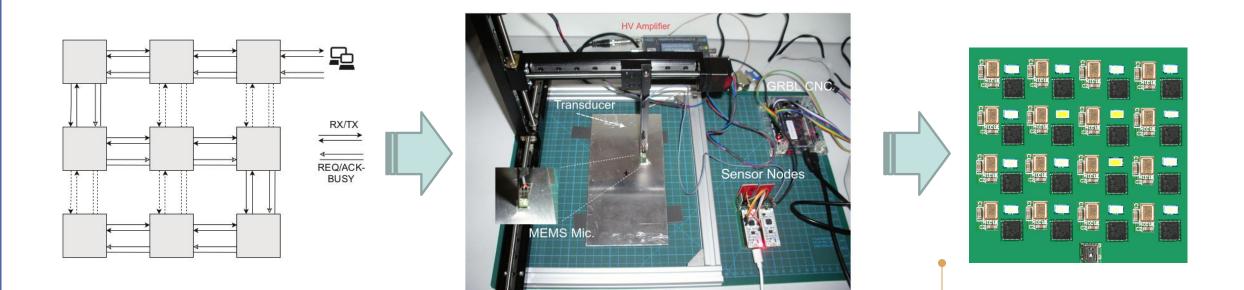
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TOWARDS AN AIR-COUPLED ULTRASONIC SENSOR NETWORK AND CAMERA FOR NON-DESTRUCTIVE TESTING WITH INTEGRATED MACHINE LEARNING

Stefan Bosse

Schall 2025 Conference



CONTENT



Introduction

Air-coupled GUW Distributed Sensornetwork



Air-coupled GUW Camera

Air-coupled GUW Sensing Multi-sensor System Sensor Network Architecture

03

Virtual Machines

Abstraction and Virtualization in distrbuted Sensor Network



Data-driven NDT

Data-driven Defect and Damage Prediction using Multi-instance ML



Evaluation

Workflow - Experiments - Damage and Defect Prediction - Fusion



Conclusions and Outlook Issues and pitfalls Lessons learned



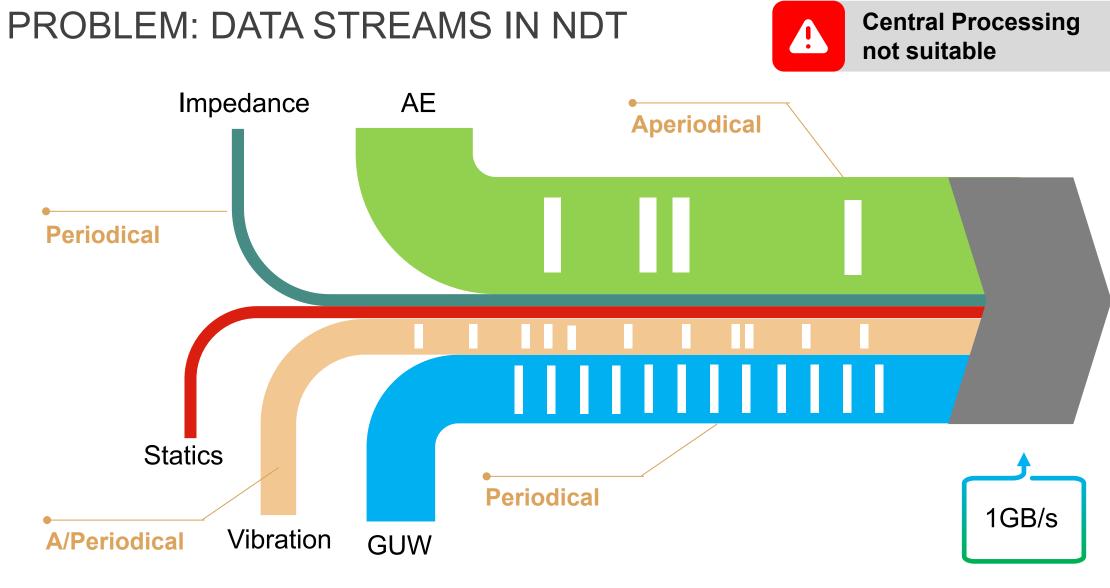
INTRODCUTION

- For non-destructive testing (NDT) of structures, various methods are usually used.
- Among other methods, acoustic emission (AE) and guided ultrasonic wave (GUW) tests are often used to assess structures and to detect damages and defects.
- Both methods are characterized by high-dimensional time-dependent data.



