Tactile Afferents Encode Grip Safety before Slip for Different Frictions

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Abstract— **Adjustments to frictional forces are crucial to maintain a safe grip during precision object handling in both humans and robotic manipulators. The aim of this work was to investigate whether a population of human tactile afferents can provide information about the current tangential/normal force ratio expressed as the percentage of the critical load capacity – the tangential/normal force ratio at which the object would slip. A smooth stimulation surface was tested on the fingertip under three frictional conditions, with a 4 N normal force and a tangential force generated by motion in the ulnar or distal direction at a fixed speed. During stimulation, the responses of 29 afferents (12 SA-I, 2 SA-II, 12 FA-I, 3 FA-II) were recorded. A multiple regression model was trained and tested using cross-validation to estimate the percentage of the critical load capacity in real-time as the tangential force increased. The features for the model were the number of spikes from each afferent in windows of fixed length (50, 100 or 200 ms) around points spanning the range from 50% to 100% of the critical load capacity, in 5% increments. The mean regression estimate error was less than 1% of the critical load capacity with a standard deviation between 5% and 10%. A larger number of afferents is expected to improve the estimate error. This work is important for understanding human dexterous manipulation and inspiring improvements in robotic grippers and prostheses.**

I. Introduction

The ability to handle and manipulate objects is crucial to a person's capacity to perform everyday activities and maintain a high quality of life. To ensure that an object is held safely in the hand, humans adjust the grip force (normal to the object), which is scaled proportionally to the destabilizing load forces tangential to contact area. If the object is more slippery or heavier, a stronger grip or normal force is required. The normal/tangential force ratio at which the object can no longer be held in the grip is called the slip ratio. Thus, the central parameter to be regulated during object manipulation is the normal/tangential force ratio, which should always be kept above the slip ratio within a certain safety margin [1]. Studies in humans and monkeys have shown that cutaneous mechanoreceptors in the fingers [2, 3], play a critical role in providing information about an object's shape, weight and distribution of mass [4-6]. However, how information about the frictional condition is extracted from a population of tactile afferent responses is not known and has never been demonstrated.

Humans have four types of tactile afferents in the glabrous (non-hairy) skin of the hand. Two types respond to static stimuli with a sustained discharge and are called slowly adapting (SA), and two only respond transiently to changing stimuli, called fast adapting (FA) [2]. Afferents are further classified as Type I, which have small receptive fields with distinct borders, or Type II, which have receptive fields which lack distinct borders. Thus, the glabrous skin of the human hand contains SA Type I (SA-I), SA Type II (SA-II), FA Type I (FA-I) and FA Type II (FA-II) afferents.

Only one study has investigated afferent responses mediating adjustments to frictional conditions upon initial contact of the finger with an object [7]. Silk and sandpaper were used as the surface materials to achieve two frictional conditions. Contact forces (analogous with grip forces) were generated by the subject (lifting an object) or with a hand held force probe, resulting in considerable trial-to-trial force variability. Three out of eight FA-I afferents were reliably influenced by the changing frictional conditions, and thus could potentially signal friction upon initial contact with an object. Since changes in friction were achieved by changing the surface material, subjects could recognize the material at the time of initial contact and at least partly scale the resulting grip force via anticipatory mechanisms.

Since this work, there has been little advancement in understanding how tactile afferents may encode friction and regulate the normal/tangential force ratio. This is extremely important for understanding human dexterous manipulation as well as for improving control strategies for robotic grippers and prostheses. The most advanced robotic manipulators that approach the dexterity of humans use a combination of crude low-resolution tactile sensing and very high speed vision systems [8]. These vision systems, however, are not a suitable substitute for tactile inputs when operating in unstructured environments, as many contact properties cannot be determined visually; e.g., manipulation forces and friction. Further advances in the control of sophisticated robotic manipulators and smart prostheses will not be possible without inspiring innovations in the design of tactile sensors and associated signal analyses algorithms. An understanding of the encoding of tactile stimuli which are relevant to object manipulation could lead to the development of improved biomimetic artificial sensors which

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might also be able to replace (in whole or in part) lost sensory information for amputees, improving sensorimotor control of prosthetic limbs [9].

