Hybrid SHM Sensor Network Feeding Multiple SHM Systems for Monitoring Plate-Like Structures Under Cyclic Fatigue: First Results of a Dataset Under Construction

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ABSTRACT

Several Structural Health Monitoring (SHM) technologies and approaches have been developed so far to continuously monitor the condition of a structure. They can be categorized as active and passive systems, giving different insights regarding the monitored specimen when it comes to damage detection. Regardless of the specific system, the goals are to detect, localize, and characterize emerging defects much prior to they can induce catastrophic failure. However, qualifying such a condition monitoring system is paramount to achieve industrial deployment. Nonetheless, assessing reliability of the resulting system remains a challenging task, even when resorting to standard methods such as probability of detection. In general, it is hard to simulate all the influencing factors through laboratory tests and demonstrate whether the qualification procedure can be transferred from specimen to specimen or whether it is strongly system dependent.

Having these challenges in mind, this paper presents the first few specimens of a novel fatigue crack dataset under construction recorded from a hybrid sensor network feeding multiple SHM systems based on ultrasonic guided waves, electro-mechanical impedance, acoustic emission, fiber Bragg gratings and any combination thereof. The idea of this data set is to publish it as open access in order to enable people and especially early-career researchers and students to test and explore including aspects like specimen-to-specimen variability, data merging, etc.

INTRODUCTION

For various structural health monitoring (SHM) methodologies, several established datasets are already publicly available. These datasets have provided significant value to the SHM community in the past and are still commonly used today as benchmark datasets for the initial validation of new data analysis methods. Notable examples include the I-40 bridge dataset, Los Alamos vibration data, and OGW datasets [1–3].

However, many of these datasets are focused on a specific SHM method. As a result,

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it is generally not possible to compare different SHM systems on the *same* damage scenarios within the *same* structure. In addition, long-term analyses of damage progression using alternative methods are rare.

In addition, most datasets are limited to a single structural configuration. The aspect of reproducibility is rarely addressed in detail; many studies remain at the level of a proof of concept. A notable exception is the publication in [4], in which fatigue specimens were investigated over time, and [5] where the sample to sample variability was analyzed. Within the community, there is an ongoing debate as to whether, for aspects such as sensitivity assessment (e.g., MAPOD, POD studies), it may be appropriate to perform structure-specific analyses [6–8]. For the development and validation of AI-based approaches in SHM, a large amount of training and testing data is essential [9–11]. The combination of measurements from different sensing systems is another promising research direction [12], yet currently lacks sufficient publicly available datasets.

As part of the DFG-funded project *Towards a holistic quality assessment for guided wave-based SHM*, the foundation was laid for a new data set to address these gaps. A total of 19 aluminum specimens were manufactured, each pre-damaged and equipped with an SHM system based on piezoelectric transducers. Unlike [4] with only one pair of transducers, a network of 10 transducers inspired by investigations in the OGW context was implemented. This enables a more comprehensive analysis of multiple sensor paths during post-processing. In addition, the sensors themselves were monitored using EMI measurements while stepwise fatigue tests were performed. Digital Image Correlation (DIC), a well-established non-contact technique, was integrated for periodic analysis of crack growth.

This paper presents selected results from the first three tested specimens. Section 2 provides a detailed description of the experimental setup and the measurement systems employed. Specific challenges encountered during the experimental campaign are discussed to provide practical insights for future researchers intending to conduct similar studies. Section 3 presents selected results from a specific sensor path and individual sensors, alongside an analysis of crack progression based on non-contact DIC measurements. The final analysis presented in Section 4 does not aim to fully evaluate the dataset. Rather, it provides exemplary insights into the types of evaluation that can already be conducted using this initial subset of data from three specimens.

DESCRIPTION OF EXPERIMENTAL SETUP

Samples

During the experimental campaign, 19 identical metallic specimens are tested under fatigue loading. These samples are of size 400mm length by 180mm width and a thickness of 2mm. They have been made from pure Aluminium and processed with a hole pattern in order to allow for fatigue testing as well as a 10 mm long initial crack in the centre of the plate, parallel to the width, as starting point for fatigue cracks at both sides. The SHM system consists of total 10 transducers of 10mm diameter and 2 mm thickness; 5 transducers of type PIC255 above as well as below the crack. These transducers are attached to the plate with vacuum sealing and an increased bonding layer including copper mesh in order to realize good energy transfer and at the same time reduce the risk of sensor damage during fatigue testing.