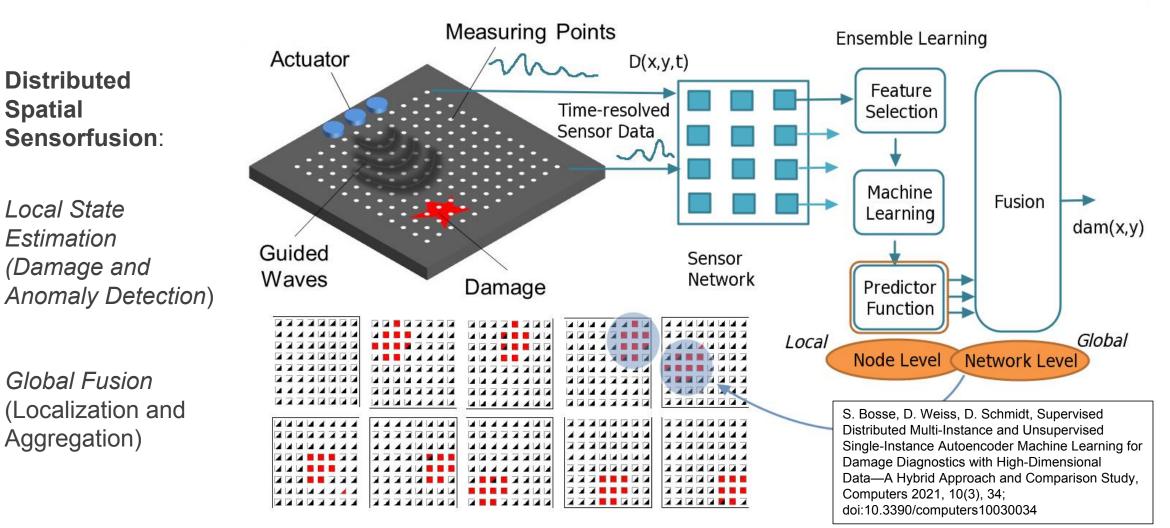
The use of a guided wave-based approach is due to the fact that these waves can propagate over relatively long distances and interact sensitively and specifically with various types of defects.







SENSORFUSION VERSA MODELFUSION IN DISTRIBUTED SENSOR NETWORKS

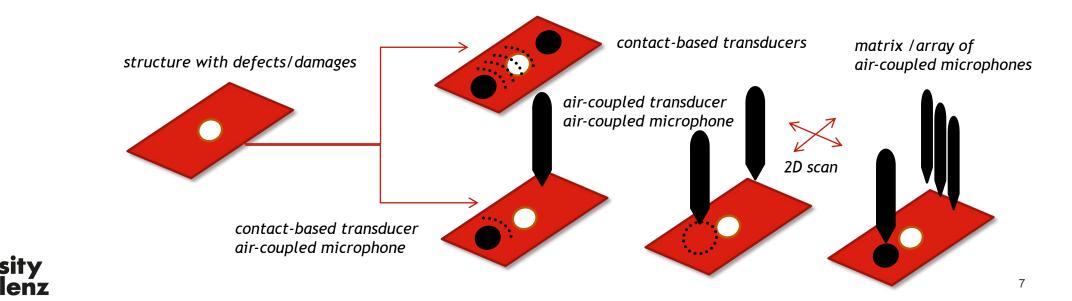




NDT MEASURING TECHNIQUES

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- Suppose you have a composite material consisting of multiple layers, e.g., a sandwitch structure of alternating metal and fibre layers.
- Now suppose there is a hidden defect or a damge that we cannot see or feel from the oustide.
- How can we detect and localize these hidden defects and damages with in-field measuring techniques quickly and robustly?



AIR-COUPLED GUW CAMERA



Goal: Single Board Distributed Sensor Network with multiple sensors, message- and signal-based communicating sensor nodes, and integreated spatially resolved damage and defect prediction with TinyML models and a Virtual Machine.

