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A DNN-based Metamodel for Simulating Fingertip Deformation

Yashwardhan Deshmukh[1], Katherine J. Kuchenbecker[1] and Gokhan Serhat[1,2]

I. Introduction

Human fingertips play a crucial role in material assessment, grasping, dexterous manipulation, and most user input devices, and they are visually displayed in many virtual environments that involve the hands. These important functionalities have inspired significant efforts to understand fingertip deformation mechanics, as accurate predictions can aid scientific understanding of the sense of touch and inform the design of myriad products. However, the complex anatomy of this body part limits the validity of known analytical models in any realistic scenarios. Therefore, accurate prediction of the fingertip's mechanical behavior often necessitates using computational methods such as *finite element (FE) analysis*.

Various FE models with different levels of detail have been developed to realistically simulate the deformation of fingertips, including intricate geometry and non-uniform material properties. Early investigations mostly involved low-fidelity 2D analyses where all types of soft tissue are lumped together in a single elastic structure. An instance of such simple models was used by Srinivasan and Dandekar [1] to investigate the role of fingertip mechanics in the tactile perception of primates. Later, Wu et al. [2] built a similar model to analyze the influence of static compression on the vibration response of the human fingertip.

Over time, the fidelity of FE simulations of fingertip mechanics has increased. In one study, Dandekar et al. [3] showed that multi-layered models are required to realistically represent the deformation behavior. This necessity primarily originates from the significant difference between the elastic moduli of the stiff outer skin (stratum corneum) and the soft inner tissues [4]. Serhat and Kuchenbecker recently introduced DigiTip (Fig. 1), a 3D high-fidelity FE model that includes the characteristic profile of the fingertip bone (distal phalanx) and the soft tissue layers, with parametric geometry that is easily customized to different individuals [5].

Despite their utility, high-fidelity fingertip models require fine FE meshes for an accurate representation of the complex interior structure. Besides the considerable modeling effort, performing analyses via such large models imposes long runtimes, which exponentially increase with the mesh size. These factors limit such models' usability in practical applications, especially when the skin deformations need to be computed in real time. Such computational cost problems can be alleviated using *metamodeling*, also known as *surrogate modeling*. This approach relies on running the original high-cost model for a set of inputs that spans the anticipated range to generate the corresponding outputs. The obtained data set is then used to create a lower-cost metamodel that can be used to predict reasonably accurate responses in a significantly reduced time. In this context, machine learning techniques have recently been receiving particular attention due to their versatility and high predictive performance. For instance, Liang et al. [6] used convolutional neural networks to accurately map the material properties of the human aorta to the corresponding stress distributions. With this approach, they achieved a speed-up of three orders of magnitude compared to the traditional FE method.

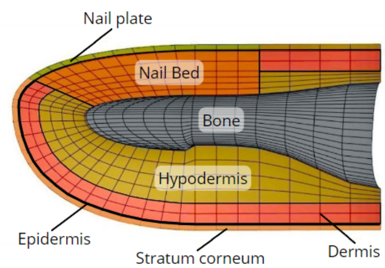

Fig. 1. Cross-sectional view of the high-fidelity fingertip model DigiTip [5].

The advantages of deep learning-based metamodels have not yet been explored for the analysis of the human fingertip. This work addresses this gap by utilizing a collection of deep neural networks (DNNs) as an efficient alternative for expensive FE models. Our approach enables rapid simulation of the deformation of the human fingertip under static or dynamic normal point forces. This interactive tool allows users to predict the deformation of the fingertip for different force locations, force amplitudes, excitation frequencies, and tissue damping values (Fig. 2).

II. Finite element analysis

We build our framework on the high-fidelity fingertip FE model DigiTip [5], which consists of six soft tissue layers including the stratum corneum, epidermis, dermis, hypodermis, fingernail, and nailbed (Fig. 1). The tissue layers in the model are discretized by eight-node linear 3D elements that have three displacement degrees of freedom at each node. The number of nodes (N) was selected as 7 677, which provides satisfactory precision (determined via a mesh convergence analysis) and moderate computational cost (during data generation). The nodes at the surface of the

