




Crack detection through spatio-temporal pattern recognition

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Crack detection through spatio-temporal pattern recognition

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Outline

- 1 Introduction
 - The challenge of defect localization
 - Outline of investigated methodology
- 2 Use-case
 - Simulation setup
 - Pre-processing
 - Feature Extraction
 - Filtering strains explained by macroscopic modes
- 3 Sequential Monte-Carlo estimation
 - Algorithm outline
- 4 Defect identification results
 - Defect localization
 - Discussion

Problem statement

Motivation

- Localized (small) faults have a limited effect on the global modal characteristics of the structure
- Local patterns of strain due to faults may allow for detection of (small) faults without prior knowledge of the undamaged response

Assumptions

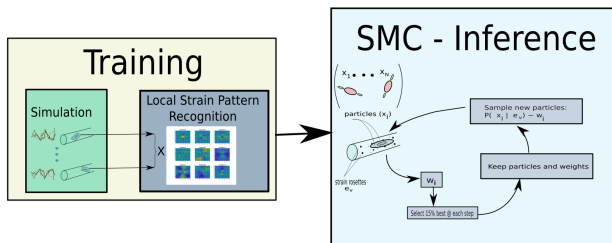
Assumptions

- A **small** structural defect (i.e a small crack), affects the strain field (predominantly) around the region of the defect and to a limited extent globally.
- It is possible to approximate local strains as a superposition of *healthy* and *defect-related* responses.

Problem statement and proposed methodology

Proposed methodology

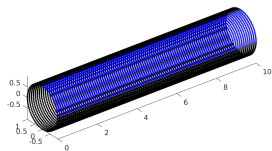
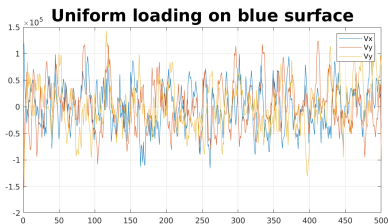
- 1 Simulate for random loads and random defect parameters and yield the local strain field around a crack
- 2 Construct parameterized features that match well with spatial patterns of strain when a defect is present (i.e. through Principal Components Analysis)
- 3 Filter out irrelevant information for crack localization
- 4 On an arbitrary structure, under arbitrary loads, approximate the probability of the existence of a particular defect, corresponding to a set of defect parameters
- 5 Estimate feature probabilities sequentially by employing incoming measurements (Sequential Monte-Carlo).



Simulation setup

In order to obtain features that have the potential to perform well, independently of external loading and crack configuration, we need a rich sample, **spanning the cases** we hope to generalize over. To demonstrate the concept, the following simulations were run:

- 30 hollow steel tubes, containing a single random crack-like defect, supported on one end with length 10m and diameter of 1m were simulated (in time domain and in 3D).
- The crack-like defects, are of randomly sampled lengths and are randomly positioned and oriented for every simulation run (each 1 second).
- Gaussian white-noise excitation, different for every run is used along 3 directions (different random loading on each direction).



Spatial Feature Extraction for Crack Detection

General considerations:

- It is assumed that the patterns associated with the defect, vary linearly for small variations of the crack geometry. In the use-case presented in the following this is expected to approximately hold.
- However, the individual components of strain depend on the orientation of the strain rosettes.

Pre-processing:

- Exploiting properties of strain measurements:
 - A **rotationally invariant** measure of strain is needed for pattern matching
 - For this study, only the **volumetric strain**, estimated from the surface of the tube was used.

Spatially Localized Feature Extraction for Crack Detection

Pre-processing: Data need to be in an appropriate format in order to be analyzed with PCA.

