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Using Force Sensors and Neural Models to Encode Tactile Stimuli as Spike-based Responses

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Abstract

Tactile sensors will augment the next generation of prosthetic limbs. However, currently available sensors do not produce biologically-compatible output. This work seeks to illustrate that a force sensor combined with a bi-phasic, neural spiking algorithm, or spiking-sensor, can produce spiking patterns similar to that of the slowly adapting type I (SAI) mechanoreceptor. Experiments were conducted where first spike latency and inter-spike interval, in response to a rapidly delivered (100 ms) sustained displacement (1.1, 1.3, 1.5 mm for 5 s), were compared between the spiking-sensor and SAI recording. The results indicated that the predicted spike times were similar, in magnitude and increasing linear trend, to those observed with the SAI. Over the three displacements, average dynamic ISIs were 7.3, 4.2, 3.8 ms for the spiking-sensor and 6.2, 6.9, 4.1 ms for the SAI, while average static ISIs were 69.0, 45.2, 35.1 ms and 159.9, 69.6, 38.8 ms. The predicted first spike latencies (74.3, 73.9, 96.3 ms) lagged in comparison to those observed for the SAI (26.8, 31.7, 28.8 ms), which may be due to both the different applied force ramp-ups and the SAI's exquisite dynamic sensitivity range and rapid response time.

Keywords

Tactile; prosthetic force sensor; neural model; spikes

1 Introduction

In the near future, artificial tactile sensors will augment neural prosthetics for upper limb amputees. Such prostheses might provide feedback, crucial for performing everyday tasks, in a fashion similar to that of native cutaneous mechanoreceptors.

Of the four main types, slowly adapting type I (SAI) mechanoreceptors detect and respond to spatial edges and curvature under both vibrational and sustained stimuli [1, 2]. When a stimulus is applied to the skin, each SAI afferent transforms forces at its end organ site into a train of action potentials, or neural spikes, which are then interpreted by the central nervous system. These trains can be quantified by the firing rate, which is linearly related to indentation intensity [3], or conversely the time between spikes (inter-spike interval: ISI). Furthermore, the SAI afferent has two distinct phases of spike firing: dynamic and static. The dynamic phase, i.e., when the stimulus is moving, consists of a burst of spikes with high firing rate or low ISI. The static phase, i.e., when the stimulus has stopped moving and is

held into the skin, exhibits comparably lower firing rate thus greater ISI than those of the dynamic phase.

At present, instead of the spiking behavior that is interpretable by the nervous system, artificial force sensors used in robotic applications produce continuous analog voltage [4]. Efforts have begun only recently to move in the spike-based direction with a focus on vibratory and tapping stimuli [5]. Our group, in addition, has contributed to modeling the spike-based response to sustained stimuli, by implementing a skin-mechanics model, to reproduce firing in the static phase [6].

The objective of this work is to construct a spiking-sensor, by integrating an artificial sensor-substrate with a spiking algorithm, that can produce both phases of spike firing. Experiments compare the predicted results to neural recordings from a single SAI fiber in the mouse, under similar indentation depths [7].

2 Methods

A force sensor was embedded into a silicone substrate whereby a compressive stimulus could elicit time-changing voltage output. A bi-phasic algorithm model of the SAI neuron, representing both transmembrane current and neuronal spike signaling, was designed to convert recorded force into spike times. Experiments were conducted with the sensor-substrate such that a sustained displacement of a flat rod was delivered at three depths (1.1, 1.3, 1.5 mm) within ~100 ms and held for 5 s. The objectives were to a) demonstrate the production of a bi-phasic spiking response and b) compare the responses to similar *ex vivo* skin-nerve recordings. To evaluate part b), we analyzed dependent measures of first spike latency and ISI over both dynamic (time of first spike to time of max load) and static (2-5 s) phases.

2.1 Materials

2.1.1 Sensor-Substrate—The commercially-available piezoresistive sensor (Flexiforce A201, Tekscan Inc., South Boston, MA) responds to normal force in a 0-1 lb range over its thin (0.20 mm) and circular (dia 9.53 mm) pressure sensitive area. When integrated into a force-to-voltage circuit, force applied on the pressure sensitive area reduces the resistance across the sensor so that applied force translates to a change in the measured voltage. Custom-built circuitry amplifies (Burr Brown, INA214) the voltage before being fed into an analog-to-digital converter (National Instruments, DAQCard-6036E, Austin, TX), sampled at 100 Hz. Associated software (National Instruments, LabVIEW 8.5 Professional) recorded and translated voltage into force detected at the sensor's location, per Tekscan's specifications and our own calibration experiments.

