PROSTHESIS GRIP FORCE MODULATION USING NEUROMORPHIC TACTILE SENSING

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ABSTRACT

For many prosthesis users, the lack of tactile feedback in their limbs can make grasping difficult, especially when handling delicate objects. The lack of tactile feedback is not a new problem for prosthesis users, but how tactile information is handled can have a significant impact on the performance of the system. As prosthetic limbs become more advanced, there is an interest in developing systems that are biologically inspired to more closely mimic how the healthy human system operates. In this work, we utilize a leaky integrate and fire neuron model with spike rate adaption for representing tactile information in a prosthetic hand. We investigate the use of the simulated neuron spike rate in an EMG gain modulating function to limit the amount of grip force applied by a prosthetic hand during grasping of a delicate object. We compare this method with the use of the grip force as an input to the EMG gain modulating function as well as to grasping with no tactile feedback. Results show a reduction in the percentage of broken objects during grasping from 27.5% with no feedback to ~14% when using either grip force or neuromorphic spiking feedback. This demonstrates the feasibility of using a biologically relevant representation of tactile information for improving prosthesis functionality in real-time.

INTRODUCTION

The sense of touch offers a multitude of functionality such as exploring intricate objects, performing complex finger movements, or even providing comfort to loved ones. The seemingly unparalleled performance of tactile sensation gives rise to our instinctive behavior to reach out and explore new objects or surroundings with our hands. Our sense of touch helps provide information on texture, shape, weight, and temperature, which we rely on for understanding objects [1]. One problem faced by people with upper limb loss is the lack of tactile information in most commercial prosthetic limbs available today [2]. Although recent developments in myoelectric (EMG) prosthesis control have shown improvements in pattern recognition control strategies [3]–[5], a major component of creating fully functioning upper limb prostheses is tactile feedback. This has led to progress in novel closed-loop tactile feedback control algorithms [6], [7] and sensory feedback via peripheral nerve stimulation [8]–[10].

As technology moves towards more human-like prosthetic arms it is necessary to develop faster, more efficient, and more natural ways of processing tactile information to be used for sensory stimulation. Early work with sensory feedback of tactile information used force sensor information to drive peripheral nerve stimulation where increased grip force translated to increased stimulation frequency, which was used for object discrimination [8] and grip force modulation [9]. More recently, a neuromorphic stimulation model was implemented using signals from a tactile sensing prosthetic finger for texture discrimination [10]. There is a trend towards developing neuromorphic devices and models to mimic the natural behavior of biological systems to improve efficiency and performance over traditional methods. Recent examples include the vestibular system [11], cortical neurons [12], and touch [13]. For tactile feedback in upper limb prostheses a neuromorphic approach includes modeling of the slowly adapting (SA) and rapidly adapting (RA) mechanoreceptors found in our skin. The goal being that this approach will offer more efficient transmission of relevant tactile information, similar to a healthy peripheral nervous system, to the prosthesis controller as well as for driving nerve stimulation for sensory feedback. Previous work using models to simulate tactile afferent patterns have investigated implementation of the models with little emphasis on real-time functionality [14], [15]. Here we investigate the ability of a prosthesis controller to functionally interpret a neuromorphic model of tactile information using a leaky integrate-and-fire (LIF) neuron with spike rate adaption to estimate grip force and prevent breaking a delicate object during a prosthesis grasping task.

