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Acoustic Emission Simulation for Online Impact Detection

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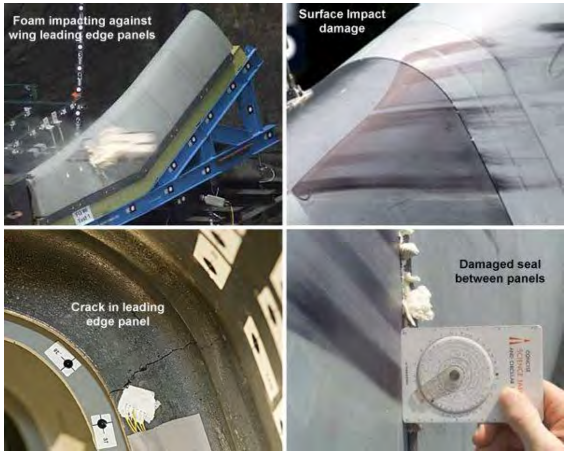
Outline

- Introduction
- Feature extraction
- Gaussian Process (GP)
- Simulation
- Results

Movitation:



Impact Damage in Aeronautic and Aerospace Structures Courtesy of NASA

Impact in Metallic Structures Courtesy of SLODIVE

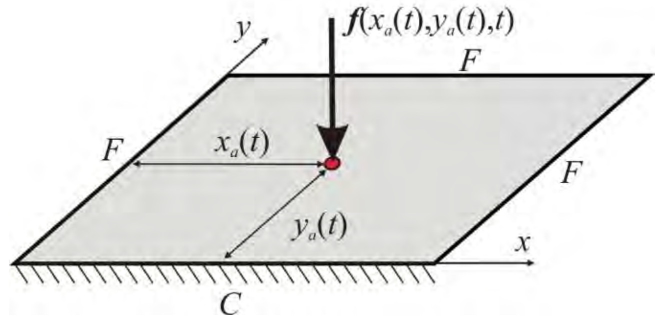
- Impact is a common source of in-service damage that compromises the safety and performance of engineering structures (civil engineering, automobile, aeronautics…)

- Online impact detection systems are essential and require automatic and intelligent techniques providing a probabilistic interpretation of their diagnostics.

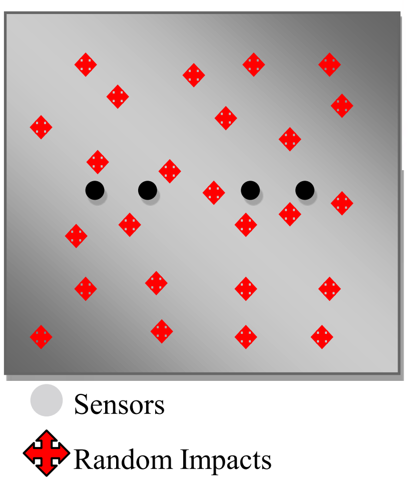
- Machine learning algorithms generally require huge amount of data, in order to make the process cost-effective, simulation of impacts has been performed to get the training data set from modeling.

