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Improving Computational Efficiency of Finite Element MEMS Transducer Models by Fine-Tuned Homogenization

Sira Bielefeldt[1]*, Florin Püntener*[1]*, Chris Rüttimann*[1]*, Cosmin Roman*[1]
[1]*ETH Zurich, Rämistrasse 101, 8092 Zurich, Switzerland*
croman@ethz.ch

Summary:
We present a top-down homogenization approach for simplifying the finite element (FE) model of a complex MEMS transducer, here a capacitive tactile sensor (taxel). This method addresses the challenge of high computational costs in modeling MEMS devices. The number of degrees of freedom (NDOF) of the homogenized model is reduced by a factor of 34.6. The model achieves a normalized root mean squared error (NRMSE) with respect to the measurement data of 5.5±0.5% for force- and of 9.4±1.5% for capacitance-displacement characteristics. Our method thereby achieves significant computational savings while maintaining accuracy of a non-homogenized model.

Keywords: model simplification, homogenization, finite elements, MEMS transducers, tactile sensors

Background

Finite element (FE) models have become a cornerstone of MEMS transducer design, offering accurate multiphysics simulations and device optimization. In spite their success, FE models require significant computational resources. To reduce their complexity, approaches based on projection [1] or homogenization [2] have been proposed. While the former is commonly used by the MEMS community, the latter is more familiar to the multiscale material modeling community.

Description of the New Method

In this work, we explore the potential of homogenization for reducing the complexity of finite element (FE) models of MEMS transducers. Our approach follows a top-down strategy, starting with a detailed 3D FE model and simplifying both its geometry and materials through homogenization. To refine the effective material parameters, we employ targeted 3D simulations of individual sub-parts of the device. We refer to this approach as *fine-tuned homogenization* (FTH). Key parameters of the homogenized model are extracted using experimental measurements. The computational efficiency of the homogenized model makes it suitable for numerical optimization, thus expediting both fine-tuning and model calibration.

We showcase the FTH method on a MEMS capacitive tactile sensor (taxel). In our previous work we demonstrated a soft artificial finger featuring 144 taxels (Fig. 1B) [3]. Each micro taxel comprises a circular suspended membrane stabilized by a solder ball, with peripheral spring structures (Fig. 1A). A small contact area polyimide structure on the bottom electrode acts as stoppers, preventing membrane pull-in [4].

Integrating tactile sensing into robotic grippers is aiming to improve their dexterity and automation. An accurate model of the taxel array is crucial for training a robotic hand [5] equipped with tactile artificial fingers. Due to multiple scales, layers, materials, and complex topography, modelling even one taxel, let alone an array, has been challenging.

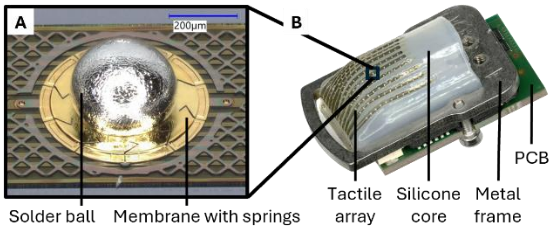

Figure 1: Tactile sensing technology. (A) Close-up of a tactile sensor (taxel) on an (B) artificial silicone finger containing an array of 144 taxels.

Individual taxels have been characterized electro-mechanically, with the setup shown in Fig. 2, using a flat-tip aluminum needle mounted on a force sensor (Novatech F329) on a stepper motor (step size: 0.31 µm, max. reaction F=15 mN).

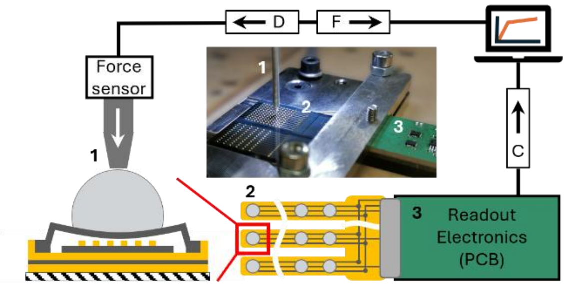

Figure 2: Experimental taxel characterization setup. A force sensor (1) with flat tip needle actuates a taxel in the array (2). The applied displacement D, measured force F, capacitance C are recorded simultaneously.

An axisymmetric taxel model (NDOF 2D:32.6K, 3D:465K) was set up in COMSOL Multiphysics (Fig. 3 top), using the parameters in Tab. 1. Geometrical features of the taxels have been extracted from FIB-SEM cross-sections, focusing on layer thickness, stopper region and membrane shape in the spring region.

