ADVANCE COMPUTING AND BIG DATA

An MCMC approach powered by Deep Learning for stochastic damage localization

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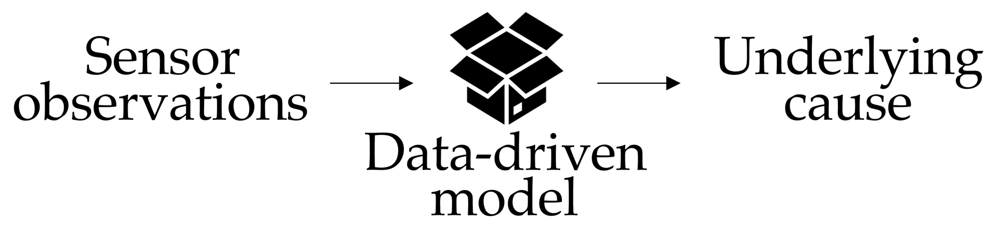
The idea

The recent advances in learning systems and computational science have allowed the emergence of new data-driven diagnostic frameworks for structural systems. Data-driven strategies easily manage large quantities of noisy vibration recordings, enabling informed evaluations of the structural health, often with inexpensive computational efforts at prediction stage. The use of Deep Learning further empowers this scenario by automatizing the selection-extraction of damage-sensitive features. This work focuses on damage localization, a supervised learning problem in structural health monitoring (SHM).



Methodology

Damage and usage parameters are estimated with their probability distribution using a Markov chain Monte Carlo (MCMC) sampling strategy. **MCMC** sequentially update the probability distribution under the guidance of the evidence of sampled parameters to represent sparse sensor recordings, by means of a surrogate model. An ultra-fast surrogate model is adopted to accelerate the **computation of the conditional likelihood**. Such **surrogate model** is built upon a multi-fidelity (MF) deep neural network (DNN), used to map usage and damage parameters onto approximated sensor recordings, while alleviating the computational burden of the training stage. **A Siamese DNN** is used to obtain the prior knowledge on the usage parameters to feed the MCMC analysis. **The training** of the surrogate model and of the usage monitoring tool is carried out leveraging synthetic data, which account for a **simulated effect of the damage**; see, e.g., [1].

References

[1] L. Rosafalco, M. Torzoni, A. Manzoni, S. Mariani, and A. Corigliano, "Online structural health monitoring by model order reduction and deep learning algorithms," *Comput. Struct.*, vol. 255, p. 106604, 2021.

[2] M. Torzoni, L. Rosafalco, and A. Manzoni, "A Combined Model Order Reduction and Deep Learning Approach for Structural Health Monitoring Under Varying Operational and Environmental Conditions," in *Proceedings of ECSA-7*, p. 94, 2020.

Virtual experiment

1. Numerical models:

- **HF model** → FE model for elasto-dynamics;
- **LF model** → POD-Galerkin ROM no damage, no damping.