- The (known) crack parameters are used to scale and rotate the strain field around a patch of length equal to 3 times the length of a crack with unit length (arbitrary choice)
- The strain field is interpolated on a 30x30 grid

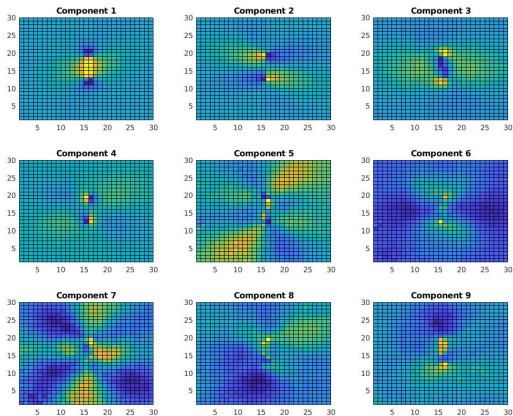
Principal Components Analysis

$$\epsilon_v^{PCA}(t, x_l, y_l) \approx \sum_{n=1}^N P_n(t) F_n(x_l, y_l) + \bar{\epsilon}_v(t, x_l, y_l) \quad (1)$$

Where t denotes time, and x_l, y_l position on the defect-local grid.

PCA features

PCA volumetric strain features for damage localization



Filtering strains explained by macroscopic modes

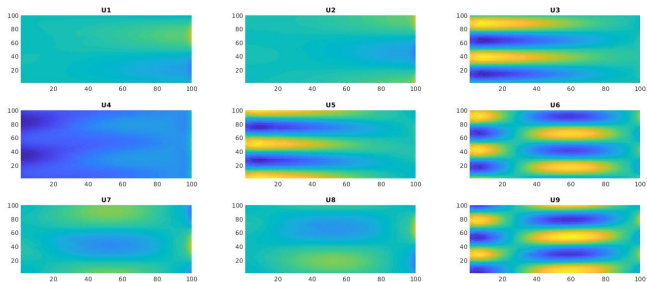
Volumetric strain due to macroscopic, non-localized vibration modes:

- Strain eigen-modes obtained from the SVD of randomly sampled snapshots of the global strain from the whole ensemble of simulations (different crack geometries and positions).
- The effect of these modes is removed by projecting the measurements from a sparse network of sensors to the spatially smooth basis obtained by the randomized SVD.

$$\underbrace{U}_{(N_{grid} \times N_{grid})} \underbrace{\Sigma}_{(N_{grid} \times N_t)} \underbrace{V}_{(N_t \times N_t)} = \underbrace{\mathbf{X}_t}_{N_t \times N_{grid}}$$

Basis for smooth (global) response

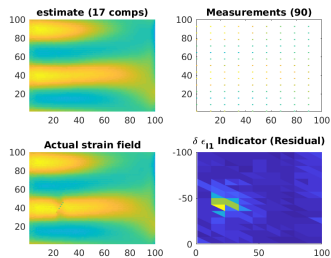
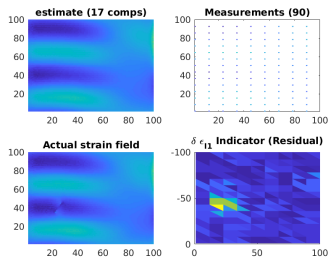
derived basis for the approximation of volumetric strain: Strain modes $U_i(x, y)$ are visualized:



Spatial patterns of 1st rot. invariant of strain (volumetric strain)

Removing the non-localized strain

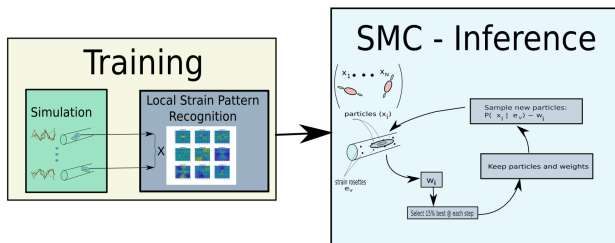
Spatial patterns of volumetric strain derived from projection to randomized SVD space:



Problem statement and proposed methodology

Proposed methodology

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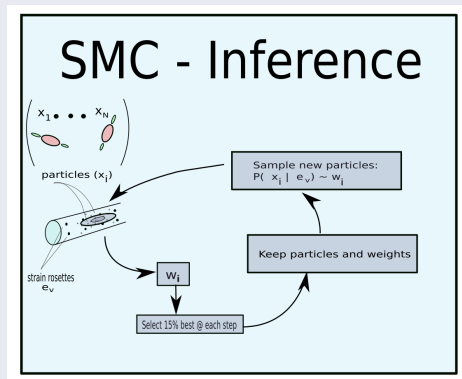


Particle filter - basic components

We need to incorporate the sensor information in order to sample from the parameter space of crack positions and orientations. Since there may exist multiple cracks, the sampling procedure should be flexible enough in order to capture multi-modalities.