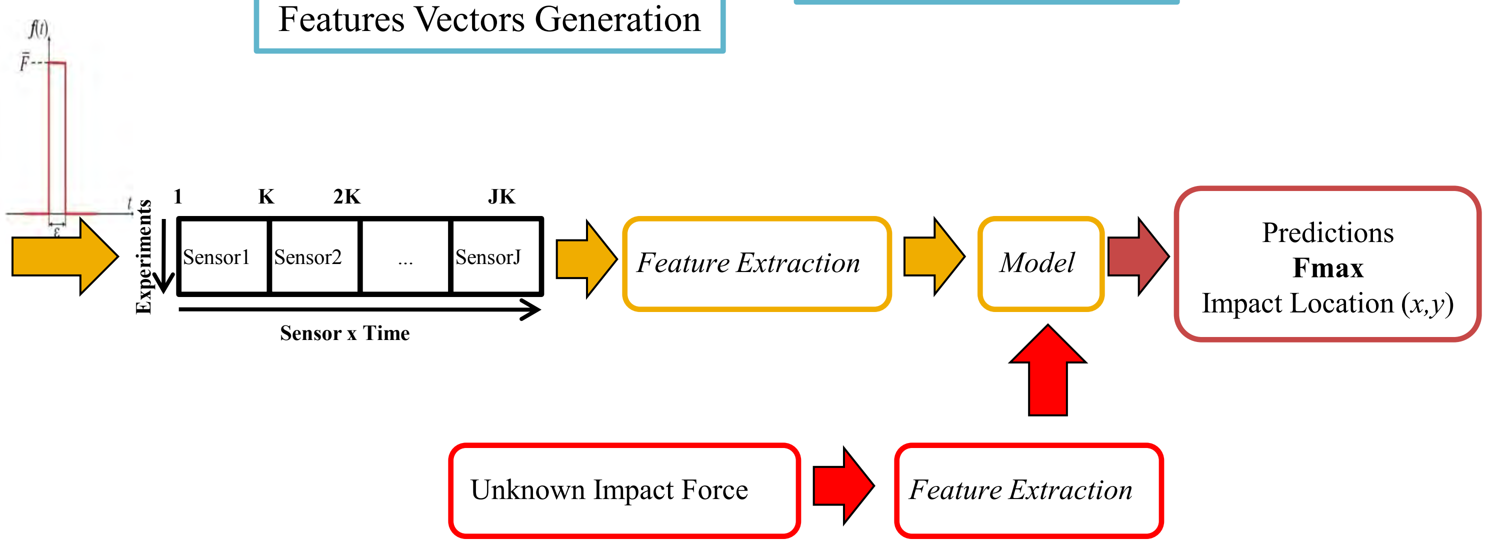
General method:

- Step1: Obtain the training data *f(x,y)*
- Step2: Signal processing and feature vectors construction
- Step3: Gaussian Models construction and Optimization
- Step4: Estimate *f(x,y)* for new inputs



Training Set Generation → Data Base Generation / Feature Extraction / Dimension Reduction / Features Vectors Generation → Model Generation / Model Optimization → Predictions

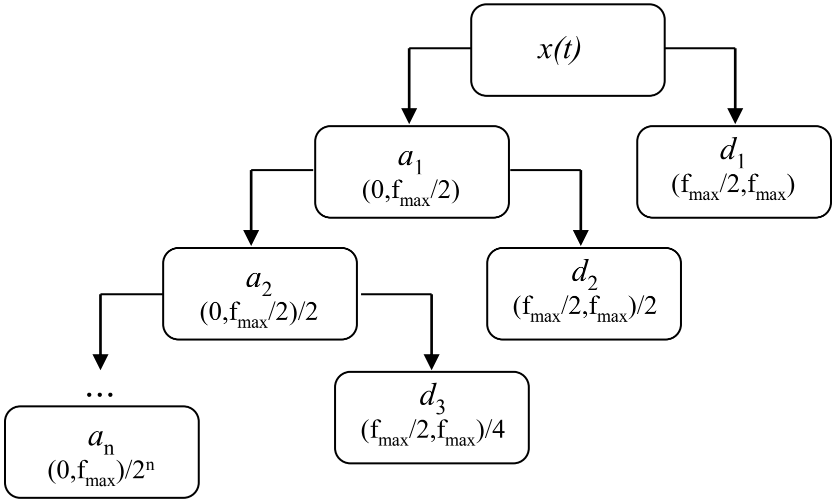




Multiresolution Analysis (MRA)

- The purpose of using the DWT is to benefit from its localization property in the time and frequency domains (Mallat, 1989)
- Relevant features can be extracted for improvement of future inferences