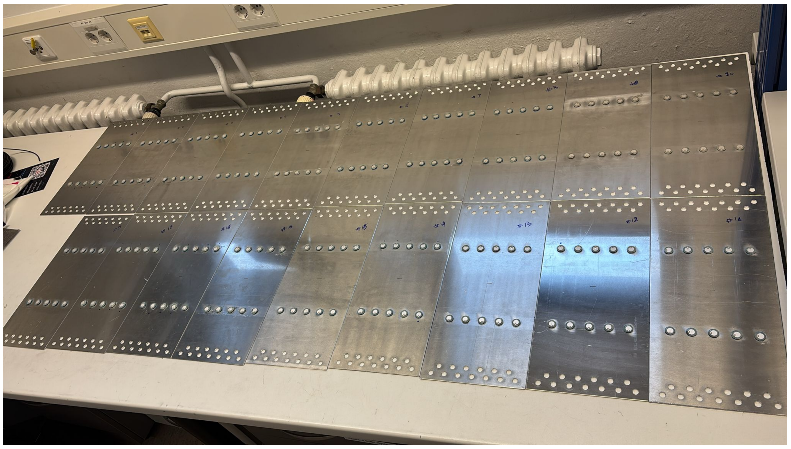
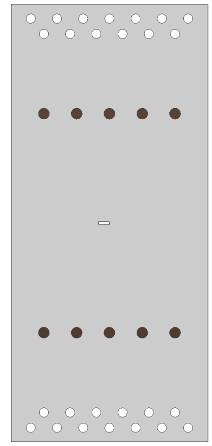
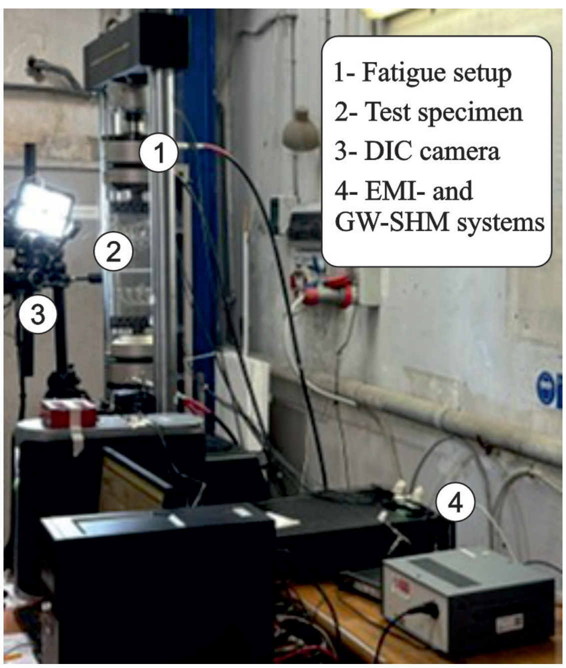
a)  b) 

Figure 1. (a) All samples with attached transducers, b) sketch of the sample setup

SHM system measurements and fatigue testing setup

Each specimen is tested in a servohydraulic fatigue testing system, Instron 8801, with 100kN load capacity. The overall setup connecting fatigue facilities and SHM systems to the specimen is depicted in Figure 2 along with an enlarged view of the cabled transducers.

a) 

b) 

Figure 2. Specimen under fatigue test. a) Overall setup, b) specimen detail

These transducers are used for guided wave testing in intervals before and during fatigue testing campaign. The transducers adopted are connected to a data-center acquiring both loads and transducers signals [13]. As input signal, a Hann-windowed sine with 5 cycles and a five different test frequencies has been used; 80kHz, 120kHz, 140kHz, 150kHz and 160kHz. Each excited frequency has been repeated 3 times. Additionally, some samples are equipped with local measurement using fibre optical sensors, but the results have not been analyzed for this first data analysis. EMI measurements have also been conducted periodically for all sensors in order to validate that the sensors did not deteriorate and still work properly, [14].

