ADVANCE COMPUTING AND BIG DATA

Two-scale deep learning model for polysilicon MEMS sensors

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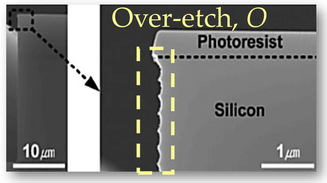
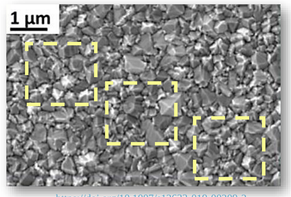
1. Introduction

- Available physical models **do not** account for existing **stochastic effects,** arising from **geometry-** and **material property-related uncertainties**, that induce scattering in the response.

Device level



https://doi.org/10.1063/1.3474652



https://doi.org/10.1007/s12633-019-00209-2

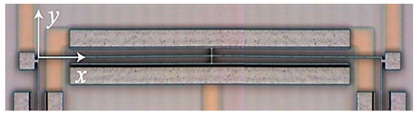
Material level

- A **two-scale deep learning model** is proposed to generate an accurate **mapping** between relevant input information, automatically accounting for these uncertainties, and the effective response of the device.

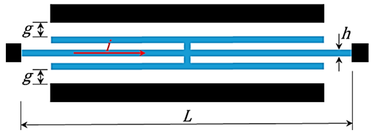
2. Model of a Polysilicon MEMS and Intrinsic Uncertainties

2.1 Oscillation Amplitude of Lorentz force MEMS magnetometer

- The device is able to sense a magnetic field aligned with the out-of-plane direction *z:*



SEM image of the resonant structure [1]



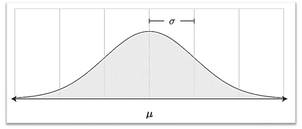
Scheme of the slender beam [2]

- The **maximum amplitude of the oscillations** at the mid-span cross-section, v_{max}, is obtained as the solution of :

$$\left(\frac{F_0}{K_1}\right) = \left(2\left(1-\frac{\omega}{\omega_1}\right)v_{max} + \frac{3}{4}\frac{K_3}{K_1}v_{max}^3\right)^2 + \left(\frac{d}{m\omega_1}v_{max}\right)^2$$

2.2 Sources of uncertainty in Polysilicon MEMS

- For **geometry-related uncertainties**[3,4] the over-etch depth $O \sim N(\mu,\sigma) = N(0\mu m, 0.05\mu m)$



https://wumbo.net/concept/normal-distribution/

- For **material property-related uncertainties**[5] the homogenized Young's modulus, $\bar{E} \sim LogN(\mu,\sigma)$

Table 1. Statistical indicators characterizing $\bar{E}$ for different SVE sizes[1].

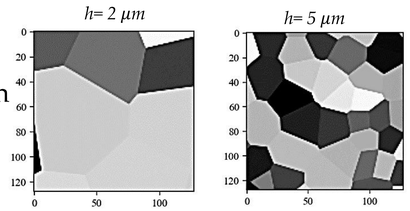
SVE size	μ [GPa]	σ [GPa]
2 μm x 2 μm	150.1	5.5
5 μm x 5 μm	149.3	2.4

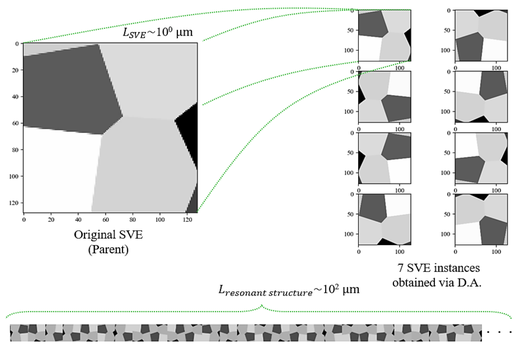
[1] Homogenization considering uniform strain boundary conditions.

