34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Decoding Tactile Sensation: Multiple Regression Analysis of Monkey Fingertip Afferent Mechanoreceptor Population Responses

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Abstract—**How complex tactile sensations are encoded by populations of afferent mechanoreceptors is currently not well understood. While much is known about how individual afferents respond to prescribed stimuli, their behavior as a population distributed across the fingertip has not been well described. In this study, tactile afferent mechanoreceptors in monkey fingertips were mechanically stimulated, using a flat disc shaped probe, with several magnitudes of normal force (1.8, 2.2 and 2.5 N) and torque (2.0 and 3.5 mNm), in clockwise and anticlockwise directions. Afferent nerve responses were acquired from 58 slowly-adapting (SA) type-I and 25 fast-adapting (FA) type-I isolated single cutaneous mechanoreceptive afferents, recorded from the median nerve. At 10 ms time intervals after the application of torque begins, a multiple regression model was trained and evaluated to estimate the magnitude of the applied normal force and torque. Averaged results over the 200 ms period after the torque reaches its maximum indicate that SA-I and FA-I afferents can both estimate the applied torque value. FA-I afferents gave the lowest estimation error mean and standard deviation of -0.051 ± 0.334 mNm for a target torque of 2.0 mNm, and 0.003 ± 0.414 mNm for a target torque of 3.5 mNm. However, while SA-I afferents could estimate normal force well, there was no significant difference (ANOVA, p=0.173) in the FA-I estimates of normal force, as this force had already been held constant for one second before the torque loading phase under analysis began.**

I. Introduction

The ability to handle and manipulate objects is crucial to one's capacity to perform everyday activities and maintain a high quality of life. To enable dexterous manipulation, tactile afferent mechanoreceptors play an essential role in providing tactile information to our motor control system.

Although a good deal of research has been performed on the behavior of single afferents, not much is known about how populations of afferents encode macroscopic tactile stimuli [1]. A deeper understanding of how tactile sensations are encoded by the peripheral nervous system (and potentially decoded by the central nervous system) could help advance the development of future technological systems which attempt to replicate or outperform this sense of touch.

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To date, the most advanced robotic manipulators which approach human dexterity use a combination of crude low resolution tactile sensing and very high speed vision systems [2]. A better understanding of how the primate sense of touch is implemented might reduce the reliance of dexterous robotic systems on visual feedback by inspiring the development of reliable high-density tactile sensor arrays.

The objective of the study presented in this paper was to investigate how information is encoded in the neural responses of primate afferents when stimulated. Specifically, the aim of this work was to apply multiple regression analysis to an ensemble of monkey tactile afferent responses, generated in response to a controlled physical stimulus of normal force and a concurrently applied torque (which approximate force/torque combinations common in everyday life). Using a supervised learning approach, these stimulus parameters were re-estimated at 10 ms intervals after the onset of the torque, illustrating the reliability with which these force and torque parameters are encoded by the neural responses.

II. Methodology

A. Data collection

Microneurographic recordings of the neural responses of single cutaneous mechanoreceptive afferents in the fingertips were made from the median nerve of three anesthetized *Macaca nemestrina* monkeys. During the recording, a set of mechanical stimuli (described in Section II B) were applied to the glabrous skin of the distal segments of the 2nd, 3rd and 4th digits to elicit a response [1, 3].

The isolated afferents were characterized into their different types by mapping their regions of sensitivity and their response to static or dynamic stimulation. There are either slowly adapting (SA) afferents which respond to low frequency stimulation, or fast adapting (FA) afferents which respond to high frequency stimulation. These can each have a small receptive field (type-I) or a large receptive field (type-II); monkeys do not have any SA-II type afferents in the glabrous skin, whereas humans do.

58 SA-I afferents and 25 FA-I which remained responsive for the entire stimulation protocol (described in Section II B)

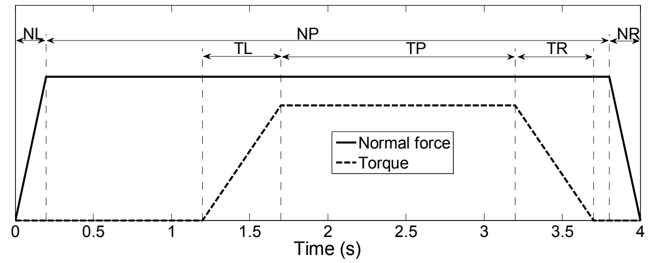


Fig. 1. Time evolution of the force/torque stimulus protocol. Normal force loading (NL), plateau (NP) and retraction (NR) phases, and torque loading (TL), plateau (TP) and retraction (TR) phases are shown. This paper analyses the TL phase and the first 200 ms of the TP phase.

were used in this study [1, 4, 5]. FA-II afferents were not analyzed as they did not respond to the stimuli reliably.