Table I describes the intervals, for which data exists for the three tested samples:

TABLE I. The number of cycles and the maximum load applied for each Structural state state

Structural state #	No cycles	Load KN
1	1000	23
2	20000	23
3	30000	23
4	40000	23
5	50000	23
6	60000	23
7	70000	21
8	75000	21
9	85000	21
10	90000	19
11	95000	18
12	100000	18
13	105000	17

The load and number of cycles are set to enable crack onset and keep a stable propagation. The fatigue test has been conducted in a way that a baseline was measured before testing and a first measurement after the first 1000 cycles also showing the potentially undamaged state. After 60000 cycles the load was reduced in several steps in order to slow down the crack porpagation speed. As pure Aluminum had been used, the maximum amplitude in order to not cause plastic deformation is relatively low. In addition the toughness of this material is very high. Therefore the time needed to generate first cracks due to fatigue is relatively high. Other alloys like Al6061 simplify this process due to higher $R_{p0,2}$ and lower K_{Ic}.

As soon as the crack starts to grow, both the damage onset from the tip of the crack and crack growth are monitored through the SHM systems using different approaches and non-destructive testing based on optical techniques, i.e. digital image correlation. As a result, the measurements return a real data set with additional information about the structural state which enables comparisons of evaluation methods on a mutual basis. Indeed, the aim of the experimental campaign is not only to ensure that detection of damage is possible with such systems once it occurs, but also to provide structured data for a comparative qualification among different techniques using probability of detection and show system dependencies in assessing reliability thereof.

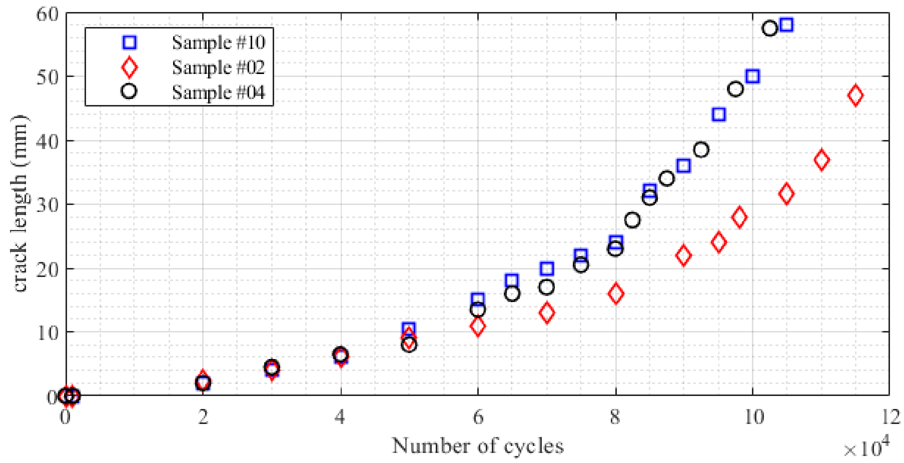


Figure 3. Crack onset and growth during fatigue test

RESULTS

Crack propagation

Crack onset and following growth during fatigue test is monitored via detailed visual inspection by magnifying glass and intense light. The results obtained on the three specimens are resumed in Figure 3. The crack length is referred to the sum of cracks occurring on the left and right side of the initial intake. Results show that at least 20k cycles are needed for crack onset and propagation of 1mm length per side, which is barely visible. Afterwards, there is a stable propagation till 60k cycles, when load reduction is need to avoid unstable propagation. Even reducing the load, after 80k cycles crack growth gets much faster with a clear increase of the curve slope.

DIC - digital image correlation

The analysis of the ongoing crack using DIC shows that this method is very much useful to be used as a reference for measuring the crack length. Figure 4 shows an increasing crack in four different damage states. The DIC on the left corresponds well to the almost invisible crack on the right side.