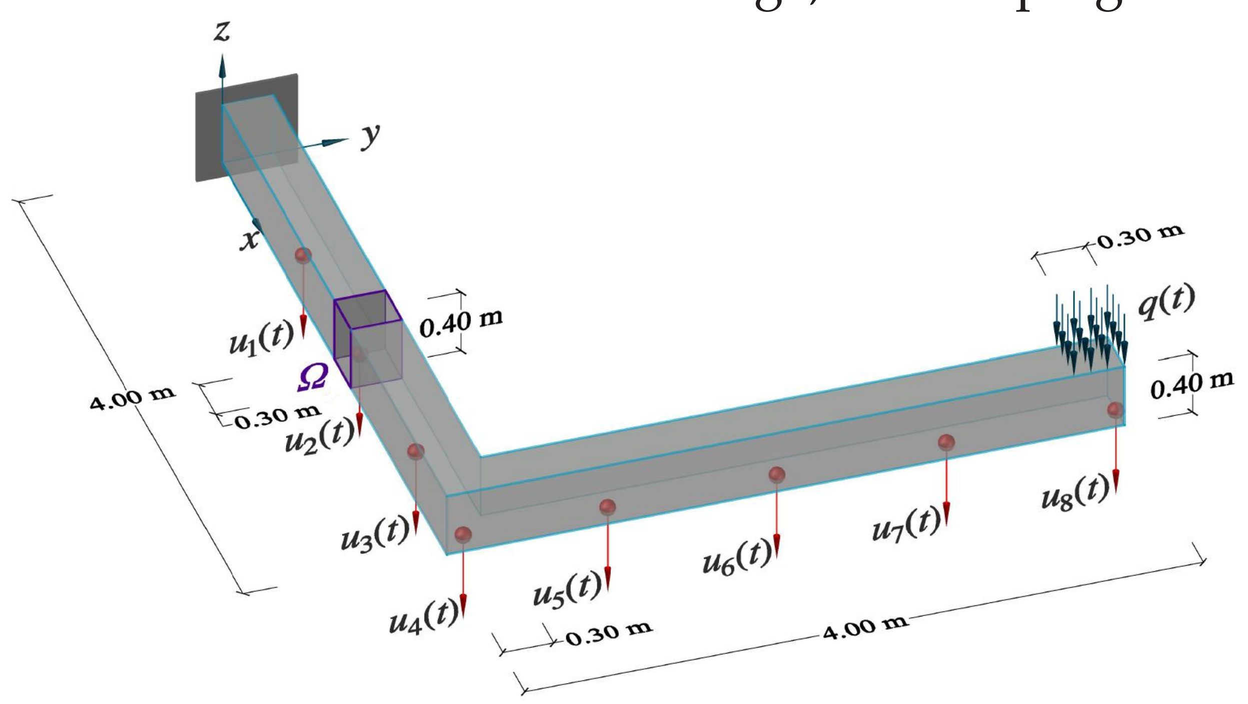


Figure 1: Digital twin of the monitored structure.

2. Parametrization of the problem:

- **Damage position** → abscissa θ_Ω, center of subdomain Ω;
- **Operational conditions** → load amplitude θ_A, load frequency θ_f;

3. Vibration data to process:

- **LF training data** → LF recordings $\mathbf{U}^{\mathrm{LF}}$,
- **HF training data** → HF recordings $\mathbf{U}^{\mathrm{HF}}$
- **HF testing data** → noise-corrupted HF recordings $\mathbf{U}^{\mathrm{EXP}}$

4. Usage monitoring $\mathcal{NN}_{\mathrm{US}}$: prior knowledge on θ_A, θ_f to be updated within the MCMC loop.

5. MCMC analysis: samples of the sought parameters $\boldsymbol{\theta} = (\theta_A, \theta_f, \theta_\Omega)^\top$ are simulated with a distribution proportional to their posterior probability.

6. Surrogate model $\mathcal{NN}_{\mathrm{MF}}$: provides $\hat{\mathbf{U}}^{\mathrm{HF}}$ for each $\boldsymbol{\theta}$ sample, during the likelihood computation

$$p(\mathbf{U}^{\mathrm{EXP}}_{1,\ldots,N_{\mathrm{obs}}}|\boldsymbol{\theta}, \mathcal{NN}_{\mathrm{MF}}) \propto \propto \prod_k^{N_{\mathrm{obs}}} \exp\left(-\frac{\sum_{\tau=1}^{L}(\mathbf{U}^{\mathrm{EXP}}_k-\hat{\mathbf{U}}^{\mathrm{HF}})^\top_\tau \boldsymbol{\Sigma}_e^{-1}(\mathbf{U}^{\mathrm{EXP}}_k-\hat{\mathbf{U}}^{\mathrm{HF}})_\tau}{2}\right). \quad (1)$$