MODEL & METHODS

One particular model that is commonly used to simulate the behavior of SA and RA mechanoreceptors is the leaky integrate and fire (LIF) neuron model [14]–[16]. For this work, we implemented an LIF neuron model with spike rate adaption, which introduces a hyperpolarizing current that makes the neuron less likely to fire once it has previously fired. This adapted model is used to create the neuromorphic response and represent a more realistic neuron spiking behavior. The model can be written as

$$\tau_m \frac{dv}{dt} = v_r - v(t) + RI(t) - g(t)(v(t) - E_k) \quad (1)$$

where $v(t)$ represents the membrane potential at time t, and τ_m is the membrane time constant. R is the membrane resistance. This is a simple RC circuit where the leakage is due to the resistor and the integration of $I(t)$ is from the capacitor in parallel. When the membrane potential reaches a spiking threshold, v_{th}, it is reset instantaneously to a lower value, v_r. The refractory conductance of the neuron is given by $g(t)$ and E_k is the reversal potential for the spike rate adaption. The change of the conductance is given as

$$\tau_g \frac{dg}{dt} = -g(t) \quad (2)$$

where τ_g is the conductance refractory period. The conductance is incremented by Δg after each spike. A more detailed and complete discussion of this model and its extensions can be found in [16].

To create a neuromorphic tactile feedback system, we use the output of force sensors as the input stimulus, $I(t)$, to the model. The model is tuned so that the maximum firing rate is 100 Hz, which occurs when the grip force of the prosthesis is 20 N. This model represents a SA type neuron due to its sustained response to a given input. The neuromorphic tactile feedback method presented here differs from our previous work in that it uses more realistic, continuous neuron model dynamics to simulation spiking behavior. The neuron firing rate of the mechanoreceptor model is used to determine grip force, which is then used to prevent accidental damage to delicate objects during grasping. Our previous work utilized event-based spikes to trigger the onset, offset, and changes in force but used the raw sensor signal for determining grip force [6].

The sensors are placed on the thumb, index, and middle fingertips of a bebionic3 prosthetic hand (Steeper, Leeds, UK) (Fig. 1a). The sensors are force sensitive resistors made up of stretchable textiles. These piezoresistive sensors (Fig. 1b) have been previously developed and used for measuring grip force on a prosthetic hand [6], [17]. Each fingertip cuff has 3 sensing elements. A custom control board developed by Infinite Biomedical Technologies (Baltimore, USA) is used to interface with the prosthesis and read in the fingertip force sensor signals. The grip force is found by summing the output of the sensing elements. Electromyography (EMG) electrodes (Infinite Biomedical Technologies, Baltimore, USA) are used to record motor neuron activity in the forearm from the prosthesis user to control the hand. The neuromorphic model is implemented using MATLAB

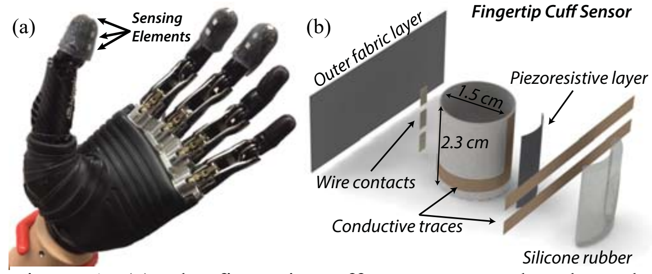

Figure 1: (a) The fingertip cuff sensors are placed on the thumb, index, and middle fingers of a bebionic3 prosthesis. Each sensor cuff contains three sensing elements. (b) The cuff is made up of conductive and piezoresistive textiles as well as silicone rubber.

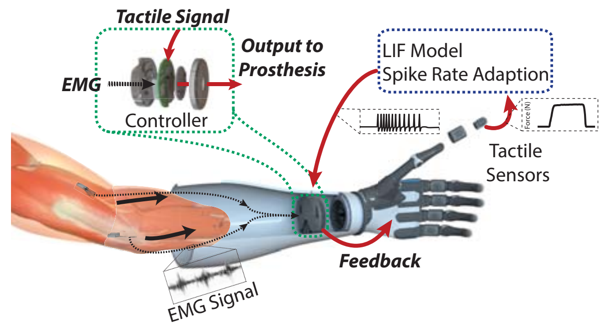

Figure 2: The prosthesis grip force serves as the input to the neuromorphic model. The prosthesis controller processes both EMG and tactile signals, which allows for efficient modulation of the information being sent to the prosthesis as feedback. In this work, the feedback to the prosthesis is a modulated EMG gain that is dependent on the spike rate of the neuromorphic model.

