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Evaluating Populations of Tactile Sensors for Curvature Discrimination

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Abstract

The high density of receptors in fingertip skin is a limiting factor for replicating tactile feedback for neural prosthetics. At present, the large size of engineered sensors and the dense network of neural connections from finger to brain inhibit duplicating the approximately 100 receptors/cm². The objective of this work is to build a model of the skin and neural response with which populations of sensors can be positioned and evaluated when discriminating spheres. The effort combines a 3D finite element model of the fingertip, a bi-phasic transduction model, and a leaky-integrate-and-fire neuronal model. Populations of sensors are configured with three average densities (10,000/cm², 1,000/cm², and 100/cm²). For these populations, the firing rates for the dynamic (40–70 ms) and static (650 ms–900 ms) phases and first spike latencies are predicted. The model can differentiate indenters at a level similar to human performance at each sampling density, including of the human finger (100/cm²).

Keywords

Tactile; touch; mechanoreceptor; solid mechanics; biomechanics; finite element analysis; leaky-integrate-and-fire; neural model; neural prosthetics

1 Introduction

Our sense of touch is informed by a dense population of mechanoreceptors in fingertip skin. The replication of these receptors may augment a next generation of upper limb prosthetics to be controlled by the central nervous system [1]. The present brain-machine interfaces, however, have at most 128 connections to the cortex, many of which are used for efferent control of mechanical actuators [2], which leaves little spare connectivity for afferents. Connecting to intact peripheral fibers is another option, but the high density of slowly adapting type I (SAI) receptors (e.g., 100/cm² [3]) still presents a challenge.

Modeling techniques may aid with the reduction of sensors. Previous modeling efforts have considered both single-unit receptors and population behavior under various inputs (e.g., sustained and vibration, spatial objects) and measured different outputs (e.g., firing rate, spikes). K. O. Johnson, for example, investigated the sustained response of a single afferent as a block indenter was laterally shifted, and modeled the firing rate with continuum mechanics [4]. Wheat and Goodwin modeled the response of a single receptor to annular stimuli using a function characterized by a pair of offset Gaussian profiles [5]. This single-unit model was then extended to a population of receptors, where sensor geometry and

innervation density could be varied. Likewise, population characteristics have been modeled for rapidly adapting (RA) afferents and their responses have been compared using unique quantitative (e.g., number of active fibers, summated firing rate, average firing rate) and qualitative (e.g., plots) dependent measures [6].

While single-unit models can be compared to neural recordings, the creation and validation of population models is hindered by the inability to simultaneously record from hundreds of receptors. Therefore, population models have been aligned with psychophysical approaches. Such tests, for example, have discriminated spherical indenters in a forced-choice protocol [7]. Typically, the accuracy of a population model is first validated for a single of its receptors against a neural recording before the population response is compared with psychophysical outcomes.

While quite useful, current models face significant limitations. For example, the aforementioned single-unit continuum mechanics model produces a static firing rate (e.g., lower frequency spiking behavior once the indenter has stopped moving), but not the dynamic complement (e.g., high spike firing in the first ~100 ms of indentation). Additionally, most population models are regression functions built from the neural data associated with specific stimuli, and their predictions do not project to a wider range of stimuli.

The work detailed here investigates the evaluation of increasingly sparse sensor populations to determine the point at which the reduced sensor populations can still enable a psychophysical task of sphere discrimination. Using a three part model of the skin and neurons as a numerical platform, the density of rectangular populations is varied and the response is evaluated. As this task is spatial in nature, we model the SA-I mechanoreceptor, one of four receptors present in fingertip skin. The SA-I is important for detecting edges and curvature.

2 Methods

A three-part model of the skin and neuron is built and the response from a single receptor is fit to a neural recording of a mechanoreceptor when stimulated with a moving 3 mm bar indented in 0.2 mm increments. This response is then generalized for a population of receptors. Our objective is to evaluate ability to discriminate between spheres at three population densities (10,000/cm², 1,000/cm², and 100/cm²). Three dependent measures, dynamic firing rate (40–70 ms), static firing rate (650–900 ms), and first spike latency are examined for population densities when indented with the spherical indenters (curvature 287, 296, 365, and 730 m⁻¹).