The work presented here aims to investigate whether information can be extracted from the spike counts of tactile afferent neurons in response to forces applied by an object to the human finger pad. This is achieved by employing a multiple regression model to estimate the ratio of tangential/normal force as a percentage of the critical load capacity (also the coefficient of friction).

II. Methods

A. Stimulation Protocol

A six-axis, three-dimensional (3D) robotic manipulator (KR Agilus 6 R900 sixx, KUKA Roboter GmbH, Germany) was programmed to apply forces to the finger pad. A normal force of 4 N was applied to the finger with an approach speed of 4 mm/s. While maintaining 4 N of normal force, the stimulus applicator was moved tangentially to the finger pad surface by a total distance of 10 mm at a speed of 2.5 mm/s. The stimulus was applied first with the tangential motion in the ulnar direction, then in the distal direction. The stimulus was applied twice in succession in each direction.

The stimulus applicator was a 3D-printed circular disc (diameter 24 mm) with a smooth surface. The smooth disc was tested under three frictional conditions: with no treatment, treated with oil to reduce surface friction, and treated with a friction-increasing agent (Grippo™). By treating the surface with these agents, the coefficient of friction was modified without affecting the surface texture.

The contact forces were recorded during stimulation with a six-axis force sensor (Nano17, ATI Industrial Automation, USA) at a sampling frequency of 1 kHz.

B. Microneurography Recording

During stimulation, neural recordings of single afferents were made by inserting a tungsten microelectrode into the median nerve at the level of the wrist. The procedure was performed with approval from the University of Western Sydney Human Research Ethics Committee and written consent was sought prior to subject enrolment in the study.

The neural recordings were sampled at a frequency of 10 kHz. Spike events were identified using custom spike detection software and binned into time bins of 1 ms width to match the sampling frequency of the force traces (1 kHz).

C. Features

For each stimulus, the moment of initial slip (t_{100}) was identified manually by visual inspection of the ratio of tangential force (F_T) to normal force (F_N): $G[t] = F_T[t]/F_N[t]$. The critical load capacity is the ratio of tangential/normal force at the moment of initial slip; i.e., $G[t_{100}]$. The points t_i were identified for $i \in \{50, 55, ..., 100\}$, such that t_i is the time at which $G[t_i] = i\% \times G[t_{100}]$ where, and $t_0 < t_i < t_{100}$.

The feature s_i, corresponding to the time point t_i, was the number of spikes in the square window of length L ms, at position P, relative to the time point t_i. Each combination of three window lengths, L = 50 ms, 100 ms, and 200 ms, and three window positions, P = *Before*, *Centered* and *After* (indicating the window ending at t_i, centered at t_i, and starting at t_i, respectively) were investigated. In each recording, window overlap depends on the slope of $G[t]$.

D. Multiple Regression

An ensemble population response was constructed by grouping afferent responses which arose from the stimulus with the same frictional condition, slip direction and repetition; i.e., each feature vector corresponding to time point t_i for the stimulus with frictional condition $f \in$ {*Oil*, *No Treatment*, *Grippo*}, in slip direction $d \in$ {*Ulnar*, *Distal*}, repetition $r \in \{1,2\}$, contains N values of s_i (one s_i from each afferent; N is the total number of afferents) and one constant term. The total number of feature vectors was 132: 11 values of i (50 to 100% in increments of 5%) × 3 frictional conditions × 2 slip directions × 2 repetitions. The regression target value for each feature vector is the corresponding value of i; i.e., the percent of critical load capacity.

Leave-one-out cross validation was used to train and test each model [10]. That is, 131 feature vectors were used to learn the regression weights, and the remaining vector used for testing. This was repeated 132 times such that each vector was used as the test case once.

III. Results

Twenty nine afferent recordings were made from eight healthy subjects (four male, four female; ages 19 to 29 years). These were twelve SA-I, twelve FA-I, two SA-II and three FA-II afferents.

