signal alignment and noise
- Struggles with overlapping reflections (multi-damage)

Machine Learning handles **multiple damages** more robustly

- Learns complex signal patterns
- Can generalize to unseen configurations
- Requires labeled training data and pre-processing

Overview

TDOA triangulation vs. Machine Learning

Trade-off:

- Triangulation: interpretable, no training needed
- ML: scalable, handles complexity, but depends on data

Future work

- To combine both: use ML for detection, triangulation for refinement
- To enhance damage detection: characterization
- To improve hardware efficiency and scalability
- To move closer to real-time, plug-and-play aerospace application

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Tack!

Questions...

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