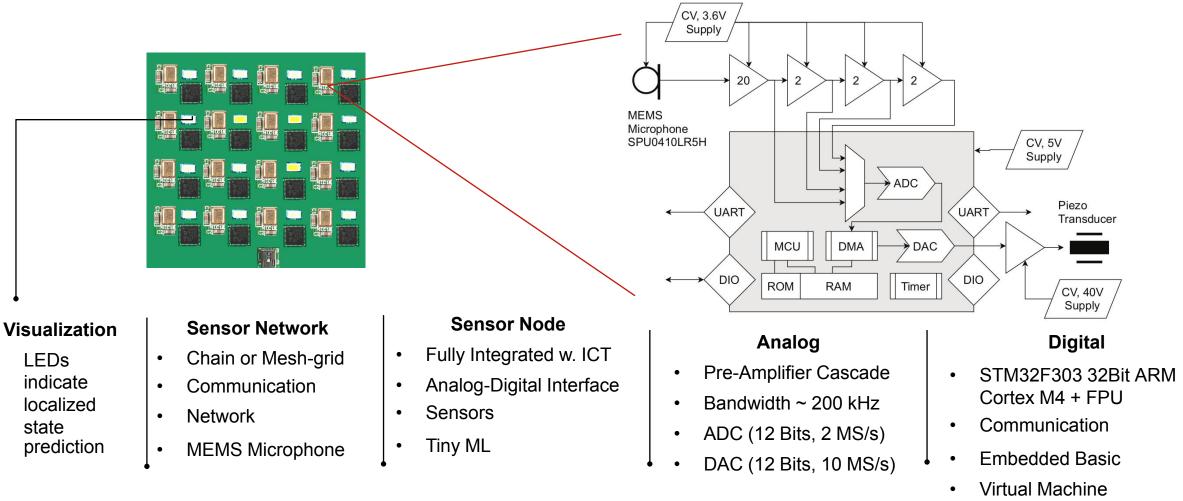
This study introduces a low-cost air-coupled measuring technique using a 1\$ MEMS microphone as a signal receiver and a surface-coupled transducer as a sender. Each sensor is integrated with data processing and communication (ICT), providing a "Smart Sensor Node" for signal processing, feature extraction, and Machine Learning for feature prediction. The approach provides higher freedom of design and scalability, especially for spatially large extended sensor networks.



Distributed multi-sensor acquisition of time-dependent signals require message- and signal-based synchronization; clock synchronization depends on low latency and jitter!