Two Channel Subband Coder



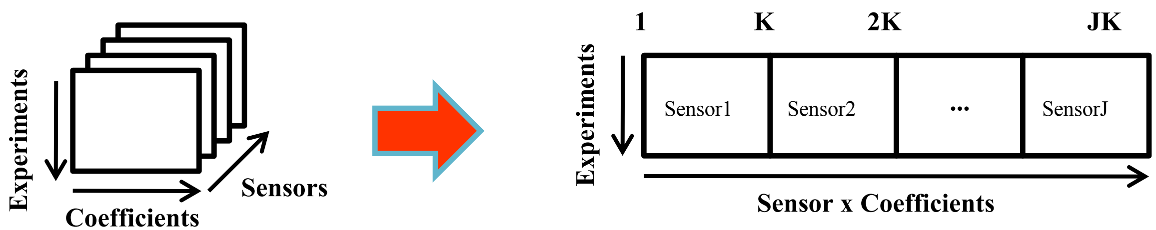
Determine the entropy content of each level a with coefficients $W_a=(w_{a,1}, w_{a,2},\ldots,w_{a,n})$

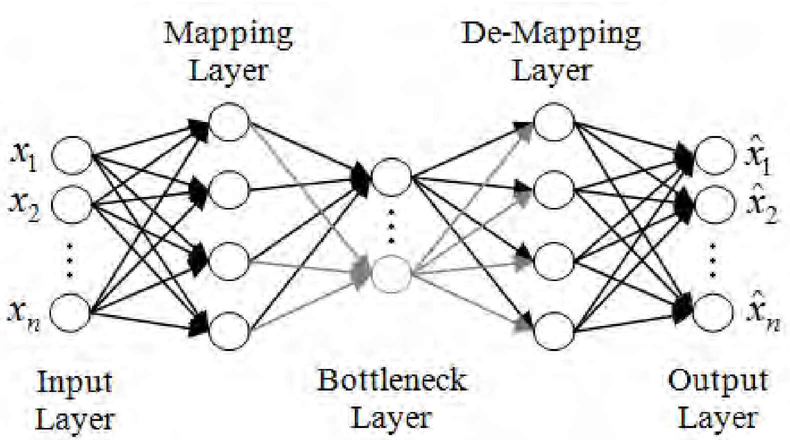
$$E(W_a)=\sum_{k=1}^{n} W_{a,k}\ln W_{a,k}$$

Select the level with the minimum entropy value for optimal decomposition

Dimension Reduction: Nonlinear Principal Component Analysis

- Multilayered perception architecture and auto-associative topology
- Retain *k* principal components based on hierarchical error (Scholz et al., 2008)
- Inputs are the approximation coefficients provided by MRA (dimension d)





NLPCA Architecture

Output forced to equal Input

$$\hat{\mathbf{x}}_k \approx \mathbf{x}_k \Rightarrow E = \sum_{k=1}^{N} \left(\frac{1}{dN} \left\| \hat{\mathbf{x}}_k - \mathbf{x}_k \right\|^2 \right)$$

Every space (k-1) is of minimal Error

$$E_{Total} = E_1 + E_{1,2} + \ldots + E_{1,2,\ldots,k}$$

Model Generation: Regression with Gaussian Processes (GP)

GP modelling allows to directly define the space of admissible functions relating inputs to outputs by simply specifying the mean and covariance functions of the process (Rasmussen&Williams,2006;Bishop,2007).

Collect measured responses of a body

- Data set **D** of D-dimensional training input vectors $\mathbf{x}_i$
- Training vector **t** with noisy training targets $t_i = f(\mathbf{x}_i) + \varepsilon$ for $i = 1,\ldots,\mathrm{N}$

Inverse analysis method

- $f(\bullet)$ modelled by GP with zero mean and covariance matrix **K**
  $$p(\mathbf{f}\,|\,\mathbf{D}) \sim \mathcal{N}(0, \mathbf{K})$$
- Optimize parameters Θ controlling **K**

Estimation from new responses

- New input vector $\mathbf{x}_{\mathrm{N+1}}$
- Predictions for noise-free output targets $f(\mathbf{x}_{\mathrm{N+1}})$

Steps

Covariance Function Selection

- The covariance in our case is squared exponential with **automatic relevance determination** (ARD) distance measure defined by

$$\mathbf{K}_{ij} = k(\mathbf{x}_i, \mathbf{x}_j) = \sigma^2 \exp\left(-\frac{1}{2}\left(\mathbf{x}_i - \mathbf{x}_j\right)^{\mathrm{T}} \mathbf{M}\left(\mathbf{x}_i - \mathbf{x}_j\right)\right)$$

