Damage detection and localization in pipeline using sparse estimation of ultrasonic guided waves signals

Mahjoub El Mountassir[†,‡], Gilles Mourot[†], Slah Yaacoubi[‡], Didier Maquin[†]

[†] Research Center for Automatic Control of Nancy (CRAN)
54500 Vandœuvre, France

[‡]Institut de soudure, Plateforme RDI CND
57970 Yutz, France

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- These structures are subject to variation of environmental and operational conditions (EOCs) which have an impact on the collected signals
- The effects of these EOCs could be similar to those produced by damage. This would result in false warnings. The differentiation between the aforementioned types of changes is a challenging task.

Experimental test bench

Tube with 6.4 m length placed in laboratory conditions where temperature fluctuates between 19˚C and 26˚C during the monitoring period.

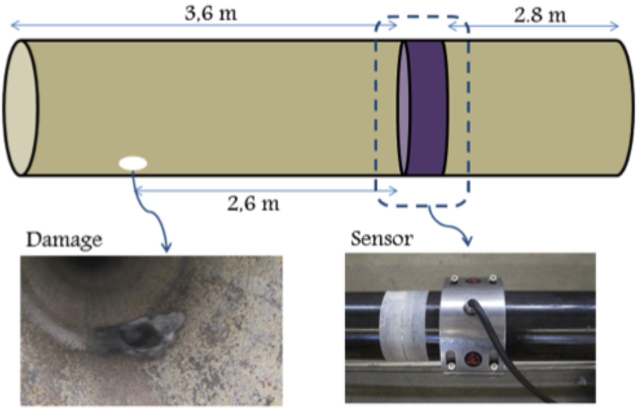

FIGURE – Test bench

The used sensor (Ultrasonic Guided Waves - UGW) can excite two separate guided waves modes which are : torsion and flexion at five different frequencies : 14, 18, 24, 30 and 37 kHz.

Data collection and preprocessing

- The tube has been monitored during a period of almost 3 months.
- Each week, multiple measurements were scheduled.
- At each measurement, five signals were acquired in the morning and at the evening in order to capture temperature changes during the day and to investigate its effects on the collected signals.

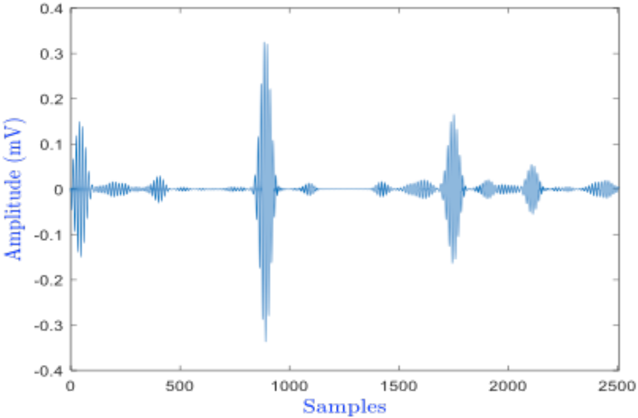

FIGURE – Ultrasonic guided wave signal excited with torsion mode (frequency : 14 kHz).

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Reference state	207 signals
Damage state	6 increasing defects (29 signals)
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- These echoes have to be removed also from the original signal because they are not useful for damage detection.