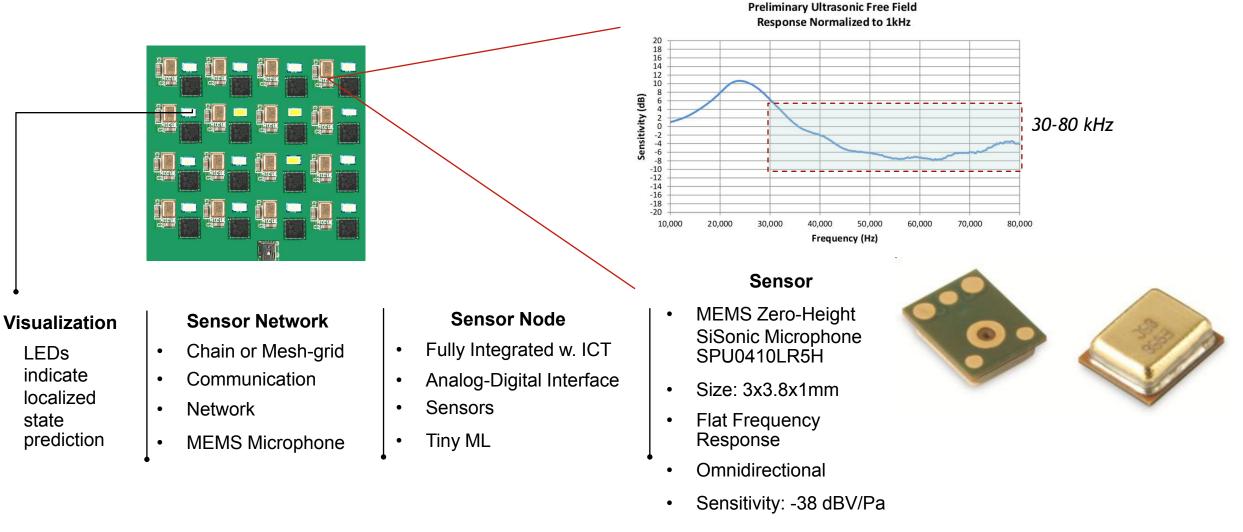


FULLY INTEGRATED SENSOR NODE: ARCHITECTURE



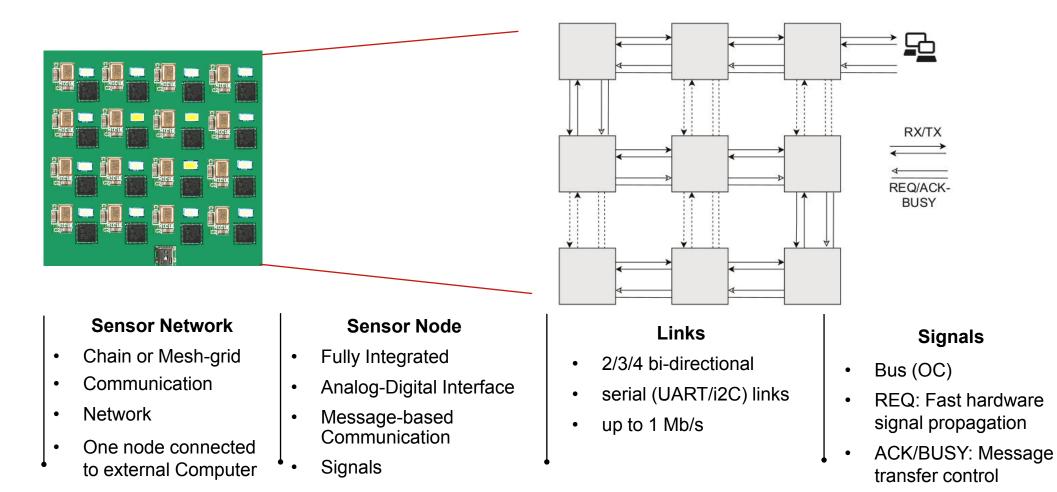


FULLY INTEGRATED SENSOR NODE: SENSOR



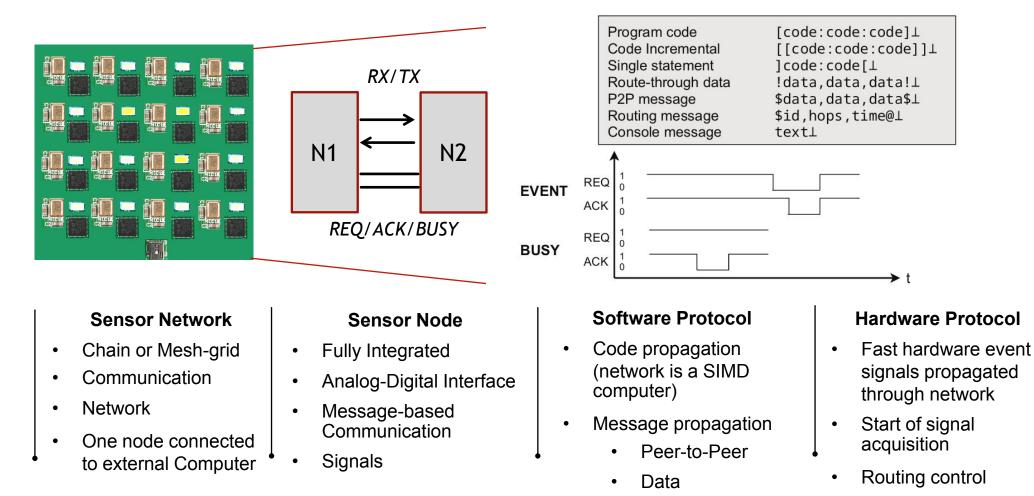


FULLY INTEGRATED SENSOR NODE: NETWORK



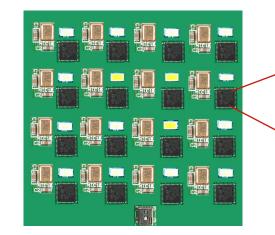


FULLY INTEGRATED SENSOR NODE: COMMUNICATION



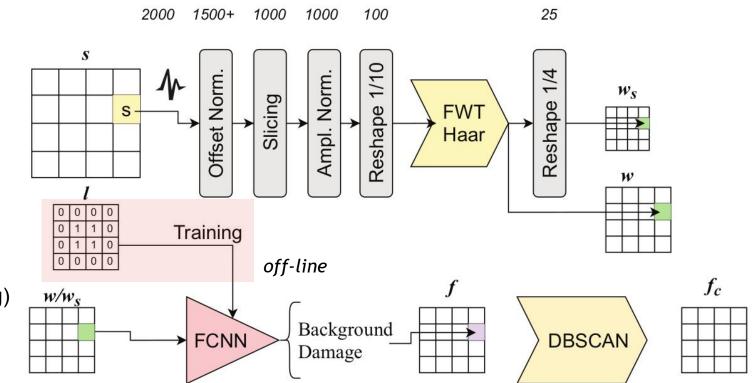
Clock synchronization

FULLY INTEGRATED SENSOR NODE: TINY ML

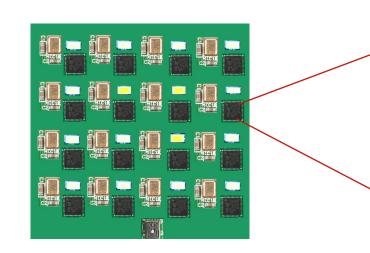


- Data-flow architecture implemented in each sensor node (except model training)
- Input: Time sensor signal
- Feature extraction: Fast Wavelet
 Transform with Haar wavelet
- Damage classifier: Fully Connectet
 Neural Network Classifier
- Output: Damage near by? 0/1





FULLY INTEGRATED SENSOR NODE: TINY ML



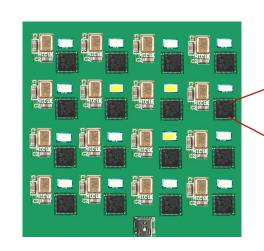
- Fully Connected Artificial Neural Networtk
- Input: FWT vector (Length N, Level 5)
- Output: Damage yes/no decision
- Three hidden layers + one softmax layer
- Trained with Float 32 Bits data type