M: *diag* $(\lambda_1,\ldots\lambda_D)^{-2}$
λ: Input dimension length scale
σ^2: Signal Variance
λ and σ_f *are hyperparameters* Θ

- The learning task correspond to tuning the parameters of the covariance function of the process

- The unknown parameters Θ in the covariance functions are calculated by maximizing the negative logarithmic marginal likelihood

$$\mathcal{L}(\Theta) = -\log\left[p(\mathbf{t} \mid \mathbf{x})\right] = \frac{\mathrm{N}}{2}\log(2\pi) + \frac{1}{2}\log\left(\left|\mathbf{K}\right|\right) + \frac{1}{2}\mathbf{t}^{\mathrm{T}}\mathbf{K}^{-1}\mathbf{t}$$

- A conjugate gradient optimization technique with line-search is used for this purpose

Predictions:

In the Gaussian Process framework, one can define a **joint distribution** over the observed training targets at the test location as

$$p(\mathbf{t}_{N+1}) \sim \mathcal{N}\left(0, \begin{bmatrix} \mathbf{K}+\sigma_n^2\mathbf{I} & \mathbf{k} \\ \mathbf{k}^{\mathrm{T}} & k+\sigma_n^2 \end{bmatrix}\right) = \mathcal{N}\left(0, \begin{bmatrix} \mathbf{C}_{\mathrm{N}} & \mathbf{k} \\ \mathbf{k}^{\mathbf{T}} & c \end{bmatrix}\right)$$

$\mathbf{t}_{\mathrm{N+1}}$: $(t_1,\dots,t_{\mathrm{N}},t_{\mathrm{N+1}})^{\mathrm{T}}$
$\sigma_n{}^2$: Noise Variance
K: N×N matrix
k: N×1 matrix btn. test and training targets
k: Training target Variance
I: Identity matrix

After optimization of the model:

- Predictions for new values of **x** can be made
- A predictive distribution over **t** is obtained

The GP formulae for the mean and variance of the predictive distribution with the covariance function is given by

$$\mu(\mathbf{x}_{N+1}) = \mathbf{k}^{\mathrm{T}}\mathbf{C}_{\mathrm{N}}^{-1}\mathbf{t}$$

$$\sigma^2(\mathbf{x}_{N+1}) = k - \mathbf{k}^{\mathrm{T}}\mathbf{C}_{\mathrm{N}}^{-1}\mathbf{k}$$

Experimental setup:

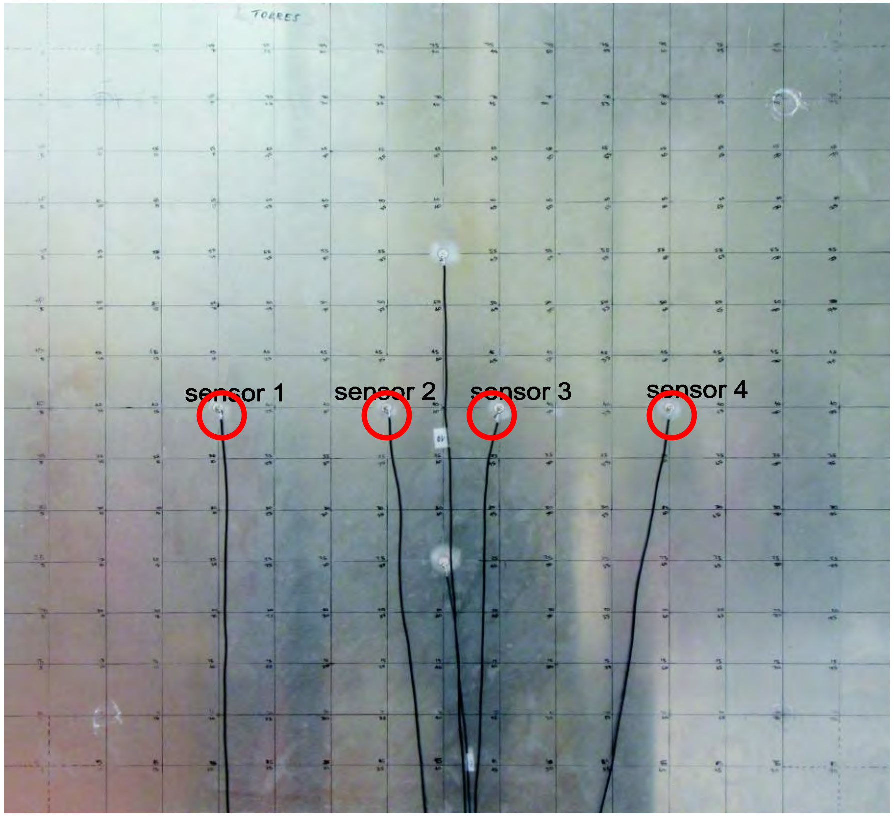


Plate specification:
- Aluminum
- 800mm*800mm
- Thickness: 2mm

Sensor specification:
- PIC255 from PI ceramic
- Diameter: 10mm
- Thickness: 0.2mm

Impact hammer specification:
- Impact hammer type 8204
- Tip diameter: 2.5mm

Impact force description:

- The impact force is in fact a discontinue function, in time-dependent problems, it may lead the time-stepping algorithm into problems when running .
- To avoid the problems of discontinuity, smoothed step functions without overshoots are chosen to describe the impact force.
- Heaviside function *flc2hs* in Comsol is applied. It is a smoothed Heaviside function with a continuous second derivative without overshoot.

$$f = F_{\max}[flch2(t,t_{rise}) - flch2(t - t_{width}, t_{fall})]$$

$$F_{\max} = \frac{\max(F)}{s_{impact}}(N/m^2)$$

$$s_{impact} = \pi\left(\frac{2.5e-3}{2}\right)^2$$

F : maximum force (2-5N)
s_{impact}: contacting area with the impact hammer

Piezoelectric effect simulation (Piezo plane strain module)

The piezoelectric sensor function is the governing equation:

$$D_i = e_{ikl} S_{kl} + \varepsilon_{ij}^{S} E_k$$

$i, j, k, l = 1,2,3$ e_{ikl} : piezoelectric constantv ε_{ij}^{S} : dielectric constant

D_i : electric displacement E_k: electric field

The piezoelectric material constants are offered by PI Ceramic.

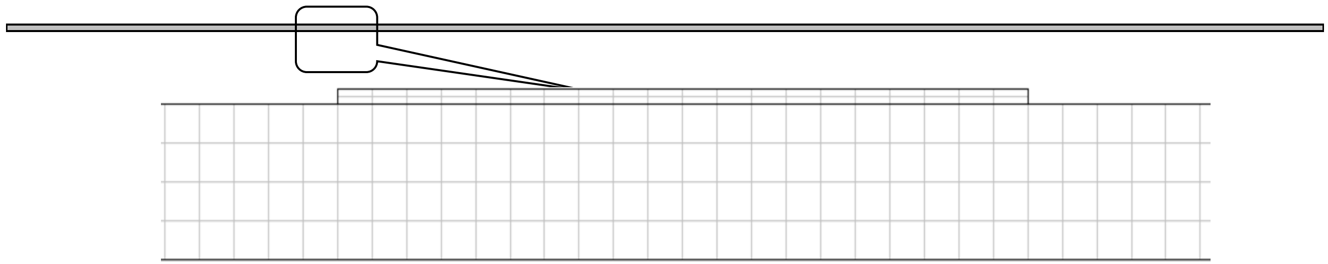
Two dimensional model and boundary conditions:

Mechanical boundary conditions: free

Electrical boundary conditions:

- Contacting layer of sensors with the plate: **ground**
- Otherwise: zero charge

Meshing (Mapped mesh):



- Element size rule of thumb: one twelfth of the maximum wave length (comsol user‘s manual)