The distribution of the coefficient of friction is shown for each frictional condition in the ulnar and distal slip direction in Fig. 1A and B respectively. The open circle is the mean coefficient of friction and the whiskers extend to ±1 SD. Treatment with oil lowered the coefficient of friction and treatment with Grippo increased the coefficient of friction with respect to no treatment.

For illustrative purposes, the time course of the tangential/normal force ratio for three cases of stimulation on the same finger are shown in Fig. 2: distal slip direction with the stimulus surface treated with oil, ulnar slip direction with no treatment of the stimulus surface, and distal slip direction with the stimulus surface treated with Grippo (Fig. 2A-C respectively). The gray triangle indicates the point of slip

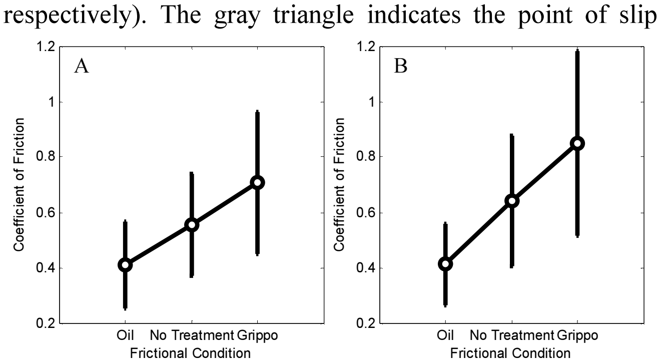

Fig. 1. Distribution of coefficient of friction (also critical load capacity) at initial slip in the (A) ulnar direction, and (B) distal direction, by frictional condition (Oil, No Treatment, and Grippo). Open circles are the mean and whiskers extend to ±1 SD.

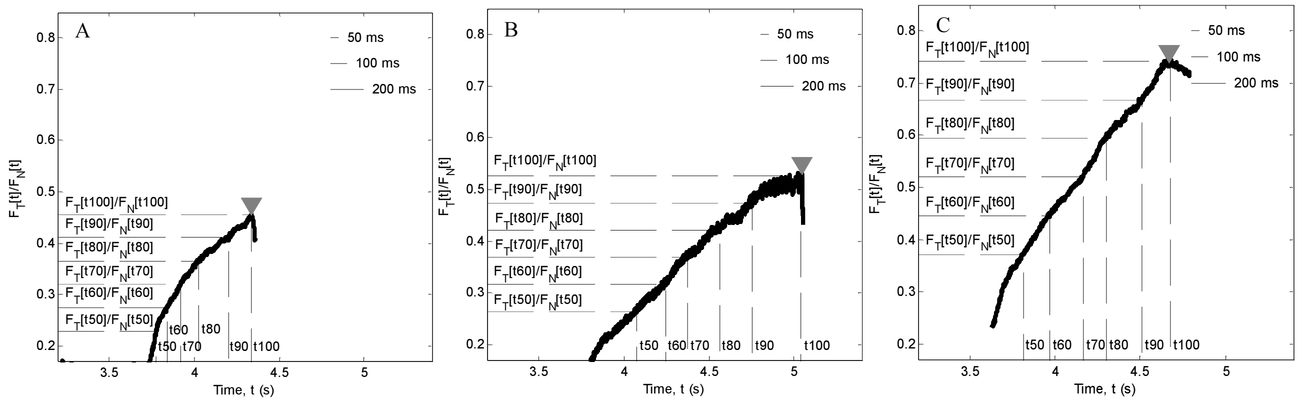

Fig. 2. Examples of tangential force to normal force ratio for different frictional conditions and slip direction on the same finger. A) Smooth surface treated with oil during application of tangential forces in the distal direction; B) Smooth surface with no treatment during application of tangential forces in the ulnar direction. C) Smooth surface treated with Grippo during application of tangential forces in the distal direction. The dashed lines indicate the points corresponding to 100, 90, 80, 70, 60 and 50% of the critical load capacity as labelled. The grey triangle indicates the point of first slip. Lines in top right hand corner indicate window length to scale.

and the dashed lines indicate the points corresponding to 100, 90, 80, 70, 60 and 50% of the critical load capacity.