(MathWorks, Natick, USA). The sensor signals are relayed via Bluetooth communication to MATLAB from the prosthesis controller. The sensor signals are sampled and sent to MATLAB at 200 Hz while the EMG electrodes are sampled at 1 kHz. The system diagram is shown in Fig. 2.

An EMG gain modulating function that uses tactile information is implemented on the prosthesis controller to limit the amount of grip force applied during grasping. This exponential decaying function, the Compliant Grasping algorithm, was presented and described in detail in [6]. We adapted the algorithm for this work to limit the maximum grip force to 10 N before forcing the EMG signal to zero. EMG modulation was only applied to the electrode signal that closed the prosthesis. Two algorithm conditions were investigated in this work. The first uses the measured grip force as the input to the EMG modulating function, which is similar to the approach in [6]. The second method uses the output of the neuromorphic model and the neuron firing rate as the input to the EMG modulating function. The goal here is to investigate the ability of a prosthesis to utilize neuromorphic input to successfully modulate a user's EMG signal to improve grasping of delicate objects.

EXPERIMENTS & RESULTS

To evaluate the neuromorphic tactile feedback system the prosthetic hand was mounted on a stand and controlled by the user's forearm EMG signals. Three male subjects participated in this experiment, a bi-lateral upper limb amputee and two able-bodied individuals. The participants controlled the prosthesis to grab, hold, and release a delicate object presented by the experimenter. The experiment was approved by the Johns Hopkins Medicine Institutional Review Board. The goal was to not break the object, a cracker ($m = 1.80 \pm 0.11$ g, force to break > 8 N), during grasping. Each user was allowed to practice with the system for up to 10 minutes before starting the experiment. Three different conditions were tested: 1) no tactile feedback, 2) grip force (GF) tactile feedback and 3) neuromorphic spike rate (SR) tactile feedback. Each trial consisted of 10 presentations of the delicate object, and the number of broken objects was recorded. Up to 10 trials of each condition were performed in a random order. Results from all participants are similar and were combined to provide a larger data set. As described in the previous section, both of the tactile feedback conditions reduced the amplitude of the EMG signal to close the prosthesis, effectively limiting the hand's ability to exert a large grip force, similar to what has been described in [6] and [18].

The neuromorphic response to the tactile signal during grasping is shown in Fig. 3. This figure shows a representative grasp, hold, and release for a single trial from the experiment. The spike rate of the neuron is found using a 60 ms sliding window and is used in the EMG gain modulation algorithm for limiting the amount of grip force applied by the prosthesis. The results from the prosthesis grasping task are shown in Fig. 4. The number of broken objects are recorded and the average percentage of broken objects for each testing condition are shown in Fig. 4. With no tactile feedback, 27.5% of the objects broke during grasping. Using the total grip force as an input to the EMG gain modulation function, 14% of the grasped objects broke whereas 14.5% of the objects broke when using the neuromorphic spiking behavior from the neuron model as the input for EMG gain modulation. The error bars in Fig. 4 represent the standard error of the mean.