2.1 Model

As shown in Figure 1, spike generation is a 3-step process. First, the finite element model is indented. Strain energy density (SED) for elements (R1-R8) in the epidermal and dermal layers is sampled at several timesteps during the indentation and serves as input into the transduction functions. The transduction functions transform SED into current (I), which, in turn, is input into the neural model. Then, current is translated into spike times upon reaching a predetermined threshold.

2.1.1 Finite Element Model—A 276,000-element finite element model was developed to mimic properties of the index finger when indented with stimuli. The model is composed of four materials, the stratum corneum, inner skin, subcutaneous tissue, and bone. Tissue layer thickness is informed by human tissue measurements [8, 9], and material properties of each

skin layer are modeled based on previous reports. In particular, the dermis and subcutaneous tissue are modeled using a polynomial hyperelastic model and follow a Prony series for the viscoelastic phase [10], and the epidermis and bone are modeled as linear elastic [11].

To inform the neural response predictions, strain energy density for individual elements is sampled at the epidermal-dermal border. These elements are 8-node linear brick hybrid with constant pressure (C3D8H) with 0.1 mm edge lengths, which corresponds to a volume of 0.001 m³, approximately the volume of a cluster of Merkel cells, the end organ for a SA-I receptor [12].

Skin surface deflection tests were performed to analyze the bulk mechanical response of the combined layers when indented with a 50 micron line load and a cylinder with a radius of 3.17 mm. Skin deflection results were compared to data acquired via human tissue imaging [13]. Predicted skin deflection matched these results reasonably well, although those results are not presented herein. All finite element analysis was done in ABAQUS version 6.6 (SIMULIA-Dassault Systemes S. A., Providence, RI). The finite element model employed differs from the one previously presented [14] in that it incorporates a denser mesh at the surface, allowing for the indentation of a wider array of indenters at various indentation angles.

2.1.2 Transduction Model—The transduction model consists of two linear functions which represent the interactions at and within the SA-I membrane. These functions are used to achieve a bi-phasic response, first a high firing in the dynamic phase and then a lower but sustained firing in the static phase. The transduction model converts SED ($f(t)$) into current ($I(t)$) via three parameters: intercept constant (β mA), static gain (k_s mA/N), and dynamic gain (k_d mA·s/N). Note that this model consists of two linear function whereas a single sigmoid function was used in previous work [15]. Model equations follow:

$$I(t) = \beta + k_s f(t) + k_d df(t) \quad (1)$$

$$df(t) = \begin{cases} 0, & \text{for } t = \text{onset} \\ \left| \frac{f(t) - f(t-h)}{h} \right|, & \text{otherwise} \end{cases} \quad (2)$$

$$h = t_{n+1} - t_n \quad (3)$$

2.1.3 Neural Model—The neural dynamics model uses a leaky-integrate-and-fire model to mimic the neural dynamics by transforming current into spike times. As current ($I(t)$) passes through the SA-I membrane, membrane potential ($u(t)$) accumulates. Once this potential reaches a predetermined threshold ($\bar{v}$) the time is noted as a spike time, the membrane potential is set to resting potential, and the process repeats. SA-I membrane is modeled as a resistive-capacitive (RC) circuit and changes in membrane potential is a function of current membrane potential, current and time (Eq. 4). τ is the time constant of the membrane. This equation is solved using a fourth-order Runge Kutta.

$$\frac{du}{dt} = \frac{-u(t)}{\tau} + \frac{I(t)}{C} \quad (4)$$

2.2 Model Fitting and Dependent Variables

The six free parameters in the transduction and neural models (β , k_s , k_d , τ , C and $\bar{v}$) are fit to the neural response of a single SA-I afferent as a 3 mm bar is stepped across its receptive field [16]. The goal of the model fitting is to find a combination of values for the parameters that maximizes the fractional sum of squares (*FSS*) between the observed *in vivo* data and predicted dynamic and static firing rates.

To obtain the predicted firing rates, a 3 mm bar indenter is stepped across the lateral-medial surface of the finger model in increments of 0.2 mm. In estimating the dependent variables, the spikes generated 40 to 70 ms after indentation onset are used to calculate dynamic firing rate, while static firing rate is calculated from the number of spikes between 650 to 900 ms [16]. Predicted and *in vivo* data are compared in Figure 2. While not used in the model fitting, the third dependent variable is first spike latency, the time from indentation onset to the first spike arrival.