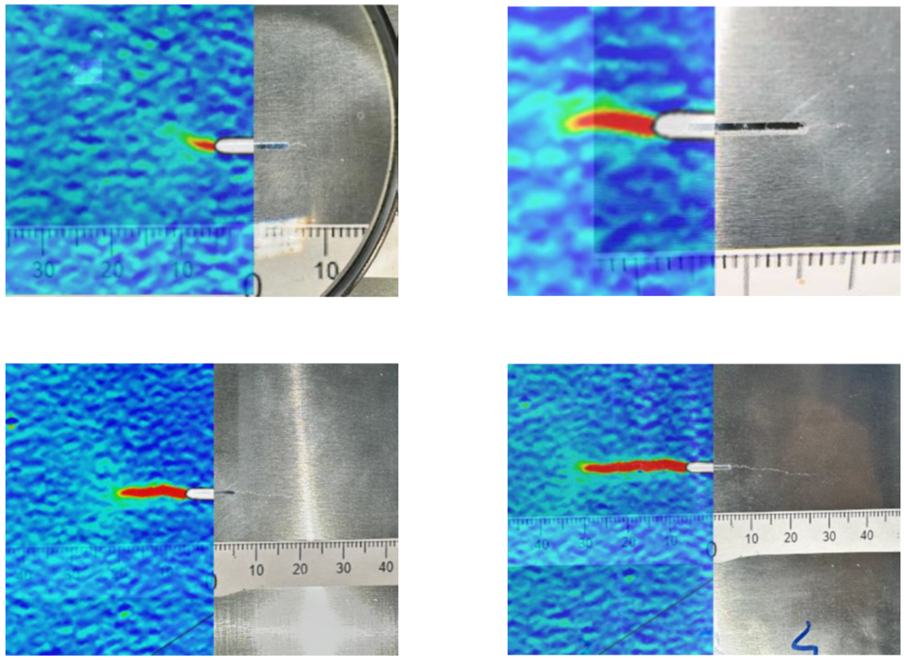


Figure 4. DIC analysis of growing crack

It is important to note that since the system is symmetric around the vertical axes, the crack propagation on both sides of the crack tip is almost equal. On top of that, the DIC has the capability to also show the plastic deformation around the crack tip, providing a more detailed information about the actual damage status.

EMI - electromechanical impedance spectra

The EMI measurements show that all transducers, used, are intact for the whole testing interval. Figure 5 shows the smoothed EMI spectra of one sensor position of all three samples for all tested steps. The three sensors exhibit different spectra, which due not change over testing period. It can be seen that no sensor degradation or attachment degradation was caused by the growing fatigue in the plate. It needs to be mentioned, that at least one of the 15 EMI spectra under test has been corrupted for sample 2, which was not the case for sample 10 and sample 4. Additionally, the data shows that although all sensors have been attached to the coupons in the same way, the spectra exhibit significant differences. This is especially the case for sample 4.

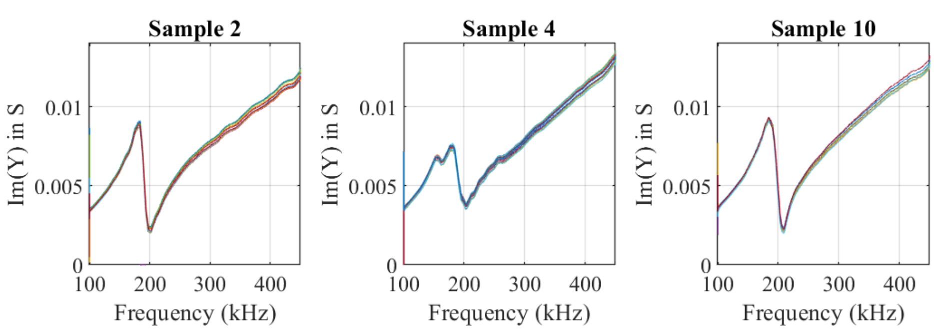


Figure 5. Susceptance spectra of all three samples over testing period

A detailed analysis on the influence of the growing crack regarding the EMI spectrum is not possible with the data as the frequency resolution has been chosen for sensor self-test purposes and the chosen features did not include the fully complex impedance spectrum.

GW guided wave signals

The GW measurements show that the damage has significant influence on the pitch-catch signals. Figure 6 shows the exemplary analysis of path 03 - 09 on sample 10, not showing the crosstalk at the beginning. This path crosses the crack on the right side of the notch. It can be clearly seen that the signal of this path is influenced by the growing crack.

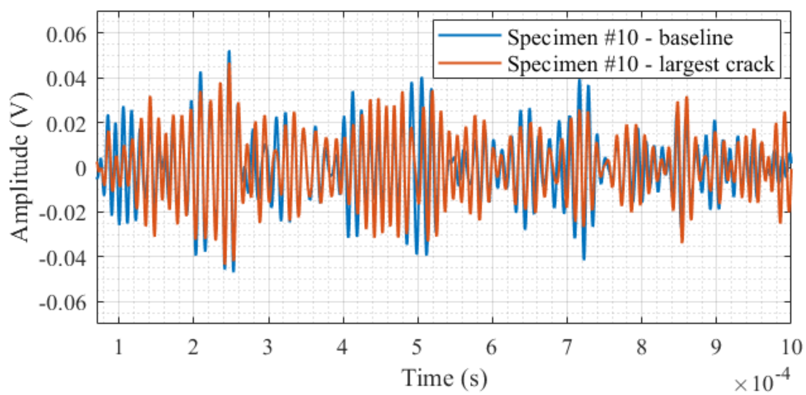


Figure 6. raw time data signal of sample 10 path 03 - 09

To give a first impression on what can be tested with this data, figure 7 shows the correlation coefficient CC as the damage indicator $DI_{CC} = 1 - CC$ over crack size.