Experimental test bench

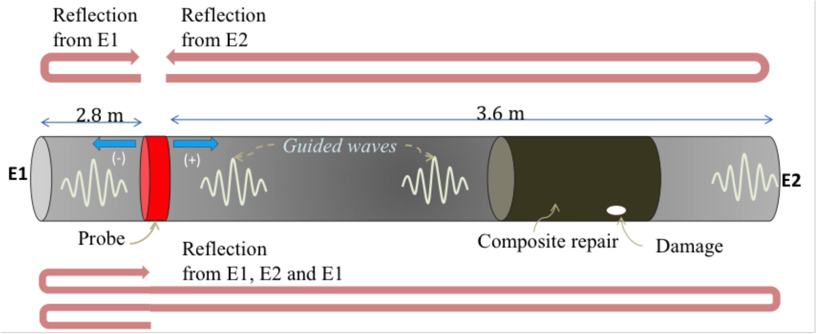


FIGURE – Propagation of guided waves

Recorded signal

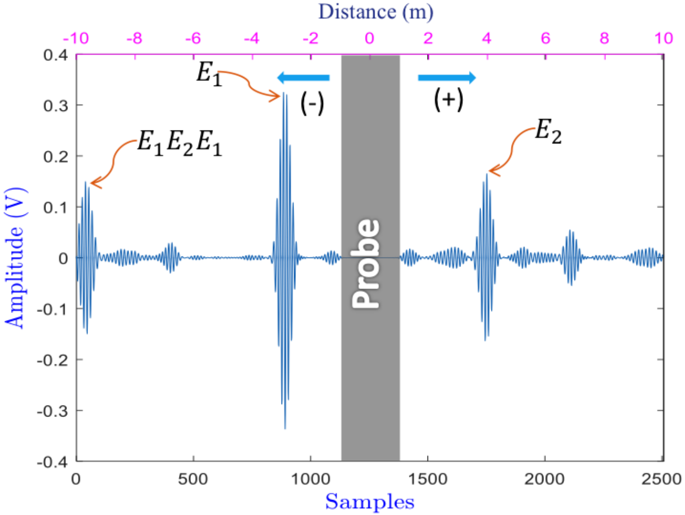
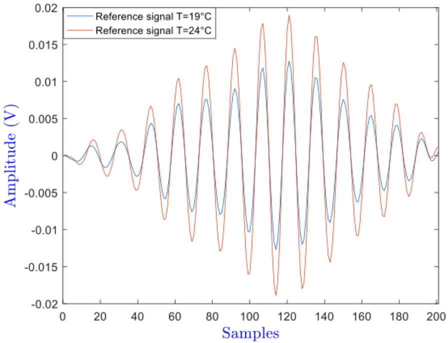


FIGURE – Torsion mode at 14 kHz

Temperature effect vs damage occurrence



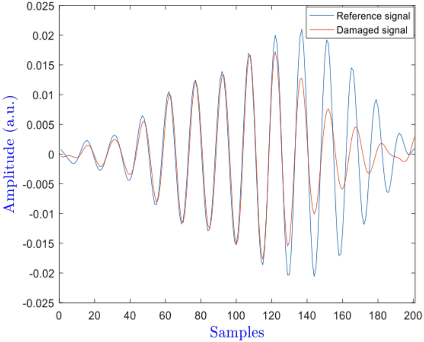


FIGURE – Right : acquisition at two different temperatures ; left : superposition of a healthy signal and a faulty signal

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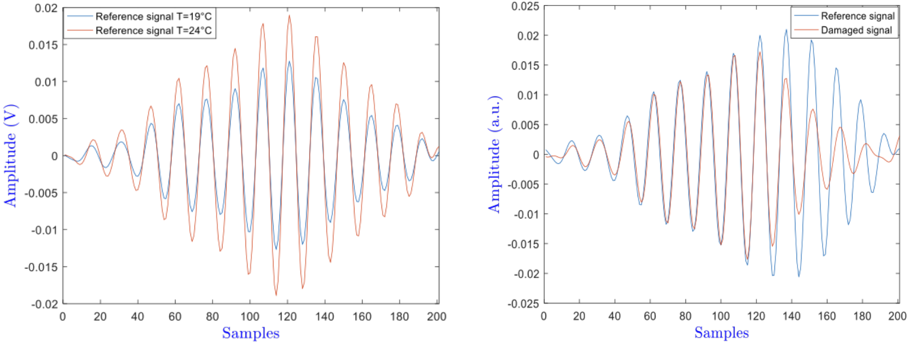

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Difficulty in differentiating the two causes

Proposed treatments

First attempt

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- ✓ One class SVM or Neural Networks
  $\rightarrow$ Fairly poor discrimination (insufficient with regard to the specifications)

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- ✓ When a new signal is acquired, we try to express it as a linear combination of the signals of the reference database
- ✓ The estimation error is then analyzed and, depending on its amplitude, it is decided whether it is a signal coming from a healthy structure or from a damaged structure