The sensor was embedded at a laterally central location in a cylindrical silicone-elastomer substrate (dia 30 mm, height 10 mm) and at a 1.0 mm depth from the surface (Fig. 1). The embedded depth was selected to maximize receptive field size (dia 20 mm), while minimizing the sensor's depth from the substrate's surface. The stiffness of silicone-elastomer (136 kPa) is controllable by varying the percentage of cross-linker (0.98% in this case) (BJB Enterprises, TC5005, Tustin, CA). This elastic modulus value closely matches that reported of epidermal skin in human cadavers' [8]. Figure 2 shows an example of a continuously-detected force trace (N) from the embedded sensor.

2.1.2 Stimulus Apparatus—Compressive stimuli were applied to the sensor-substrate via the flat part of a rigid, cylindrical tip (Delrin, diameter 20 mm, height 14 mm) in the z-direction (Fig. 1). The 20 mm tip size gave an equal state of stress over the entire receptive

field. The indenter tip was secured to a low-profile load cell (Honeywell, Model Sensotec 11 subminiature, Columbus, OH), which recorded normal force at a resolution of 0.543 N (0.012 lb) with a 44 N maximum load capacity. Although the load cell along with the sensor outputs voltage, force in N was derived (Fig. 2). The load cell was mounted to a mechanical linear z-stage (Newport, Model ILS100). The high-precision linear stage with maximum velocity 50 mm/s was controlled by a motion controller (Newport, Model ESP300), which reported indenter position (resolution 0.0001 mm) (Fig. 2).

2.2 Spiking Algorithm

The receptor model is composed of i) a bi-phasic transduction sub-model which transforms a sensor's detected force into transmembrane current and ii) a leaky-integrate-and-fire neural sub-model that translates current into spike times.

2.2.1 Transduction Sub-model—The transduction sub-model transforms force detected from the sensor into current, similar to how stress/strain applied at an SAI afferent is transformed into receptor current across its membrane. Prior models have modeled static phase spiking with a sigmoidal function, but lacked the spike bursting in the first 100 ms [6]. The transduction function (Eqn. 1, 2) developed here transforms sensor detected force, $f(t)$, and change in detected force, $df(t)$, into transmembrane current, $I(t)$, using constant terms where, β is the intercept constant, k_s is static gain, k_d is dynamic gain, and h is the resolution or step size of force detected (10 ms in our case).

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

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

The dynamic term responds to the first-order change in force, and therefore dominates in the <500 ms period, while the static term dominates thereafter (Fig. 3). Parameters β (0), k_s (3E-07), and k_d (3E-03), were determined through model fitting.

2.2.2 Neural Dynamics Sub-model—The neural dynamics sub-model implements a leaky-integrate-and-fire model to transform transmembrane current into spike times. In such a model, as current is passed through the membrane, membrane potential is accumulated and whereupon reaching threshold, a spike is fired. Upon firing, the spike time is recorded, the membrane potential is reset to resting potential, and the refractory period is entered in order to iterate the process until stimulus offset. While the biological equivalent values of these parameters are known (i.e., typical resting membrane potential is ~ -65 mV), our model assumes a positive threshold relative to a reset membrane potential of 0 mV and a refractory period of 1 ms.

We abstract the SAI membrane's leaky-integrate-and-fire behavior as a resistive-capacitive (RC) circuit (Eqn. 3) and utilize a numerical Runge-Kutta 4th order method to solve the differential equation. The neural function transforms current, $I(t)$, into individual spike times through use of membrane potential, $u(t)$, where τ is a time constant, C is membrane capacitance, and $\bar{v}$ is threshold.

$$f(t, u) = \frac{du}{dt} = \frac{-u(t)}{\tau} + \frac{I(t)}{C} \quad (3)$$

As shown in Figure 3, high spike density is associated with increased current especially in the dynamic phase. Parameters τ (72.219 ms), C (4.78E-6 mF), and $\bar{v}$ (41.476 mV) were determined through model fitting.