Implementation details: `https://jmp.sh/QJTKdjk`

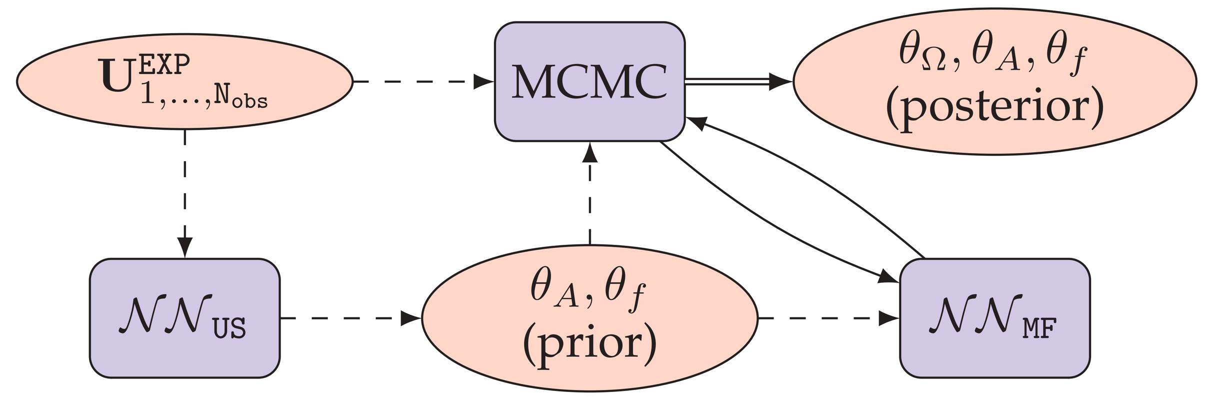


Figure 2: Flowchart of the SHM procedure.