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Mathematically

$C \in \mathbb{R}^{m \times n}$: matrix of n reference signals of dimension m

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Search for the optimum

$$\hat{\theta} = \arg\min_{\theta} J(\theta)$$

$\rightarrow$ over-learning : even if the estimation error grows
a faulty signal is “correctly” estimated

that’s explained by multiple compensations between the different signals in the database

Observation

If the reference database is exhaustive, a signal acquired with given environmental conditions should be explained using reference signals acquired according to these same environmental conditions

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Difficulty : choice of the regularization parameter λ

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All the signals in the reference database are strongly correlated

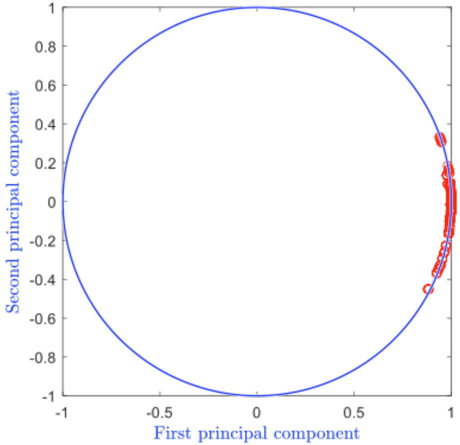

FIGURE – Image of correlation coefficients of reference signals (PCA)

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Here, we have chosen to use the active set method[2] because a recursive version of this method can be easily implemented (details in the communication).

This will be used later for the purpose of localization of damage.

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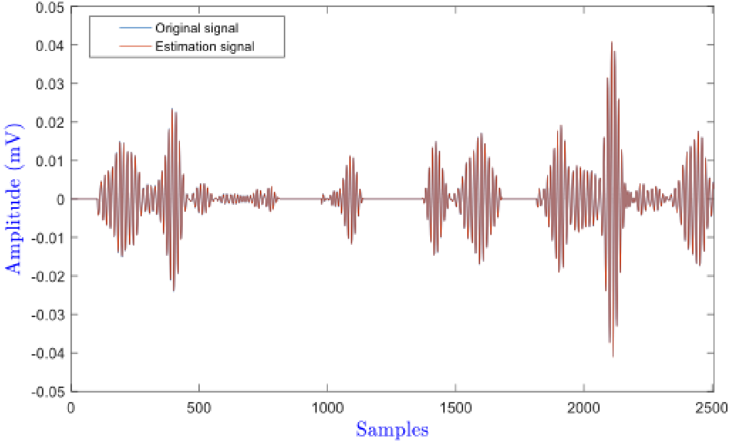