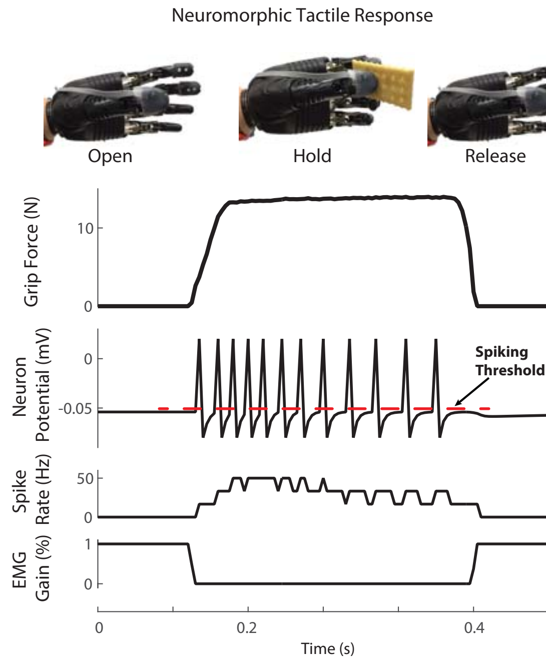

Figure 3: The grip force and neuromorphic spiking response during an actual prosthesis grasping task are shown by the top two curves, respectively. The neuron spike rate and the modulate EMG gain are shown by the bottom two curves, respectively. This data is taken from a single grasping task and is representative of the data set.

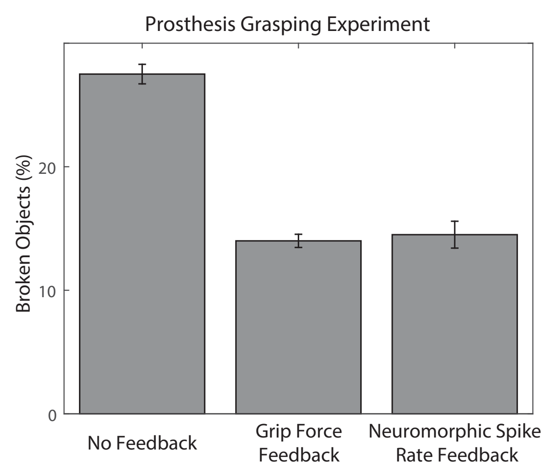

Figure 4: Results from the prosthesis grasping task show improvements while using tactile feedback. The use of grip force or neuromorphic spike rate show improvements over the case of no tactile feedback. The neuromorphic approach shows similar improvements as the more traditional method of using grip force as a feedback input.

DISCUSSION & CONCLUSION

The LIF neuron model with spike rate adaption produces biologically relevant signals with realistic dynamics as shown by Fig. 3. Using neuromorphic feedback achieves similar results as using standard grip force as a feedback mechanism (Fig. 4), but the benefit is in the to process a digital representation of touch. This neuromorphic representation of tactile information is valuable because it allows for transmission of larger amounts of data in a more efficient manner, similar to behavior in biology [1]. The spike rate adaption component of the traditional LIF model provides more realistic neuron behavior by adjusting the neuron conductance with sustained stimulation. This adaption is seen in the prosthesis implementation by the decreasing firing rate during the sustained grip in Fig. 3.

The neuromorphic approach to processing tactile information shows improved performance over no tactile feedback. With no form of tactile feedback, the prosthesis grasping task resulted in 27.5% of the objects being broken during the experiment. Including grip force information as part of an EMG modulating strategy drastically improves this number by reducing it to 14%, which is similar to results seen in [6] and [18]. The average percentage of broken objects is 14.5% while using only the firing rate of the LIF neuron with spike rate adaption for modulating the EMG gain. This is an interesting finding in that it demonstrates the ability of the prosthesis hardware to process the spiking response and transform it into EMG gain modulation. Additional user testing under more scenarios is necessary to better understand the system's performance. The results presented here have major implications for future prosthetic limbs incorporating sensory feedback to the user. Providing realistic neuron activity to the prosthesis will help streamline the information flow from sensors back into the nervous system of the user.

The goal of this work is to demonstrate the feasibility of a neuromorphic tactile feedback system for use in a prosthetic arm. The results from the prosthesis grasping task suggest the ability to use a purely neuromorphic representation of a tactile signal for improving grasping of delicate objects. This is one of the first implementations of a neuron model to represent tactile information for real-time processing by a prosthetic limb. The highlight of this work is the use of a neuromorphic tactile feedback system based on a LIF neuron model with spike rate adaption for real-time functional improvements in a prosthesis. This will play an important role for future prosthetic technology as limbs become more sophisticated and attempt to mimic the human body in both utility and performance.

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