- After training converted into Integer 16 Bits data type
- Int16 FCNN computed with Basic Vector Operation (STM32 microcontroller)

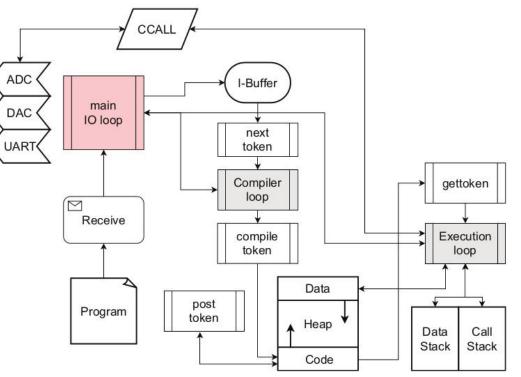


	Fully C	Jonnecu	ed Neural	Network	
	Classes Input: Output: Layers	[N	-		
	[1] in <u>r</u>	out :		out=[N,1,1]	params=0
	[2] fc	:	in=[25]	out=[10]	params=N*10+10
	[3] tan	nh :		out=[10]	params=0
	[4] fc	:	in=[10]	out=[10]	params=110
	[5] tan	nh :		out=[10]	params=0
	[6] fc	:	in=[10]	out=[10]	params=110
	[7] tan	nh :		out=[10]	params=0
-	[8] fc	:	in=[10]	out=[2]	params=22
	[9] soi	Etmax :	in=[2]	out=[2]	params=0
	Predict	tors: N			Parameters=N*10+252

Eully Connected Neural Network

FULLY INTEGRATED SENSOR NODE: VIRTUAL MACHINE





- Programming Language: High-level Basic!
- Input: Text (single statements and program code)
- Fast tokenstream compiler with optimization and code compaction (two-pass compiler)
- Single-step compiler and execution loop (live in harmony with main IO loop and host appliaction)
- Event-driven preemptive processing
- Very low resource requirements: < 14 kB RAM