FIGURE – Estimation of a signal from a healthy structure

Results

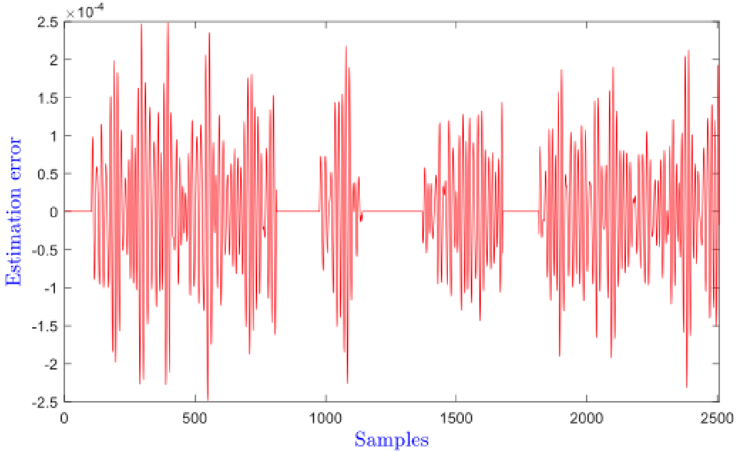

FIGURE – Estimation error of a signal from a healthy structure

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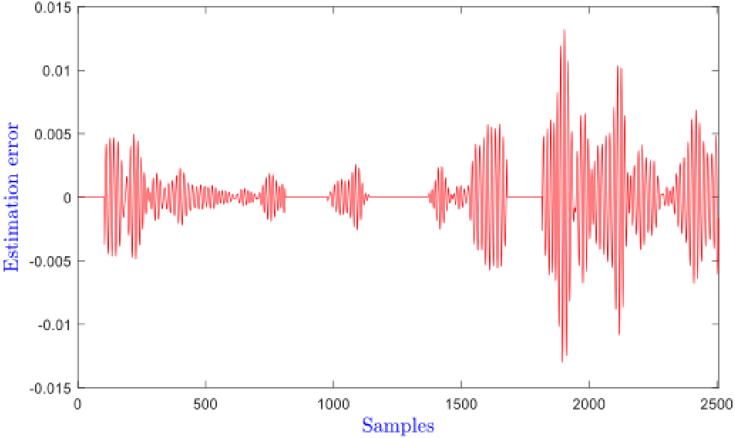

FIGURE – Estimation error of a signal from a faulty structure

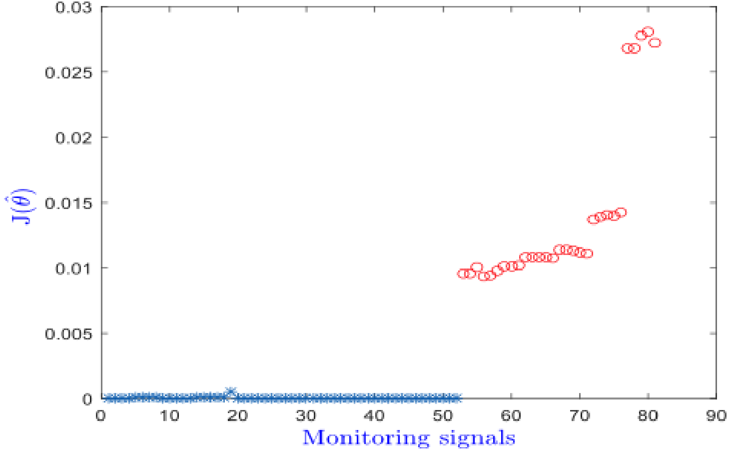

FIGURE – Quadratic estimation error $J(\hat{\theta})$ for different signals (faulty signals in red)

The values of $J(\hat{\theta})$ increase as the size of damage increases. Thus, $J(\hat{\theta})$ can be used to assess the severity of damage.

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Justification : before the wave arrives at position of the damage, it is not distorted

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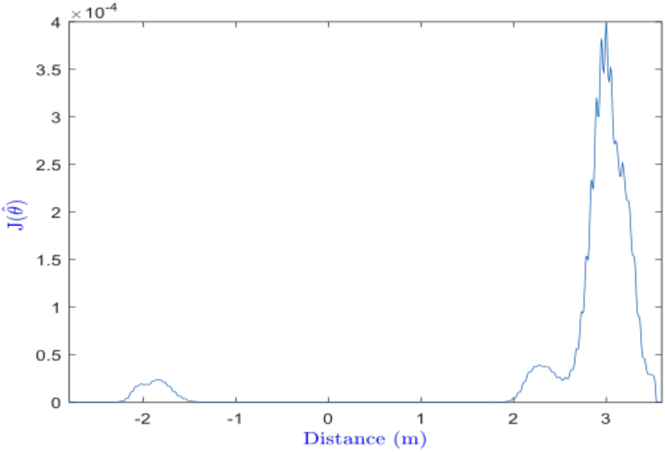

FIGURE – Quadratic estimation error $J(\hat{\theta})$ depending on the position of the window

Localization result : $D = 3 \pm 0.41$ m for a damage located at 2.6 m from the actuator/sensor

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- The localization of damage was established by implementing a recursive version of the sparse estimation on a sliding window over the damaged signal
- As a perspective of this work, an update of the database of reference signals could be considered in the case where these signals present limited variation in EOCS

Who am I ?

Didier Maquin

Professor of Automatic Control
Université de Lorraine

Ecole Nationale Supérieure d'Electricité et de Mécanique

Ecole Nationale Supérieure des Mines de Nancy

Centre de Recherche en Automatique de Nancy

Contact : didier.maquin@univ-lorraine.fr

More details ?

Personal web site : `http://www.cran.univ-lorraine.fr/didier.maquin`

Laboratory web site : `http://www.cran.univ-lorraine.fr`