All procedures were approved by the University of Melbourne Ethics Committee and conformed to the National Health and Medical Research Council of Australia's Code of Practice for non-human primate research.

B. *Mechanical stimulation*

The digits were affixed by splaying them and embedding the dorsal aspect of the hand in plasticine up to the mid-level of the middle phalanges and gluing fingernails to small metal plates. Each metal plate was attached to a post embedded in the plasticine. The glabrous skin of the distal phalanges did not contact the plasticine, thereby allowing the fingertip to deform as it might if it was actively pressed against a surface (see Methods in [1]).

A custom-made mechanical stimulator, controlled using LabVIEW 5 software (National Instruments, Austin, TX), applied concurrent normal force and torque. A six-axis force-torque transducer (Nano FT; ATI Industrial Automation, Apex, NC) measured the applied forces and torques; the force and torque resolution were 0.0125 N and 0.0625 mNm, respectively. The stimulus applicator was a flat circular surface (diameter 24 mm) covered with fine grain sandpaper (500 grade).

The normal force was applied according to the following protocol: linear ramp from zero to the desired value during the 0.2 s loading phase (NL); held constant for the plateau phase (NP) of 3.6 s; and then removed over a 0.2 s retraction phase (NR). The torque was applied according to the following protocol: after 1 s of the normal force plateau phase, the torque is increased (from zero) to the desired magnitude over a torque loading (TL) phase of 0.5 s; held at the desired value for 1.5 s (TP); and unloaded over 0.5s (TR). Fig 1 graphically illustrates the protocol for applying the normal force and torque stimuli.

Normal force magnitudes of 1.8 N, 2.2 N and 2.5 N were applied. For each normal force, the torque magnitudes applied were 2.0 mNm and 3.5 mNm, each in a clockwise and anticlockwise direction. A total of 12 combinations (3 normal forces × 2 torques × 2 directions) of stimuli were applied. Each combination was repeated 6 times, giving a total of 72 sets of recordings for each afferent.

C. *Feature extraction and regression analysis*

Since the response of each afferent was recorded independently of all others, an ensemble population response was constructed by randomly grouping afferent responses which arose from the same force/torque/direction stimulus configuration to create a set of 72 feature vectors, each with either 58 (for SA-I responses) or 25 (for FA-I) feature values.

A feature value was considered to be the total spike count for that afferent from the start of the TL phase.

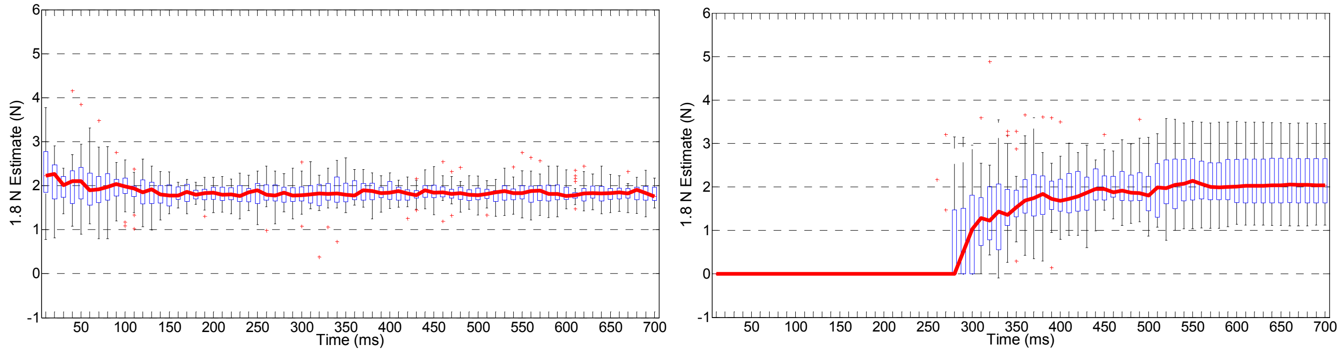
At each 10 ms interval, from the start of the TL phase (500 ms duration) until 200 ms into the TP phase, a multiple regression model was trained using either the 58 SA-I features, or the 25 FA-I features. Leave-one-out cross validation was used to train and evaluate each model. That is, 71 feature vectors were used to learn the regression weights, and the remaining vector used for testing. This was repeated 72 times so each vector was used as the test case once.