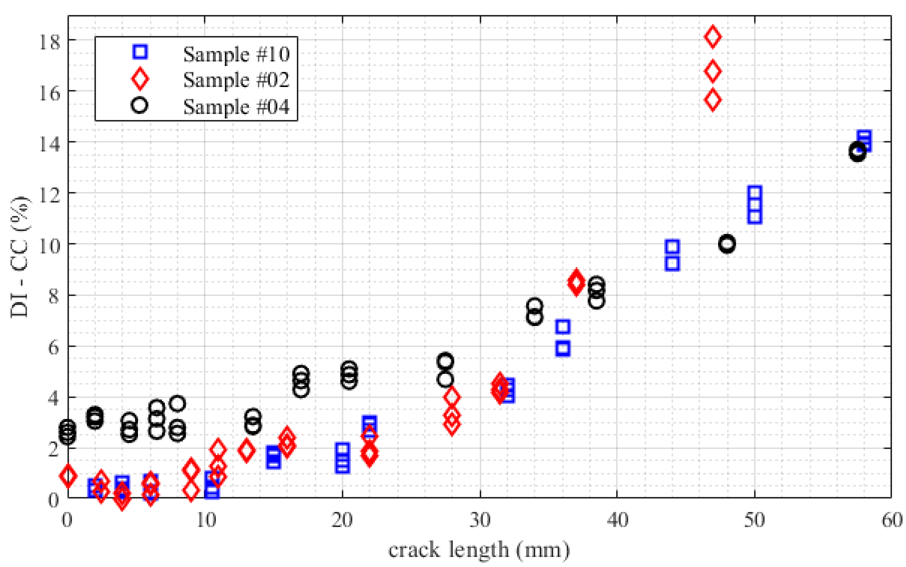


Figure 7. data analysis using DI=1-CC for path 03 - 09

The data clearly show that the three samples behave slightly differently. While samples 2 and 4 share a common level of noise, sample 10 exhibits a higher level of noise. With increasing damage size, sample 10 and sample 04 show a similar trend on the increase of DI_{CC}, while for sample 02 the damage size increases significantly more than for the other two. With the data set, it can be tested whether for the own damage algorithm the usefulness and necessity of sample-individual POD analysis is given.

CONCLUDING REMARKS

This paper gives insight into the first results of an experimental campaign in which crack onset and growth in a metallic plate are monitored via a variety of NDT and SHM solutions. The latter ones consist of a sparse transducer array for EMI and GW inspection as well as strain monitoring. This allows achieving multisensory information, which can be fed into a data fusion and multi parameter diagnosis and prognosis tool. It allows to be used to feed learning algorithms for damage characterization and residual useful life estimation, as well as data fusion approaches, paving the way towards consolidation of reliability assessment techniques for complex SHM architectures. As to this last issue, the first results show good repeatability of the test which is not necessarily connected to perfect repeatability of SHM results, motivating the need for a detailed reliability assessment framework. Other tests and data processing will be carried out based on the lesson learned so far.

The collaboration of the authors was supported by the DFG within the Scientific Network *Towards a holistic quality assessment for guided wave-based SHM* (project number 424954879). The samples haven been manufactured in Bochum, the sensors have been glued in Braunschweig, the fatigue tests have been conducted in Naples with equipment and man- and woman-power from Bochum, Braunschweig, Karlsruhe, Naples and Bologna. The authors would like to express their gratitude to Daniel Schmidt from Braunschweig for his valuable insights during preparing the samples, Lorenzo Esposito from Naples for carrying out DIC inspections, Francesco Falcetelli for the FBG measurements, and Anastasiia Volovikova from Karlsruhe for supporting the experiments and aiming to reuse the results for future AI-based analysis.

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