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In our FTH approach, first, all subdomains of each region (Fig. 3, excl. the solder ball) were merged into one domain with effective material parameters given by volumetric weighting. For example, in the spring region the Youngs moduli E of all thin-film layers and the spring cutouts were homogenized into $E_{sp,init}$. Second, separate unit-cell simulations were utilized to fine-tune the effective material parameters, where needed. For example, $E_{sp,init}$ was fine-tuned into $E_{sp,corr.}$ by fitting the 2D axisymmetric to a 3D taxel model of a 36° sector unit-cell containing one spring (NDOF: 1.6M).

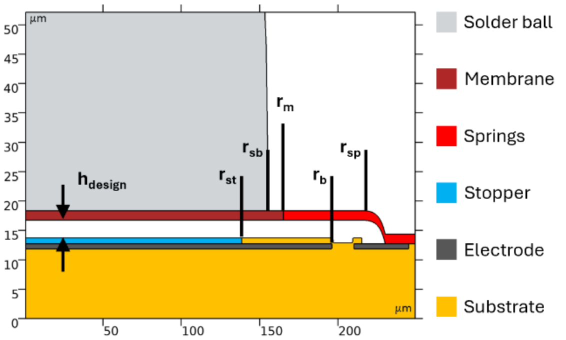

Figure 3: The 2D axisymmetric COMSOL model parameterized based on FIB-SEM cross sections of selected regions.

Initial simulations assumed an initial gap of h_{design}=3 µm. Subsequently, to calibrate the model, a taxel-specific initial gap (see Tab. 1) was determined from the experimental F-D data, as the point where stiffness changes, i.e. where the membrane hits the stoppers.

*Tab. 1: Geometrical and material model parameters utilized in COMSOL simulation (r: x-y dim.; h: z dim.). Values shown in blue are the final parameters obtained through our FTH method. (*electrical ε_{r_st}: 1.51)*

Region	Geometry [µm]	E [GPa]
Solder ball	r_{sb}: 147 ± 1	E_{sb}: 50
Substrate	r_s: 250	E_s: 12.7
Electrode	r_b: 196	E_b: 107
Membrane	r_m: 115	E_m: 109
Stopper*	r_{st}: 138	$E_{st,\ corr}$: 2.67
Springs	r_{sp}: 250	$E_{sp,\ init}$: 106 $E_{sp,\ corr.}$: 90
Initial gap	h_{design}: 3	-
	h_1: 2.27, h_2: 1.54, h_3: 1.95	

Results

Fig. 4 shows a comparison of the simulations to the experimental data for three selected typical taxels. The model parameters in Tab. 1 result in a very good agreement (see Fig. 4 NRMSE values), both in the mechanical D-F (top) and the electric D-C domain (bottom). Our proposed FTH approach to simplify FE models can be transferred to other complex MEMS transducers.

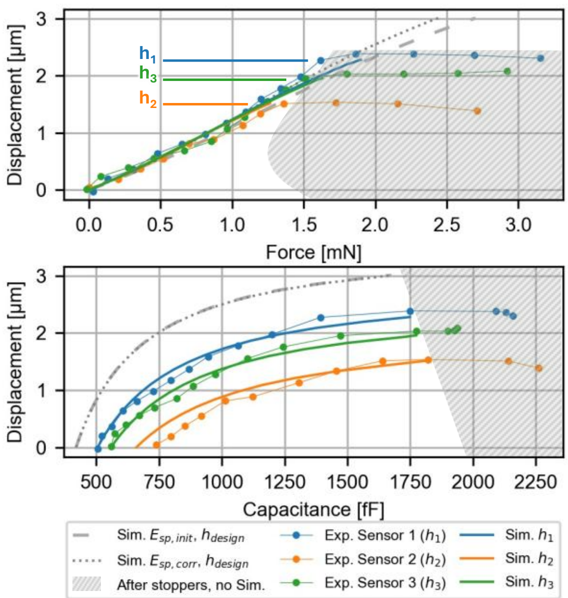

Figure 4: Experiments vs. simulation. D-F (top) and D-C (bottom) for 3 typical taxels. Initial simulation parameter values before (gray) and after tuning the initial gap (color) are given in Tab. 1. The average NRMSE of measured vs simulated values (normalized for F/C exp. range) is 6.1% (initial) and 5.5% (tuned) for D-F, and 48.5% (initial) and 9.3% (tuned) for D-C.

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