Usage monitoring – $\mathcal{NN}_{\mathrm{US}}$

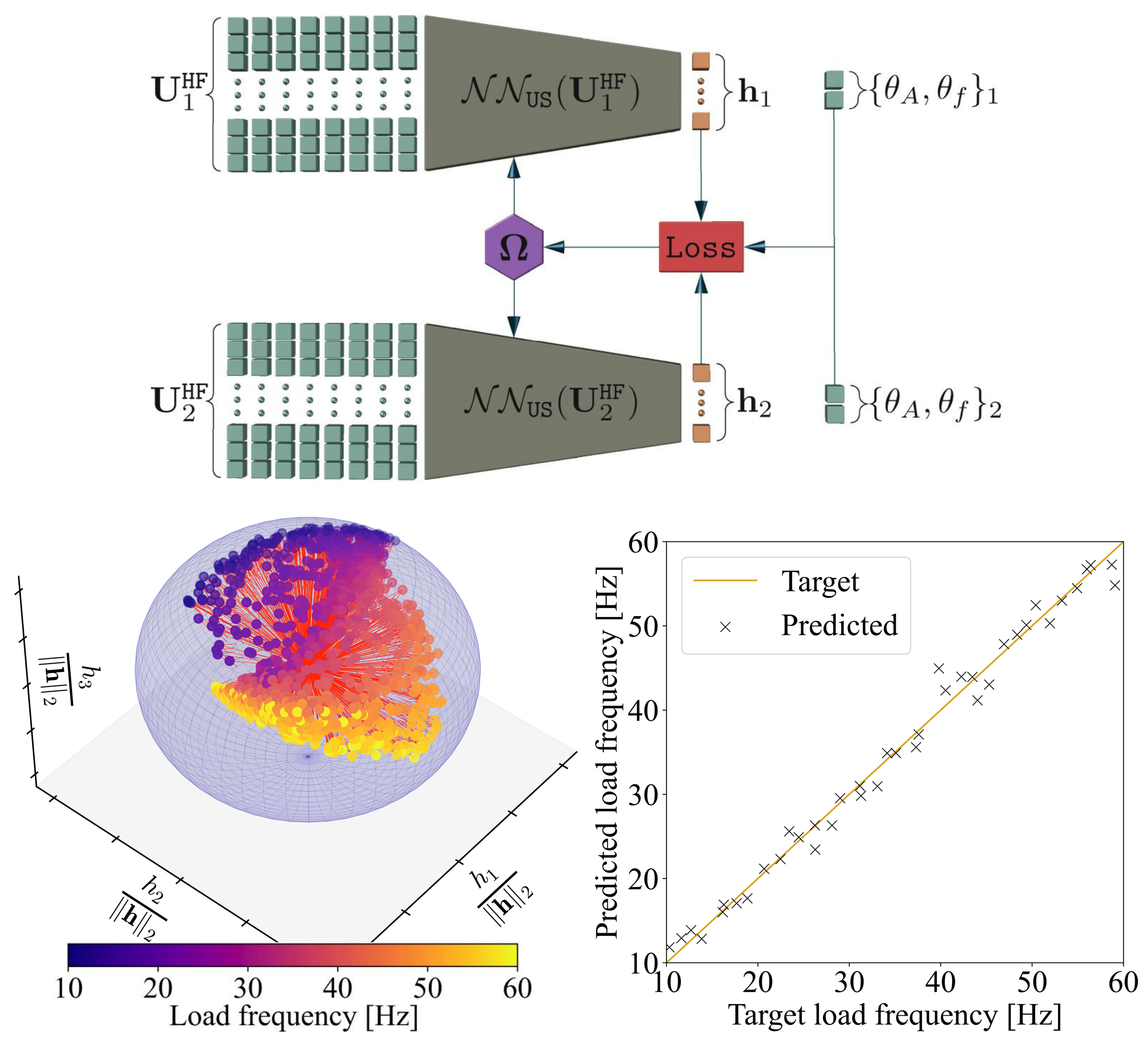


Figure 3: Siamese architecture, example of the learned embedding and k-nearest neighbors regression outcome.

Surrogate model – $\mathcal{NN}_{\mathrm{MF}}$

- **LF network $\mathcal{NN}_{\mathrm{LF}}$** → fully connected DNN used as baseline model;
- **HF network $\mathcal{NN}_{\mathrm{HF}}$** → LSTM-DNN used to learn the correlation among LF and HF data.

$$\hat{\mathbf{U}}^{\mathrm{HF}} = \mathcal{NN}_{\mathrm{MF}}(\mathbf{x}^{\mathrm{HF}}, \mathbf{x}^{\mathrm{LF}}) = \mathcal{NN}_{\mathrm{HF}}(\boldsymbol{\theta}, \hat{\mathbf{U}}^{\mathrm{LF}}),$$
$$\hat{\mathbf{U}}^{\mathrm{LF}} = \mathcal{NN}_{\mathrm{LF}}(\mathbf{x}^{\mathrm{LF}}) = \mathcal{NN}_{\mathrm{LF}}(\theta_A, \theta_f). \quad (2)$$

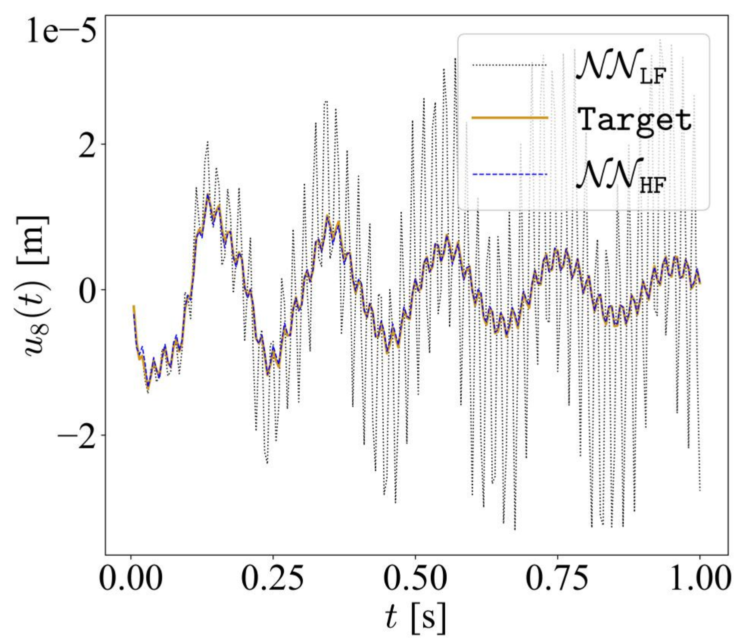


Figure 4: Regression over the HF signals.