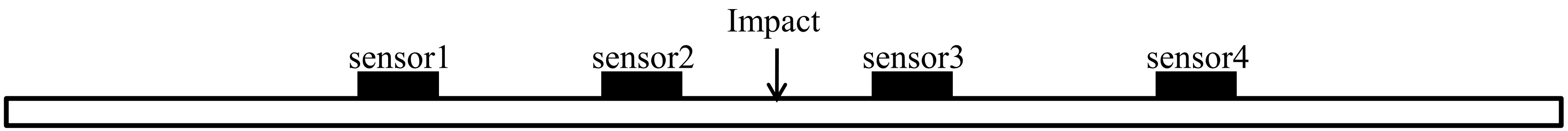
- 6560 elements (cost-effective for calculation)

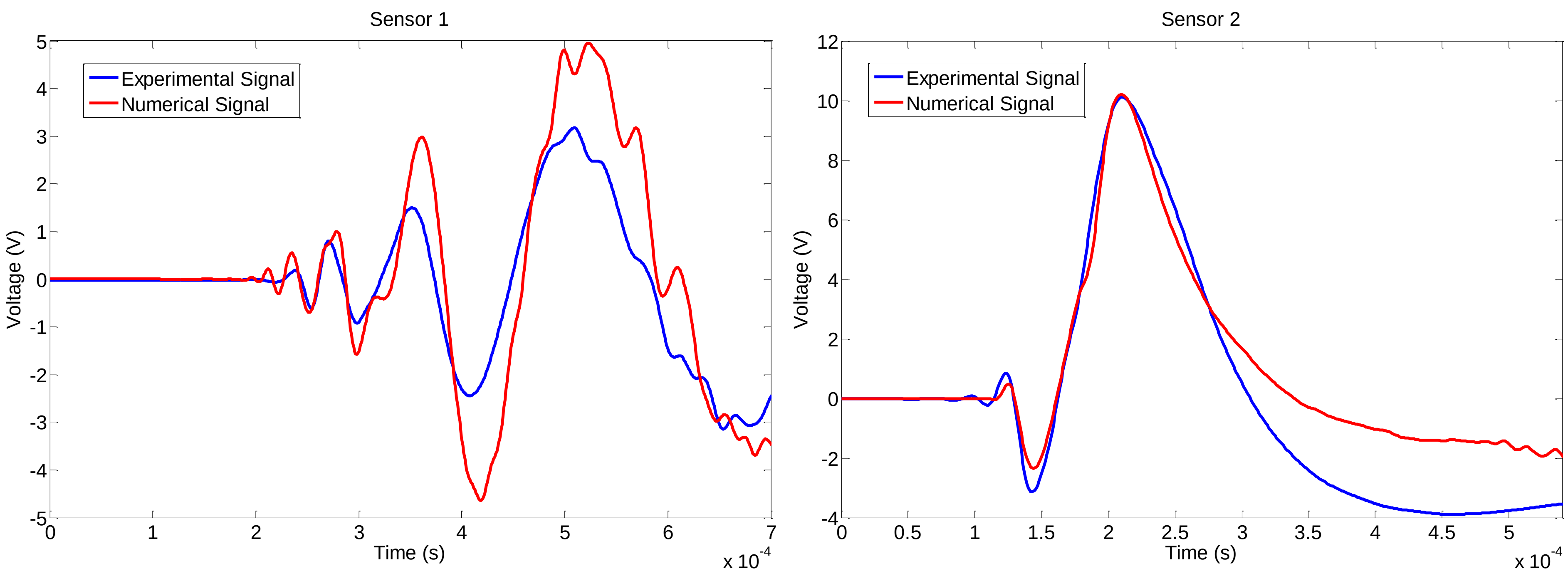
- Transient analysis:

- Signal length 2ms (enough for acoustic emission processing)
- Time stepping:1e-6s

- Output: Voltage signal on the sensor surface

Results of an example (Impact applied in the middle of the plate)