Leave-one-out cross validation was performed to train and test nine different multiple regression models (combinations of three window lengths L, and three window positions P). The regression estimate errors (estimate – target) were calculated, and the effect of window length L (all window positions), and window position P (all window lengths), on the estimate error are presented in Table I. The magnitude of the mean estimate error was small (less than 0.05% of critical load capacity) in all cases. The standard deviation of estimate error was smallest for L = 200 ms (mean -0.041%, SD 5.358%) and largest for L = 50 ms (mean 0.014%, SD 9.509%). The window position had a much smaller effect on error compared to the effect of window length. The standard deviation of estimate error was smallest when P is *After* (mean 0.000%, SD 7.149%) and largest when P is *Before* (mean -0.036%, SD 7.935%; Table I).

Tactile afferent responses provide contact information, which can trigger corrective actions commencing ~100 ms after contact [11]. For this reason, L = 50 ms is the most appropriate window length in terms of dexterous manipulation. The multiple regression estimate for the model with L = 50 ms and P is *After* (the window position with the smallest error; Table I), is shown in Fig. 3. The edges of the grey boxes are the 25th and 75th percentile estimates, the dashed line is the median estimate and the solid line is the target. Each box is generated from 12 data points: 3 frictional conditions × 2 directions × 2 repetitions. The median estimates follow the target values closely. The 25th to 75th percentile estimates span on average approximately 9% of the critical load capacity (Fig. 3), indicating that the resolution of the model is approximately 10%.

For window length L = 50 and 100 ms, the maximum number of spikes in any window from any single afferent was 4 and 7 respectively. With low spike numbers, it is difficult to observe a relationship between the number of spikes in a single afferent and the regression target. To illustrate the afferent response, the mean number of spikes in each window from an example of each afferent type is shown in Fig. 4 for the L = 200 ms and P = *After*, where the maximum number of spikes in any window from a single afferent was 13. The mean number of spikes is shown in the ulnar and distal slip direction for an example FA-I afferent (Fig. 4A and B), FA-II afferent (Fig. 4C and D), SA-I afferent (Fig. 4E and F), and SA-II afferent (Fig. 4G and H), with whiskers extending to ±1 SD.

Each example afferent response (Fig. 4) shows correlation with the percent of critical load capacity for at least a limited range. The FA-II (Fig. 4C and D) and SA-II (Fig. 4G and H) show directional sensitivity, with larger response to the ulnar and distal slip directions respectively. None of the example afferent responses in Fig. 4 could be used to estimate the percent of critical load capacity on their own.

TABLE I. ESTIMATE ERRORS OF F_T[T]/F_N[T] AS A PERCENT OF CRITICAL LOAD CAPACITY (CLC) FOR DIFFERENT WINDOW LENGTHS (L) AND WINDOW POSITIONS (P).

	Estimate Error (% of CLC)			**Estimate Error (% of CLC)**	
***L* (ms)**	***Mean***	***SD***	***P***	***Mean***	***SD***
50	0.014	9.509	*Before*	-0.036	7.935
100	-0.007	7.058	*Centered*	0.002	7.411
200	-0.041	5.358	*After*	0.000	7.149

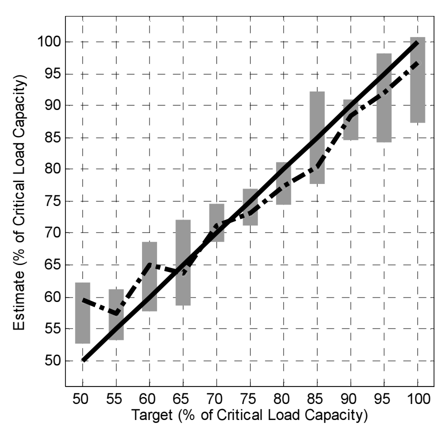

Fig. 3. Multiple regression estimate with features from 29 afferents for window length L = 50 ms and window position P is *After*. Edges of gray boxes are the 25th and 75th percentile; dashed line is median estimate; solid line is target value.