[1]Y. Deshmukh, K. J. Kuchenbecker, and G. Serhat are with the Haptic Intelligence Department, Max Planck Institute for Intelligent Systems, 70569 Stuttgart, Germany. E-mails: yash@is.mpg.de, kjk@is.mpg.de, serhat@is.mpg.de
[2]G. Serhat is also with the Department of Mechanical Engineering, KU Leuven – Bruges Campus, 8200 Bruges, Belgium. E-mail: gokhan.serhat@kuleuven.be

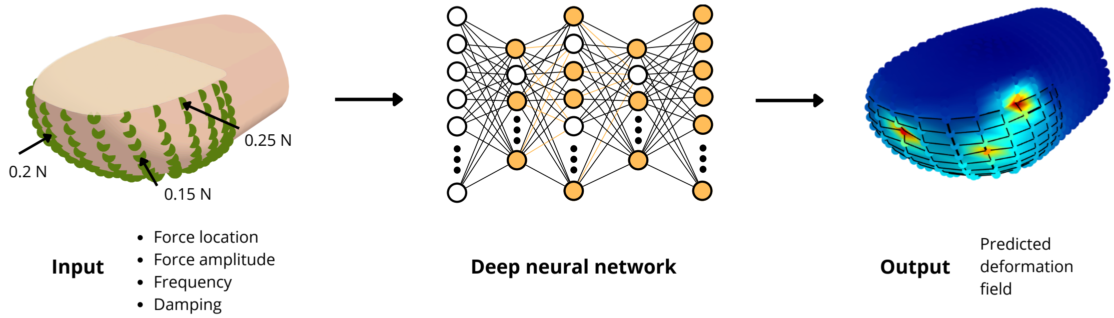

Fig. 2. Using deep neural networks to predict the deformation of the human fingertip subjected to normal point forces.

distal phalanx are immobilized due to the bone's substantially higher stiffness compared to the soft tissue layers. All other tissue nodes can move freely. The FE modeling results in a stiffness matrix K and a mass matrix M, which both have the size of $3N$-by-$3N$.

For static forces, the deformation field is computed by solving

$$Ku = f \tag{1}$$

where u and f are the unknown displacement and input force vectors of size $3N$-by-1, respectively.

In dynamic analyses, damping is introduced to the system using a complex stiffness matrix (K^*), which is obtained via a loss factor (η):

$$K^* = K(1 + i\eta) \tag{2}$$

In this case, the global mass matrix M is also present in the equations of motion:

$$M\ddot{u} + Ku = f \tag{3}$$

For harmonic excitation with the angular frequency ω, the output displacement vector u^* can be calculated by solving the following equation:

$$(K^* - M\omega^2)u^* = f \tag{4}$$

The true displacement magnitudes can be obtained by taking the absolute value of u^*.

III. Deep Learning

A. Data set generation

We generate the data systematically for different combinations of the chosen variables. All force vectors applied to the fingertip skin are oriented in the normal direction. For static indentation, the only inputs are the surface node IDs (ranging from 1 to 239), where up to three point forces can be specified. For dynamic excitation, only one point force can be applied at a time considering the significantly higher number of possible combinations due to the additional input variables of excitation frequency ([1-300] Hz with 1 Hz increments) and loss factor ([0.1-0.5] with 0.05 increments). We randomly select 20% of the generated data and reserve it for validation purposes.

B. Learning and validation

The DNNs are trained to minimize the difference between the predicted and true displacement vectors of length $3N = 23\,031$. In static analyses, since the input node IDs are the only variables present, they are first mapped to the force vector of length 23 031. This approach eases the learning process since the input and output vectors have identical sizes. Accordingly, we use transformer-based DNNs, which are effective at capturing the relationships between long pairs of arrays. In dynamic cases, we use standard DNNs since the input vector comprising node ID, excitation frequency, and loss factor is significantly smaller than the output displacement vector. Note that the force amplitude is not included as a variable since a linear FE model is used. Therefore, the simulated displacements are proportional to the amplitude of the input force, and the results will be accurate only for small forces. In the validation studies, maximum error values with respect to the ground truth were found to be below 1% and 5% for the static and dynamic scenarios, respectively. The developed metamodel predicts the deformation field in around one second, which enables fast reaction to user input.

IV. Outlook

We are currently developing a web-based graphical user interface for our DNN-based metamodel. Our future public release of this tool will facilitate access to high-fidelity static and dynamic simulation of human fingertip mechanics.

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