Response surface methodology was used to tune the six parameters simultaneously, as has been done elsewhere [15]. The resulting parameters are: $\beta = 4.81 \times 10^{-9}$ mA, $k_s = 1.52 \times 10^{-10}$ mA/N, $k_d = 1.17 \times 10^{-8}$ mA/N, $\tau = 97.66$ ms, $C = 1.09 \times 10^{-8}$ mF, and $\bar{v} = 80.20$ mF.

2.3 Numerical Experiments

We simulate a spherical discrimination task to determine whether the model can differentiate indenters using rectangular populations with three sensor densities (10,000/cm², 1,000/cm², and 100/cm²). The finite element model is indented with spherical indenters to a depth of 1.0 mm with a ramp-up period of 50 ms. SED is recorded for elements in the epidermal and dermal material layers over the time sequence indentation. These values are transformed into a spike-based response, from which we extract the three dependent measures.

In Goodwin's experiment, three spherical indenters with radii of curvature (RC) 287 m⁻¹, 296 m⁻¹, and 365 m⁻¹ were indented into human fingertips to characterize our discrimination ability [7]. Participants could distinguish a curvature of 365 m⁻¹ from a standard curvature of 287 m⁻¹ in 95% of trials. However, participants correctly discriminated between a sphere with RC 296 m⁻¹ and the standard in only approximately 58% of trials, a figure only slightly above chance performance. An additional, much smaller sphere (RC 730 m⁻¹) is used in this work.

3 Results

Figure 3 shows the a) coordinate system of the plots b) 3D plots of the dependent variables for the sphere with RC 287 m⁻¹, and c) predicted responses for the four spheres at each population density. To differentiate the spatial features of the four indenters, one can visually compare the area under the curve. Such qualitative comparisons have been made previously [6]. If the area under the curve is equal for any two indenters, they are certainly not differentiable. Conversely, a greater area between curves indicates that the two indenters might more likely be discriminable. The static and dynamic portions of Figure 5c show near identical line positions for indenters with RC 287 m⁻¹ and RC 296 m⁻¹ across all population density. The model did not produce significant differences in first spike latencies between these indenters under any density condition.

4 Discussion

The model was validated at each of three levels. First, the surface deflection of the finite element model was compared to human fingertip surface deflection values. Second, the single-unit neural response of the model was compared the response elicited by a monkey SA-I when stimulated with a moving bar indenter. Third, a psychophysical test was used to compare the population response of the model to human discrimination levels. The results of the simulated psychophysical task correlate directly with Goodwin's findings for human sphere discrimination levels at each of the sensor densities, including of the human finger. The model can differentiate between spheres with RC 287 m^{-1} and RC 365 m^{-1} , two indenters that are easily distinguishable in the psychophysical tests. However, it cannot differentiate a sphere with RC 287 m^{-1} from one with RC 296 m^{-1} . This correlates with the psychophysical findings that the two are indistinguishable.

Further optimization of the number of sensors may come only from simplifying the discrimination task. The present set of indenters, while differentiable by human standards, is quite close in size. An indenter with RC 287 m^{-1} corresponds to a diameter of 6.97 mm and an indenter with RC 365 m^{-1} has diameter 5.48 mm. Differentiating spheres of larger sizes may be more critical for performing activities of daily living.

Additionally, the location of sampling points relative to the point of indentation has a large impact on the response. Further work should run tests in which the indenter is shifted at several random locations relative to the population of receptors.

Lastly, while first spike latencies may convey spatial information to the central nervous system, we did not find a significant difference between the first spike latencies elicited by our model when indenting spheres of vastly different sizes. This is surprising given recent work by Johansson [17] but may relate to the specific indenters used or the type of task performed. While we use spherical indenters and indent at angles normal to the surface of the finger, Johansson used several indenter shapes and indented at various angles.

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Figure 1.

Reduced numbers of sensors may convey the same spatial information as more dense populations. The shaded region represents the time frame in which the indenter is moving. In this example, the spike-based response of the dense population has similar properties to that of the reduced population. The spiking frequency is higher for receptors near the center of the sphere than those at the periphery, and receptors near the center also respond more quickly.

Figure 2. Predicted (asterisks) and *in vivo* (circles) firing rate in impulses per second for a single receptor when indented with a 3 mm grating stepped across the finger.

Figure 3.

Population responses for several population densities and indenter sizes: (a) the coordinate system used throughout; the dashed line indicates the axis along which the response profiles are shown, (b) the dependent metrics for the densest population in three dimensions, (c) the response across the y axis of the finger of each population when indented with four spheres.