An analysis of the ANOVA of the means and standard deviations (SD) of the SA-I and FA-I estimates was then performed. Specifically, after calculating the mean and SD at each time point, these statistics were averaged across the 20 time points which constitute the first 200 ms of the TP phase, when the torque is held constant.

III. RESULTS

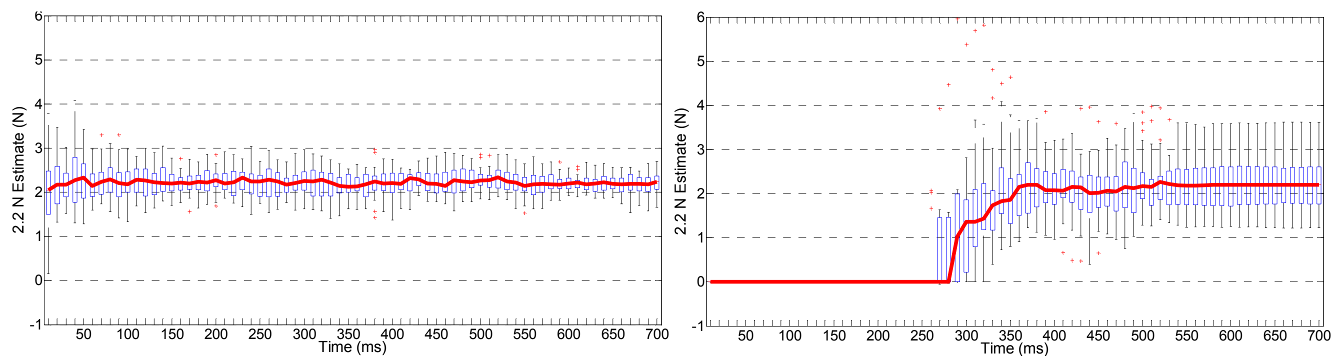
Figs. 2, 3 and 4 show the estimated values of normal force (1.8 N, 2.2 N or 2.5 N, respectively) at 10 ms intervals when using either the SA-I or FA-I afferents. To repeat what was described earlier, at each time point the multiple regression model was retrained and validated, using leave-one-out cross validation. Similarly, Figs. 5 and 6 show the estimated values of torque (2.0 mNm and 3.5 mNm, respectively) when using either the SA-I or FA-I afferents only. All of these graphs show estimates for the 500 ms time period when the torque is loaded (depicted as TL in Fig. 1) and the 200 ms afterwards, while the torque is held constant (start of the TP phase, in Fig. 1). Table I lists the mean of the mean error and the mean of the SD of the error.

Figs. 2(a), 3(a) and 4(a) illustrate that multiple regression of accumulated spike counts from the 58 SA-I afferents can estimate normal force. This is supported by significant differences (ANOVA, $p<0.0001$; Table I) in the estimates over the last 200 ms of the analysis window. Contrarily, Figs. 2(b), 3(b) and 4(b) show that the 25 FA-I afferents cannot distinguish normal forces (ANOVA $p=0.173$; Table I), and estimates are no better than chance. This aligns with the physiological understanding of how individual FA-I afferents behave; they respond to transient or high-frequency events, therefore their response to the constant normal force will have decayed and ceased some time before the application of torque in this experiment (since the NP phase (see Fig. 1) is 1.0 s old when torque application begins). This notion is supported by the zero estimates of normal force before 250 ms into the TL phase; even though normal force is applied, no response is elicited from the FA-



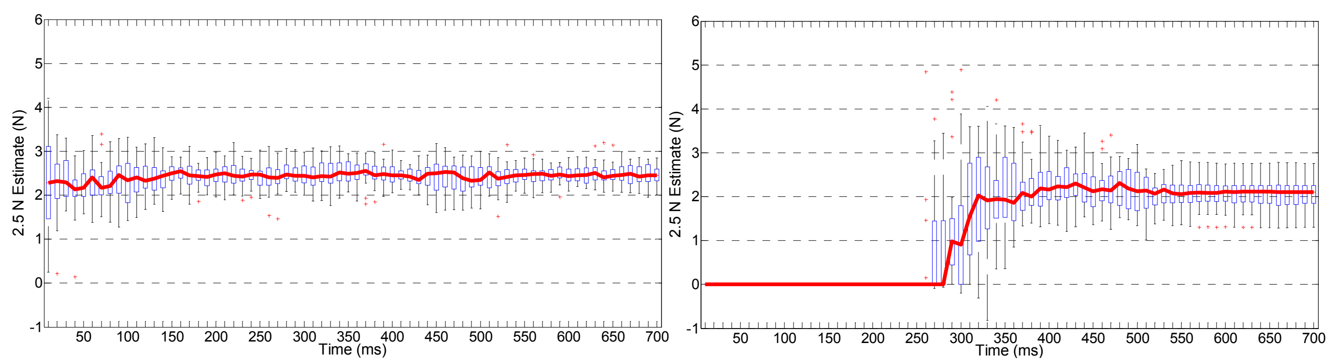
(a) (b)

Fig. 2. Estimates of **1.8 N normal force** using either (a) 58 SA-I or (b) 23 FA-I afferents. The boxplots shown at each time point correspond to 24 errors (72/3), attained from the cross validation. While three plots are shown for clarity, the results are derived from a single model for each afferent type. The median values are joined by a red plot line.