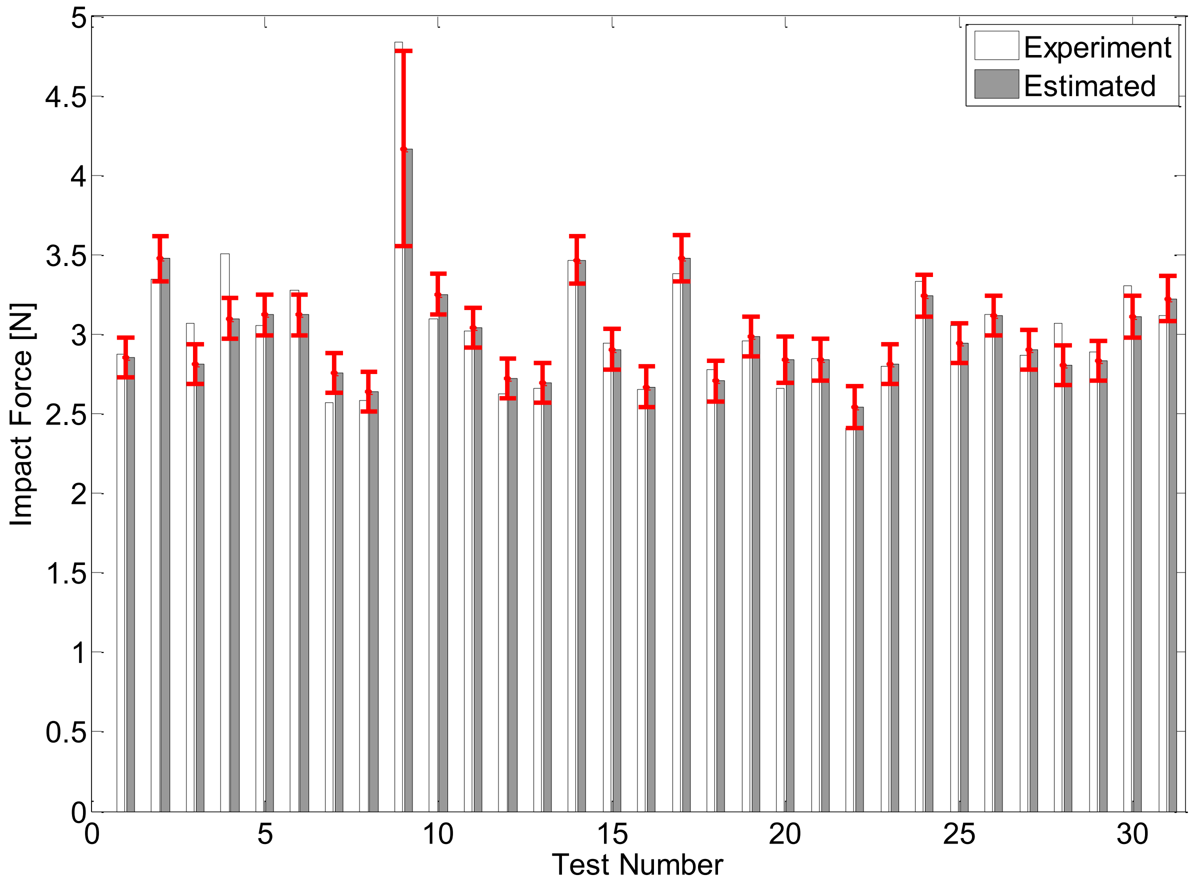
- The simulated sensor signals track well with the experimental signals
- The model is in 2D, in reality the wave will disperse.
- Compared with a 3D model, this 2D model is cost-effective, which saves calculation time and memory consumption, and is enough for future impact magnitude estimation.

- Model trained with impacts between 2-5N at random locations
- Training impacts with a grid density of 50mm.
- A single output Gaussian Process is proposed for impact magnitude estimation. The feature vectors which are the GP inputs comprise:

- The difference in time of arrivals between the sensors
- The non-linear principal components extracted from the DWT
- The area under the curve of the power spectral density

Results:

- Grey bars show the mean of the Gaussian process predictive distribution
- Error bars correspond to plus and minus 2 standard deviations (95%)
- The GP was able to estimate the impact magnitude force with an average percentage error of 8%



Conclusion:

- The proposed methodology has allowed to accurately estimate the magnitude of impact events in a simple structure.
- The finite element simulation is very cost-effective to get the training set.
- The sensor signals from the model track well with the experimental data.

Pending:

- Investigate the method applicability in more realistic and complex structures and materials
- Investigate the effect of different type of impacts in the prediction capabilities

Thank you for your attention!
Question?

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