

Uncertainty Analysis of Dielectric Elastomers

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Introduction:

- Dielectric elastomers (DE) have demonstrated promising properties for applications ranging from actuation, sensing, and energy harvesting [1]. By placing a compliant electrode on either side of these materials, one can apply voltage across the material thickness causing large electrostriction (i.e., electric field induced strain on the order of 100%).
- Considering the light weight properties of DE and its compact actuation mechanism, these soft materials are well suited for various platforms, including multi-modal legged robots, micro air vehicles, energy harvesting, biomedicine, and flexible electronics.
- Legged robots struggle to move on different surfaces as their components are typically designed for a single terrain. If a compliant structure could be incorporated into the leg mechanism, it could potentially allow for seamless transfer on to different terrains.
- In the area of flow control, one can similarly control the membrane's structure with an electrostatic field to alter the fluid-structure interactions. A more compliant membrane (as a result of electrostriction) will be significantly influenced by the surrounding flow physics.
- DE offer a route towards accomplishing these goals; however, adaptive structure designs and real-time control require accurate, robust, and numerically efficient predictions of the constitutive behavior and dynamic structure response. Whereas advanced electrostriction has been demonstrated, these elastomeric materials produce rate dependent behavior which has largely been neglected.



Figure 1: Activated electrodes compress, resulting in a decrease in tension and allowing for the outward expansion of the material.



Figure 3: Wind tunnel testing of wing-shaped membrane [2].



Figure 2: Model validation of electric displacement defined as a function of the nominal electric field [3].



Figure 4: iSprawl robotic platform. Legs move up and down in such a way to provide forward motion.

Approach:

Beginning from a nonlinear rate-dependent model we integrate the constitutive equations into a finite deforming electroactive membrane structure. From there we compare with experiments and use Bayesian uncertainty quantification to assess model uncertainty and error propagation. We use information gained from the uncertainty analysis to reassess our material model and continue improving our overall structural model.



Figure 5: Flow chart for approach to model development.

Material Modeling:

Total Energy Density:

$$\psi = \psi_{\infty}(F_{iK}, \Theta) + \Upsilon(F_{iK}, \Theta, \Gamma_{iK}^{\alpha})$$

Total Stress:

$$s_{iK} = \frac{\partial \psi}{\partial F_{iK}} = \frac{\partial \psi_{\infty}}{\partial F_{iK}} - pJH_{iK} + \frac{\partial Y}{\partial F_{iK}}$$

Nonaffine Hyperelastic Free Energy [4]:

$$\psi_{\infty}^{N} = \frac{1}{6} G_{c} \lambda_{max}^{2} \log(3\lambda_{max}^{2} - I_{1}) + G_{e} \sum_{j} (\lambda_{j} + \frac{1}{\lambda_{j}})$$
where the invariant is $I_{j} = -\lambda_{j} \lambda_{j}$

where the invariant is $I_1 = \lambda_i \lambda_i$.

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Nonlinear Viscoelastic Energy:
             \Upsilon_{NL} = \sum_{\alpha} \left[ \frac{1}{2} \gamma_{\alpha} \Gamma^{\alpha}_{iK} \Gamma^{\alpha}_{iK} - \beta^{\alpha}_{\infty} \frac{\partial \psi_{\infty}}{\partial F_{iK}} \Gamma^{\alpha}_{iK} + \beta^{\alpha}_{\infty} \psi_{\infty} \right]
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Membrane Structure Modeling:

Transverse load [5]

 $F = 2\pi \sin(\theta) r t \sigma_l$

where σ_l Cauchy stress in radial direction. Application of electric field in transverse direction decreases the Cauchy stress [5,6].

$$\sigma_l = \sigma_l^H - \kappa_r \epsilon_0 E_t^2$$

Relative permittivity, κ_r , is assumed independent of deformation. The nonaffine hyperelastic stress is







Figure 6: Membrane structure – a) Non-deformed configuration. b) Structure deformed a distance δ . Load response, F, is measured experimentally and modeled [3]. The electrostatic potential is denoted by ϕ .

Experiments:

- Uniaxial load/unload cycles using Very High Bond (VHB) 4910.
- Transverse loading of membrane structure (See Figure 6).
- Electric displacement measurements are taken on membrane structure in non-deformed configuration. Placed in Sawyer-Tower circuit with a known capacitor.



Bayesian Uncertainty Quantification [8]:

Inverse problem using Bayes' Relation $\pi(\theta | M^{data}) = \frac{p(M|\theta)\pi_0(\theta)}{\int_{\mathbb{R}^p} p(M|\theta)\pi_0(\theta)d\theta}$

 $\pi(\theta | M^{data})$ - posterior density (distribution of parameter in light of data) $\pi_0(\theta)$ - prior density (a priori knowledge about the parameter values) $p(M|\theta)$ - likelihood of model given parameters



Parameter Estimation:

Markov Chain Monte Carlo – MCMC

Assume unknown model parameters are random variables.

- Uniaxial, viscoelasticity model: $\theta = [G_c, G_e, \lambda_{max}, \gamma, \eta, \beta]$
- Transverse load model: $\theta = [G_c, G_e, \lambda_{max}, \kappa_r]$
- Electric displacement model: $\theta = [\kappa_r, \tau]$



Conclusion:

- It was shown that the nonlinear viscoelastic model quantified the rate-dependent deformation of VHB 4910 with the greatest accuracy, as it accounted for the behavior at all stretch rates with a single set of hyperelastic parameters.
- The time response of the nonlinear viscoelastic model follows a power law with respect to the deformation rate (See Figure 11). This opens up opportunities to explore origins for the power law based on the underlying polymer network physics.
- Uncertainty associated with model prediction in nonlinear rate dependent regimes is quantified using Bayesian statistics and its errors are propagated through the model to assess model accuracy with respect to experiments.
- These results show potential for applying controls to a robotic platform as the electrostrictive behavior causes significant change in the membrane stiffness as a function of applied field. Effective application of controls could assist a robot in adjusting to different terrains simply by applying different fields across the membrane.
- Determining the appropriate characteristics to enhance a robotic platform is currently under investigation to quantify fatigue behavior under electromagnetic loading. The use of Bayesian statistics is ideal to determine if posterior parameter densities evolve during fatigue which would lead to developments of more robust control algorithms and filter designs.



Figure 11: Power law viscoelastic behavior with respect deformation rate.

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