3. Methodology

3.1 Representation of the resonant structure

- SEM-like subdomains representing epitaxially grown polysilicon's microstructures are digitally-generated[5]

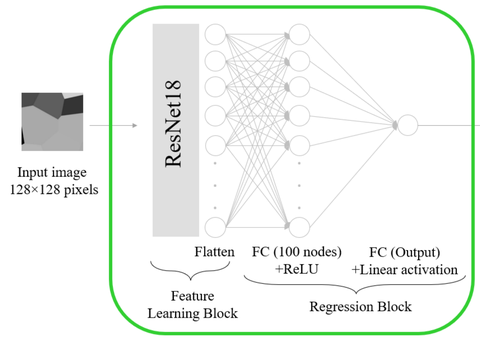


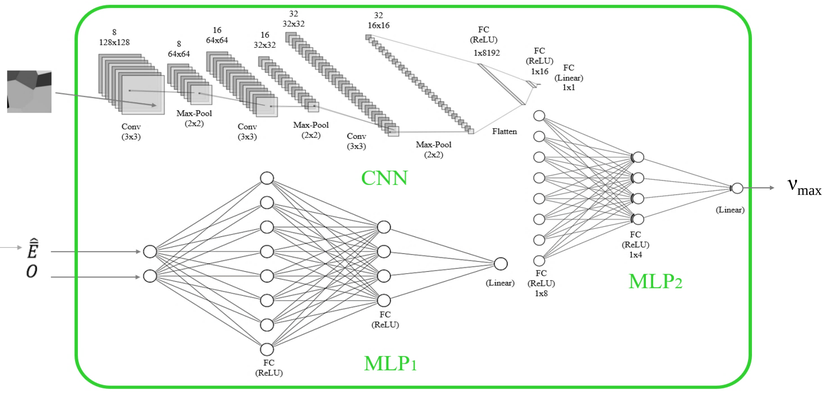


- A **data augmentation** procedure, based on similarity transformations, allows to obtain 7 new instances for each original or parent SVE.
- The resonant structure is regarded as a **random concatenation** of a parent SVE and its corresponding instances.

3.2 The Neural Network-based Model

Material Level



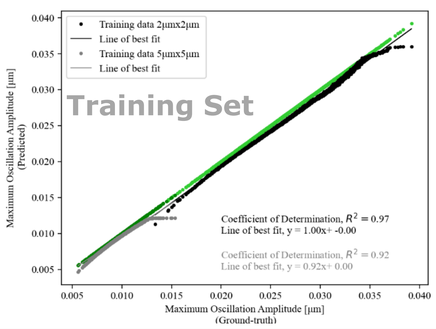


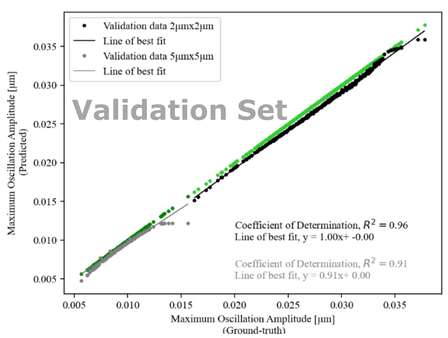
Device Level

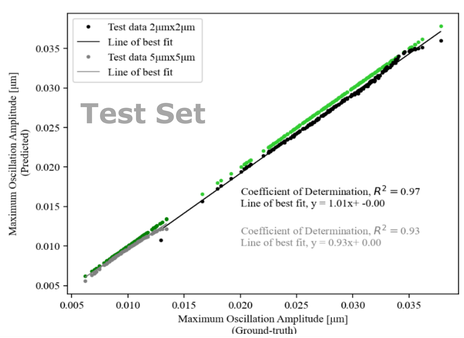
- **Two stages** can be distinguished in correspondence to the proposed **two-scale deep learning approach**.

5. Results

Prediction of Maximum Amplitude of Oscillations







6. Conclusions

- The proposed neural network-based model achieved accurate mappings for the maximum oscillation amplitude of the resonant structure.
- Intrinsic uncertainties accounted for in a straightforward data-driven manner.
- The data-driven model demonstrated good generalization over unseen samples.

References

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