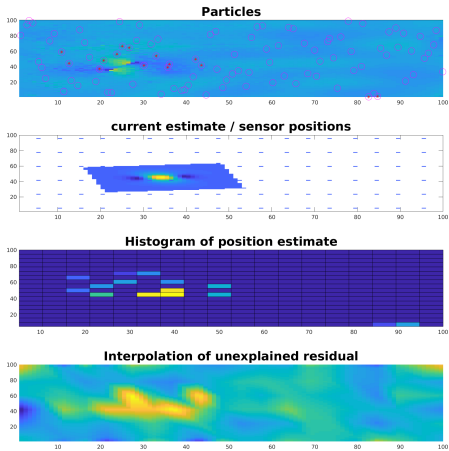
Particle filter

Representation of the probability of the parameters:



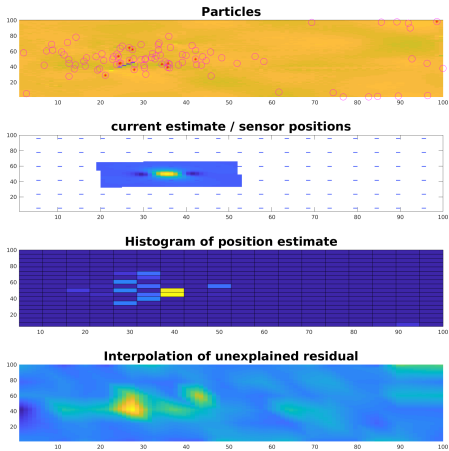
Results

Timestep 1



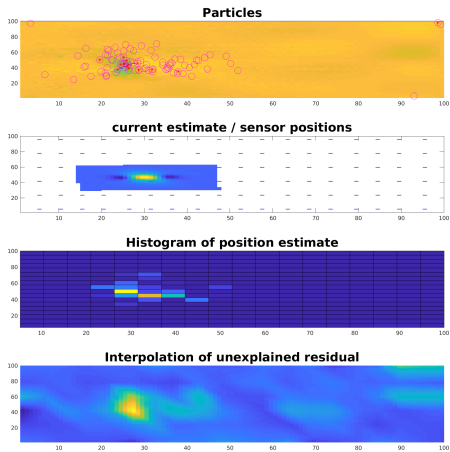
Results

Timestep 2



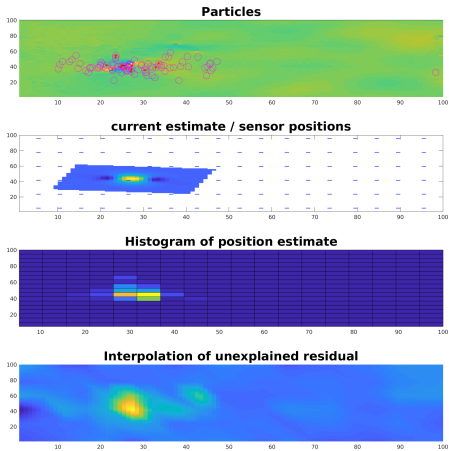
Results

Timestep 3



Results

Timestep 4



Discussion of results

Results

- PCA/SVD do yield useful features for localization of cracks
- While using such features it is important to have a way to filter out the "healthy" strain field first
- the Monte-Carlo strategy employed affects drastically the results!

Possible improvements

- PCA is a matrix factorization (linear)- it may be possible that other alternatives (functional PCA, autoencoders) yield better features. Moreover, PCA is not expected to generalize well for larger cracks (the patterns of strain are expected to depend in a non-linear manner on the parameters of the crack).
- The sequential Monte-Carlo procedure could be greatly improved by better proposal distributions
- Low rank factorization of the full strain sensor was also considered, but it unnecessarily complicates the incorporation of mechanics of materials in the process of feature extraction (i.e. rotational invariance of strains).

Acknowledgement



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