2.3 Experiment

A set of experiments used the sensor-substrate and spiking algorithm to test its ability to predict lower ISI to greater indentation depth. This observed phenomenon is illustrated via compressive displacements of 1.1, 1.3, and 1.5 mm into the sensor-substrate. Through predicted spike times, the first spike latency and average ISI of both dynamic and static phases were calculated and compared to that of neural data recorded from a single mouse SAI fiber.

2.3.1 Procedure—Prior to each experiment, i) the sensor-substrate's receptive field was centered under the indenter tip via a supporting low-profile x-y stage (dual-mounted: Newport, Model 443, Mountain View, CA), ii) the tip was positioned just above the substrate surface via visual aid of a camera, and iii) the sensor-substrate was preconditioned by repeatedly (3 times) indenting 1.5 mm into the sensor-substrate at a speed of 5.8 mm/s for 10 s.

For each experiment, while oriented over the sensor's entire receptive field, the indenter tip was displaced 5.8 mm/s and held for 5 s whereupon the tip was retracted to its original position. This process was repeated 5 times at each indentation depth with the order randomized. Due to the stiffness of the substrate, the ramp-up of the applied force (time from force onset to time when max load is reached) takes ~100ms.

2.3.2 Mouse Neural Data—Neural recordings from *ex vivo* skin-nerve preparations were conducted on a single mouse [7]. In addition to the extracellular voltage recordings, force at the probe tip was recorded via a force transducer. The apparatus and experimental runs (described elsewhere) were similar to those here whereby an indenter tip, the flat-part of a cylinder, was applied over the entire receptive field. Individual trials consisted of a 5 s displacement at a speed of ~30 mm/s. The time to ramp-up to max force was around 50 ms.

2.3.3 Data Analysis—The independent measure is indentation depth (1.1, 1.3, and 1.5 mm), which was set in the spiking-sensor experiments to match those used in neural recordings. The dependent measures are a) first spike latency, b) dynamic ISI, and c) static ISI. The first spike latency is calculated as the time between the stimulus onset and the first spike elicited. As there is a delay between the signal sent to the controller and the load cell's applied force, the stimulus onset is defined as the time the load cell reports > 0.1 N. Figure 2 illustrates the stimulus onset for the spiking-sensor experiments. Average dynamic ISI is calculated as the sum of ISIs from the first spike to the spike time immediately before the time of max load divided by the number of ISIs within this window, averaged over replications for both the artificial and neural responses. Furthermore, average static ISI is calculated similarly over a 2–5 s window and averaged across replications for both responses.

3 Results

Figure 5 compares the average first spike latency and average ISI within dynamic and static windows (from both the spiking-sensor's predicted spike times and the SAI afferent neural recordings) for indenter depths of 1.1, 1.3, and 1.5 mm. The 95% confidence intervals illustrate the spread across replications.

4 Discussion and Conclusions

With the development of a spiking-sensor, this work a) converted continuous sensor-detected force into a bi-phasic, spike-based response, which is b) comparable to SAI spiking behavior for three indentation depths. With increased indentation depth, average static ISI decreases for both artificial and neural responses, while average dynamic ISI is not affected. However, the artificial first spike latencies are different than those of the neural recordings. The discrepancy in first spike latency is in part due to the different ramp-up times used between the artificial and neural experiments (Fig. 4). Since the indenter tip in the artificial sensor prep is 20 mm in diameter (compared to 3 mm for the mouse prep), greater force is required to traverse into the substrate and therefore slows the maximum rate of the actuator. In addition, the SAI response may be more rapid due to its exquisite sensitivity. Furthermore, predicted spike patterns are noticeably irregular, a hallmark of SAI responses. This effect is partially due to the amplification of small deviations in sensor response.

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Figure 1.
Sensor-substrate and stimulus apparatus during experiment.

Figure 2. Indenter displacement, applied force on sensor-substrate, and detected force from embedded sensor recorded during a 1.5 mm depth indentation run over 5 s; data transformation of sensor force into bi-phasic (dynamic and static) spiking behavior.

Figure 3.

Transformation of sensor detected force into transmembrane current and then into spike times via membrane potential; transmembrane current has static and dynamic terms affected, respectively, by magnitude of force and change in force.

Figure 4. Comparison of predicted and actual spike times for the three indentation depths, where magnitude of and rate of change in force are affected by indentation depth; the first spike latency and both dynamic and static ISIs vary correspondingly.

Figure 5.
Comparison of first spike latency (above) and average ISI (below) from spiking-sensor and SAI afferent