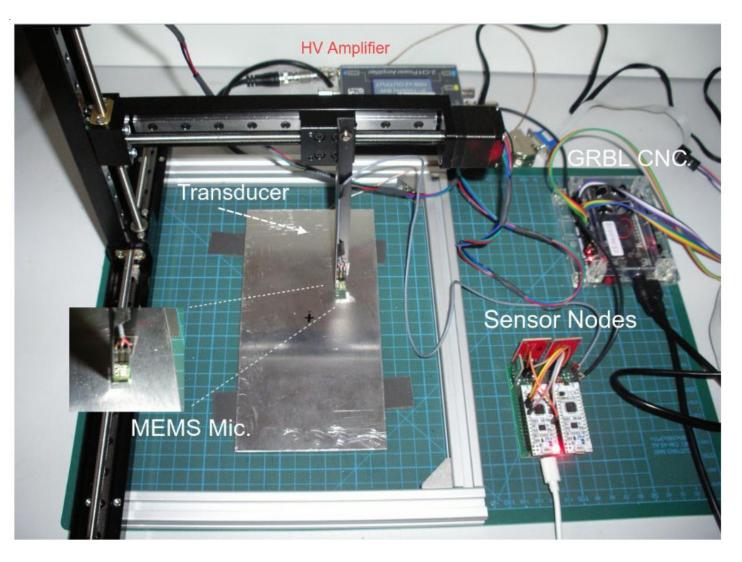
Programming Features

- Event handler
- Error handler
- Extended I/O
- Math

- Vector operations for Tiny ML
- 16 Bits data width (Int 16)
- can be easily extended
- C Call API

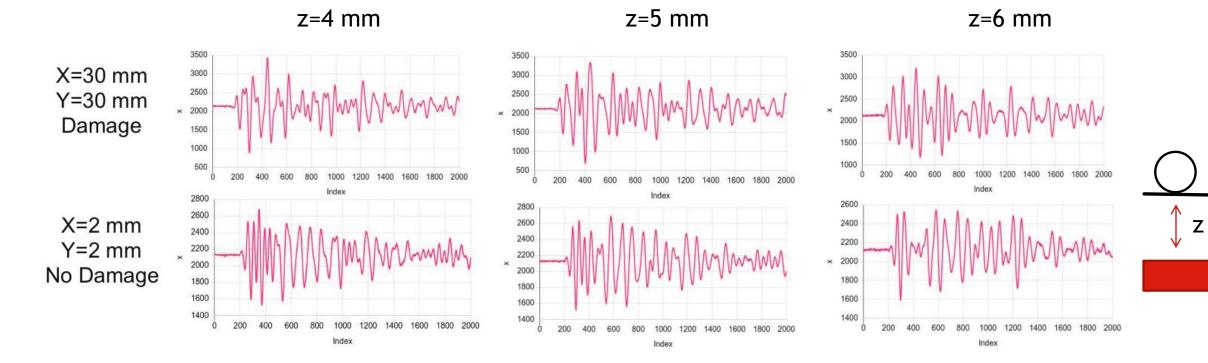
AIR-COUPLED SCAN TECHNIQUE

- Proof-of-concpet: Experimental data acquisition to evaluate the damage prediction model (ML)
- The experimental prototype: The 3-dim. portal arm device with a mounted MEMS microphone and the test plate.
- On the lower right side there is an experimental demonstrator consisting of two sensor nodes and the amplifier cascade circuit.
- On the upper right side there is the GRBL CNC controller driving the portal arm machine
- The transducer is mounted on the down side of the plate and driven by a highvoltage amplifier (V_{max} =40 V_{pp}, f_{-3dB} =100 kHz, G=20 dB)