(a) (b)

Fig. 3. Estimates of **2.2 N normal force** using either (a) 58 SA-I or (b) 23 FA-I afferents. Boxplots and lines are as described in Fig. 2.



(a) (b)

Fig. 4. Estimates of **2.5 N normal force** using either (a) 58 SA-I or (b) 23 FA-I afferents. Boxplots and lines are as described in Fig. 2.

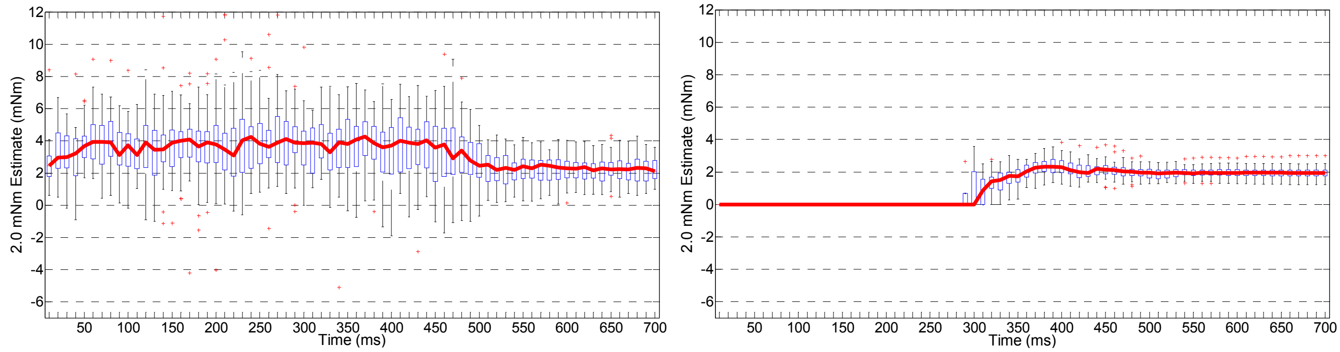
I afferents with which to produce an estimate. With the later application of torque these afferents respond, but contain no reliable information relating to normal force.

Figs. 5 and 6 and Table I show that once the torque is applied, shortly after the torque is registered (at about 250 ms into the TL phase), a good estimate of the torque magnitude is achieved. This is applies to both SA-I or FA-I afferent responses (ANOVA $p<0.0001$ for both afferent types; Table I).

IV. Discussion and Conclusion

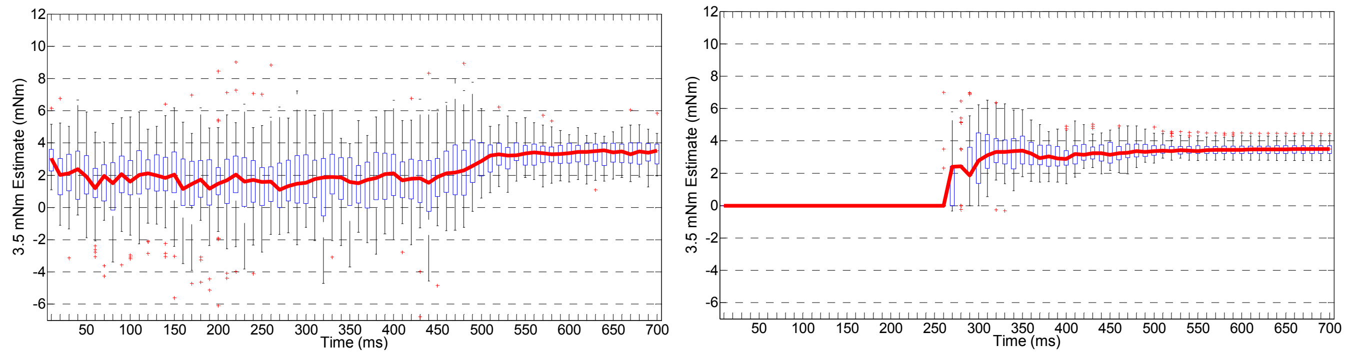
Obviously, there would be some improvement gained by leveraging the combined information contained in the responses of both the SA-I and FA-I afferents, but this has been omitted here due to space limitations, and the more instructive results from the afferents analyzed by type are presented instead.