MCMC analysis (posterior)

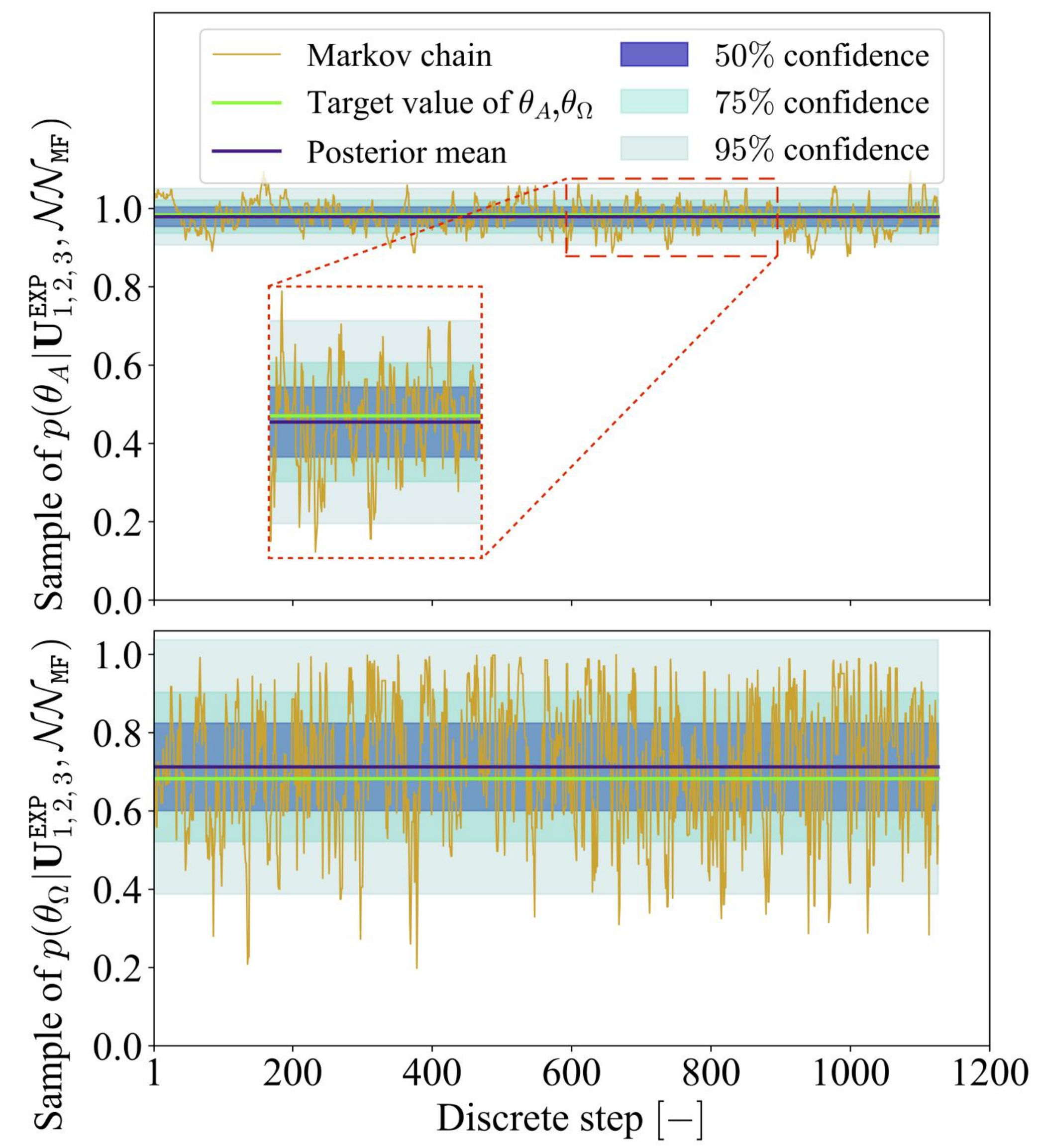


Figure 5: Example of MCMC analysis.

Open issues

This work has presented a stochastic approach for SHM. The presence of damage has been postulated as already detected, and only the localization task has been analyzed. This is the first application of MCMC in SHM incapsulating a MF-DNN surrogate model. The method has been assessed on a numerical case study, showing remarkable performance.

Besides experimentally validate the proposed methodology, the next studies will consider the effects of temperature, as done, e.g., in [2]. A prior sensor placement system should also be envisaged in order to maximize the effectiveness of the method.