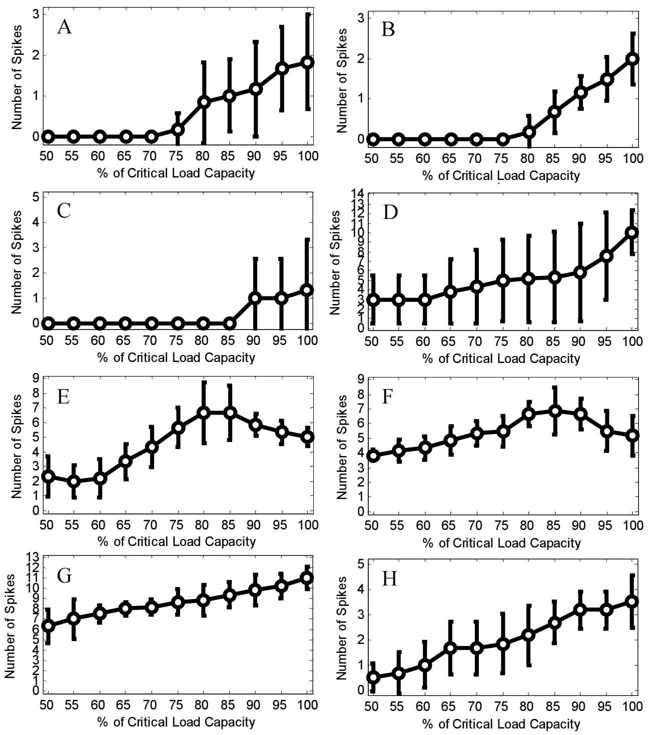

Fig. 4. Example number of spikes for window length L = 200 ms and window position P = *After* for: FA-I afferent in ulnar (A) and distal (B) slip direction, FA-II afferent in (C) ulnar and (D) distal slip direction, SA-I afferent in (E) ulnar and (F) distal slip direction, and SA-II afferent in (G) ulnar and (H) distal slip direction. Open circles are the mean spike count and whiskers extend to ±1 SD. The model weights for the FA-I, FA-II, SA-I and SA-II afferent were 4.30, 2.57, 1.80 and 2.08 respectively.

IV. Discussion

For the first time this study has demonstrated that a population of tactile afferents is capable of encoding the tangential/normal force ratio, expressed as a percentage of the critical load capacity. This information is crucial to ensure grip safety when holding and manipulating objects, as when the tangential/normal force ratio approaches the critical load capacity, the object may slip out of the grip. This principle is fundamental and universal in all types of dexterous manipulation. It is advantageous to encode the tangential/normal force ratio in this way as this single parameter reflects the relationship between three constituents: normal force, tangential force and the coefficient of friction.

The window length with the smallest regression estimate error was L = 200 ms (Table I). However, a 50 ms window length is more biologically relevant [11]. The improved performance for the larger window length is likely due to a larger number of spikes in each window. The window position with the regression estimate error was P = *After* (Table I). This is likely due to the delay between stimulation of the mechanoreceptor in the fingerpad and the recording of an afferent spike via the microelectrode at the wrist [12].

Each fingertip is innervated by approximately 2000 tactile afferents [13], however it has been demonstrated here that a relatively small number of afferents is sufficient to obtain information required for adequate manipulative force adjustments. It is expected that with a larger number of recorded afferents the accuracy of the model estimate could be improved. Single afferents cannot encode this information with just spike count, and a population input is required. Here, the multiple regression model can be considered as a synaptic neural network, where all input afferents synapse onto one post-synaptic neuron. The model weights (which do not change) represent the synaptic strength between each afferent and the post-synaptic neuron.

V. Conclusion

In this work it has been shown that the ratio of tangential force to normal force can be satisfactory determined as a percentage of the critical load capacity using multiple regression applied to the responses of only a small number of afferents. This information is crucial to ensure safe grip during object manipulation.

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