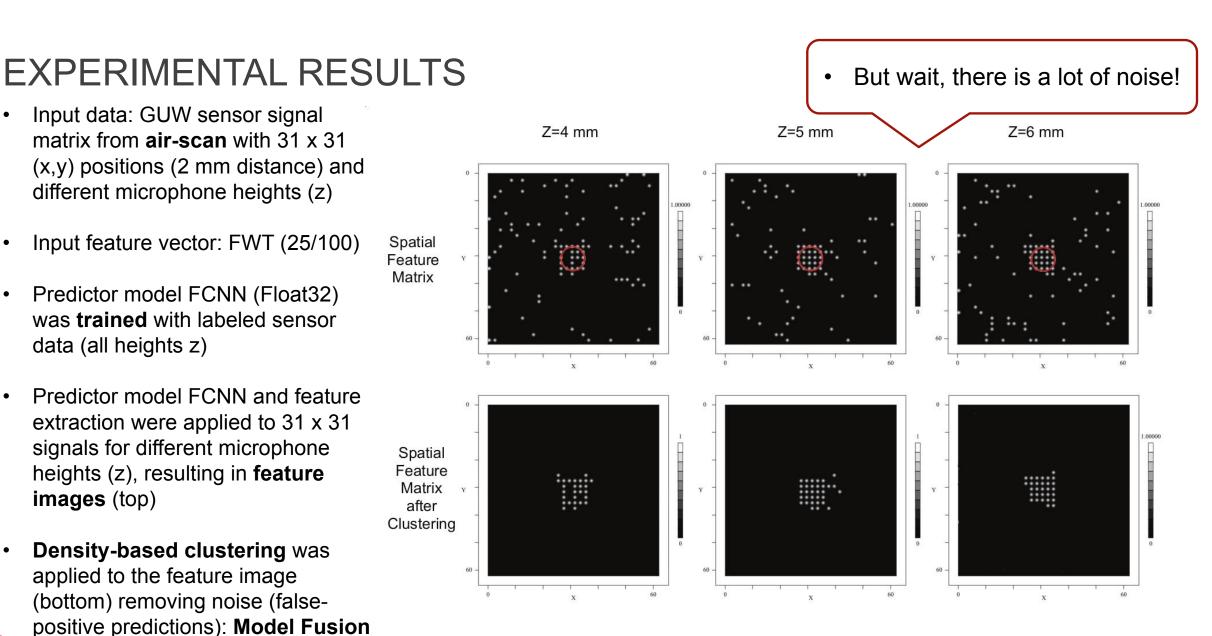


AIR-COUPLED SCAN TECHNIQUE



Sensor signals are significantly dependent on the distance from the material surface to the microphone (microphone height z)!





images (top)

university

Computer Science

obleńz

FWT: L5-N100 FCNNF32 L3[10-10-10]:tanh

EXPERIMENTAL RESULTS

	Error	F1 Score	False Positive	False Negative	Localization	
FWT=100 DT=Float32	8.3%	0.89	10%	0%	±5 mm	
FWT=25 DT=Float32	6.8%	0.90	10%	4%	±6 mm	
FWT=100 DT=Int16	8.3%	0.90	12%	2%	±6 mm	
FWT=25 DT=Int16	6.6%	0.89	10%	2.6%	±6 mm	
	Average		Variance Resso		ources:	
Hardware Signal Propagation (Node-to-Node)	3μs			<100 n	<100 ns STM	
VM Execution Time (1 Token==VMachine Instr.)	2μs			<1µs		4 kb Rom 4 kb Ram
FCNN Computation (STM32)	<100 ms			-		
Signal Recording	12 Bits, 2MS/s, 2000 points (1ms)			-		



Only proof-of-concept study!

CONCLUSIONS

Air-coupled MEMS Microphone and GUW	Distributed Sensornetwork	Distributed ML
 Contactless GUW monitoring Small size Easy integration, high miniaturizatiob 	 Fully Integrated Sensor Node with low-resource microcontroller (STM32): Less than 64kB ROM and 20 kB RAM Chain- or mesh-grid network 	 Each sensor node records a GUW signal, performs a Wavelet transformation, and predicts the local state using a simple FCNN model trained off-line
 Ultrasonic frequency response 30-80 kHz 	 Synchronization is performed via hardware signals and messages 	 False-positive rate is increased - therefore no robust local damage or
 High sensor density 1-Sensor 2D-scan or Distributed N sensor network 	 A Virtual Machine provides a Basic scripting engine, event-driven preemptive processing, signal processing (e.g. FWT) and TinyML (vector operations) 	 defect prediction is possible But clustering and global model fusion (or within a given range) improves damage predicition and localization significantly
 Signal is z-dependent and damage/defect information is time- and location dependent 	 (vector operations) VM supports single-step (single- token) compilation and execution 	 Instead gloabl density-based clustering a local neighboring approach can be used



THANK YOU

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