Similarly, rather than summing from the onset of torque a sliding analysis window could be used, which would have two advantages, but other disadvantages. Namely, the advantages are: a single regression model can be used at all time points, since on average the spike count will not increase with time (as the window width widens, which is the case in this study); and the SA-I responses before the torque is applied will not influence the estimates towards the end of the analysis epoch (as is currently the case due to the accumulation from the start of the TL phase). The disadvantage of taking this approach is that the window size must be optimized for the task, and an obvious question is



(a) (b)

Fig 5. Estimates of **2.0 mNm torque** using either (a) 58 SA-I or (b) 23 FA-I afferents. The boxplots shown at each time point correspond to 36 errors (72/2), attained from the cross validation. While two plots are shown for clarity, the results are derived from a single model for each afferent type. Again, the median values are joined by a red plot line.



(a) (b)

Fig. 6. Estimates of **3.5 mNm torque** using either (a) 58 SA-I or (b) 23 FA-I afferents. Boxplots and lines are as described in Figs. 5.

TABLE I. MEAN OF MEAN ESTIMATION ERROR, AND MEAN OF STANDARD DEVIATION (SD) OF THE ESTIMATION ERROR, FOR THE 200 MS (DURATION FROM 500 TO 700 MS, IN FIGURES ABOVE).

Estimation target	Errors using SA-I afferents Mean(Mean) ± Mean(SD)	Errors using FA-I afferents Mean(Mean) ± Mean(SD)
Normal Force: 1.8 N	0.035 ± 0.234 N	0.308 ± 0.638 N
Normal Force: 2.2 N	0.009 ± 0.225 N	-0.002 ± 0.596 N
Normal Force: 2.5 N	-0.040 ± 0.221 N	-0.442 ± 0.334 N
Torque: 2.0 mNm	0.215 ± 0.839 mNm	-0.051 ± 0.334 mNm
Torque: 3.5 mNm	-0.178 ± 0.884 mNm	0.003 ± 0.414 mNm

then raised as to how older spikes contribute to the spike count; that is, should their contribution exponentially decrease as time elapses?

This multiple regression analysis provides an interesting alternate perspective to previous work by our group using the same dataset, which adopts a discrete classification approach [1, 3]. While classification to discrete force or torque levels allows for nonlinear interrelations among afferent responses to be accounted for in the feature space, this approach to decoding the afferent population response is perhaps not how the central nervous system would interpret these neural signals; but this is an open question.

This study provides insight into force or torque resolution which can be ideally decoded when both stimuli are simultaneously presented to the somatosensory system. It is hoped that this research will inspire the development of similar or improved (biomimetic or otherwise) sensors and decoding methods for use with robotic manipulators; closing the control loop for robotic manipulation with tactile sensors which approach the density and robustness of those with which humans are endowed is something which still remains out of reach.

V. REFERENCES

[1] I. Birznieks, P. Jenmalm, A. W. Goodwin, and R. S. Johansson, "Encoding of direction of fingertip forces by human tactile afferents," *J Neurosci,* vol. 21, pp. 8222-37, 2001.

[2] Yoshiro Imai, Akio Namiki, Koichi Hashimoto, and M. Ishikawa, "Dynamic Active Catching Using a High-speed Multifingered Hand and a Highspeed Vision System," in *Proceedings of the 2004 IEEE International Conference on Robotics and Automation*, New Orleans, LA, USA, 2004, pp. 1849-1854.

[3] S. J. Redmond, I. Birznieks, N. H. Lovell, and A. W. Goodwin, "Classifying torque, normal force and direction using monkey afferent nerve spike rates," presented at the Proceedings of the 2010 international conference on Haptics: generating and perceiving tangible sensations, Part I, Amsterdam, 2010.

[4] K. O. Johnson, "Reconstruction of population response to a vibratory stimulus in quickly adapting mechanoreceptive afferent fiber population innervating glabrous skin of the monkey," *J Neurophysiol,* vol. 37, pp. 48-72, 1974.

[5] P. S. Khalsa, R. M. Friedman, M. A. Srinivasan, and R. H. Lamotte, "Encoding of shape and orientation of objects indented into the monkey fingerpad by populations of slowly and rapidly adapting mechanoreceptors," *Journal of neurophysiology,* vol. 79, pp. 3238-51, 1998.