



Première journée nationale SHM-France

Accuracy of flaw localization algorithms: application to structures monitoring using ultrasonic guided waves

Alain Le Duff

Groupe Signal Image & Instrumentation (GSII), Groupe ESEO, Angers, France Laboratoire d'Acoustique de l'Université du Maine (LAUM UMR CNRS 6613), Le Mans, France

Who am I?

- Alain Le Duff, Ing., PhD, HDR
- Teacher-researcher at ESEO, Angers, France
 - Head of the Department of Electronics and Control Engineering
 - Member of the « Signal, Image & Instrumentation Group » (GSII)
- Research fellow at LAUM, Le Mans, France
 - Instrumentation and signal processing for acoustics
 - Field of applications : LDV, Musical acoustics, ENDT, SHM



LAUM

NDT & SHM: Work context



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SHM Work context

- Guided waves (Lamb modes) in "plate" type structures;
- Use of active ultrasound method;
- Flaw localization in plate structures.



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- 2 examples
 - 1. Damage localization estimation

1. Temperature estimation

- 2 examples
 - 1. Damage localization estimation



1. Temperature estimation

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 - 1. Damage localization estimation



1. Temperature estimation



Example #1: damage localization in a plate

Context

- Array of piezoceramic sensors and actuators
- TOF measurements

• Localization accuracy depends on

- Spatial distribution of the transducers
- Signal to Noise Ratio (SNR) of acquired signals
- Defect location itself
- **Proposition**:
 - Study of the of damage localization \rightarrow CRB
- Experimental assessement of CRB in an aluminium plate using Guided Waves (GW)

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Problem:

- damage localization
- Isotropic plate
- guided waves
- TOF
- Array of 3 transducers distributed on the struture.









Accuracy of localization estimation #2

Errors in time delay estimation \$\$\screwt\$\$ error on damage position estimation

 $(\boldsymbol{x},\boldsymbol{y})$

Accuracy of localization estimation #2



Accuracy of localization estimation #2 Errors in time delay estimation \downarrow error on damage position

Uncertainty area (extend of error) \checkmark Accuracy of the time delay measurement σ_t^2 (estimation variance)

estimation

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(x, y)

 $f(\sigma_t)$

(

Accuracy of localization estimation #3

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• Give a lower bound for the covariance matrix of any unbiaised estimator

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- Provide a benchmark against which the performance of estimators can be compared
- In this work: the CRBs give an indication on the *a priori* accuracy of the localization procedure

Observed data: $t_1 = \tau_1 + n_1$ $t_2 = \tau_2 + n_2$

Hypothesis : n_1 and n_2 are independent White Additive Gaussian Noises (WAGN)

Time delay estimations variances

$$G_1(x,y) = \sqrt{d_{1a}d_{1s}} \quad G_2(x,y) = \sqrt{d_{2a}d_{2s}}$$

$$\sigma_{t_1}^2 \propto G_1^2(x, y) \cdot \sigma_v^2$$

$$\sigma_{t_2}^2 \propto G_2^2(x, y) \cdot \sigma_v^2$$
Additive noise variance

$$CRB(x) = c^{2}\sigma_{t_{1}}\sigma_{t_{2}} \cdot \frac{K_{21}^{2} + K_{22}^{2}}{(K_{11} \cdot K_{22} + K_{12} \cdot K_{21})^{2}}$$
with
$$K_{21} = \frac{y - y_{0}}{d_{1a}} + \frac{y - y_{1}}{d_{1s}} \quad K_{11} = \frac{x - x_{0}}{d_{1a}} + \frac{x - x_{1}}{d_{1s}}$$

$$K_{22} = \frac{y - y_{0}}{d_{2a}} + \frac{y - y_{2}}{d_{2s}} \quad K_{12} = \frac{x - x_{0}}{d_{2a}} + \frac{x - x_{2}}{d_{2s}}$$

In summary:



Numerical validation

- Statistical performance of the procedure \rightarrow illustrated by MC simulations
- Several locations of the 3 sensors



Numerical validation

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Principle of TOF measurement $\varphi^{Q}_{s_{idif}f^{s_{ib}}}$ S_{idiff} Ψ_{sidiff^sib} Sid Hilbert Transform cross-Enveloppe $\rightarrow \hat{t}_i$ maximizatior correlation estimation $\hat{\varphi}^{\mathbf{I}}_{s_{idiff}s_{ib}}$ S_{ib} t_{0i} step 2 step 5 step 3 step 4 step 1 step 6



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 $\rightarrow \hat{t}_i$







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- Performance of the estimations follows the theoretical STD
- CRBs \rightarrow good indication of the expected accuracy of a particular configuration of a SHM system
 - as a function of the geometry of a transducers array;
 - and SNR of the data acquisition.

Example #2: temperature estimation

- Context
 - Temperature estimation
 - − Scale factor estimation → CWI (Coda Wave Interferometry)



- Study of temperature change → CRB
- Experimental assessement of CRB using GW





« Historical » estimators: cross-correlation - Stretching

Scale transform based estimator

Work done

1. Study of 4 scale factor estimators (including 2 original)



Algorithmic complexity and CRB

Work completed

- 2. Algorithmic complexity study
- 3. Analytical CRB: as a function of the testing signal parameters and SNR
- 4. Validation \rightarrow Monte-Carlo simulation



Experimental validation #1

Application to aluminum

Work completed (cont'd)

5. Experimental validation (aluminum plate)

Contribution to the scientific community

- CRB → influence of parameters on accuracy
- Methods comparison
 - \rightarrow selection guide

Other works

- Application to composite materials
- Temperature compensation
 - Concrete (IFSTTAR)
 - Aluminum (GAUS)









Experimental validation #2

Application to composite material

- Material: glass-epoxy FR4
- Estimator: short-time Xcorrelation
- Temperature controlled
- Embedded transducers





```
Embedded transducer
```







15,5 15 16 Time [H]

0,05

0

variation α [%]

Velocity

-0.1

24

Experimental validation #3

- Study of the behaviour of concrete specimens under axial loading
- Temperature compensation using a reference specimen

Application to concrete

 α_{ref}

 α_{test}

16,5

 α_{e}







Conclusions

- CRBs give a good indication of the expected accuracy of a particular configuration of a SHM system as a function of
 - the geometry of a transducers array;
 - the SNR of the data acquisition.
- The approximated expression for the CRB provides a way to select optimal values for the signal parameters, especially for the sampling period