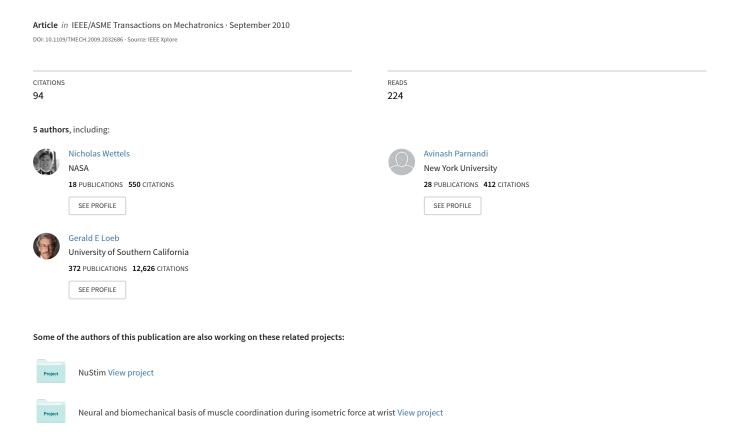
# Grip Control Using Biomimetic Tactile Sensing Systems



# Grip Control Using Biomimetic Tactile Sensing Systems

Nicholas Wettels *Student Member, IEEE, ASME, Avinash R. Parnandi, Ji-Hyun Moon, Gerald E. Loeb, Senior Member, IEEE* and Gaurav S. Sukhatme, *Senior Member, IEEE* 

Abstract— We present a proof-of-concept for controlling the grasp of an anthropomorphic mechatronic prosthetic hand by using a biomimetic tactile sensor, Bayesian inference and simple algorithms for estimation and control. The sensor takes advantage of its compliant mechanics to provide a tri-axial force sensing end-effector for grasp control. By calculating normal and shear forces at the fingertip, the prosthetic hand is able to maintain perturbed objects within the force cone to prevent slip. A Kalman filter is used as a noise-robust method to calculate tangential forces. Biologically-inspired algorithms and heuristics are presented that can be implemented on-line to support rapid, reflexive adjustments of grip.

Index Terms— Biomimetic, dexterous manipulators, grip control, tactile sensor

#### I. INTRODUCTION

When humans grasp an object, they use anticipated load conditions plus reflexes based on tactile feedback, to continuously adjust the applied forces. This strategy reduces unnecessary energy consumption and the chances of damaging the object or causing instabilities as a result of excessive or poorly directed grip forces. It would be useful for robotic and prosthetic mechatronic hands to be capable of similarly reflexive adjustment, both to improve their performance and to reduce the cognitive burden on their human operators.

While tactile sensing is not necessary for stable grasp, we posit that it is necessary for 1) grasp force minimization/optimization once object contact has been made and 2) grasp

Manuscript received March 1<sup>st</sup>, 2009; revised July 1<sup>st</sup>, 2009. This work was supported by a grant from the National Academies Keck Futures Initiative and by the Alfred E. Mann Institute for Biomedical Engineering at the University of Southern California.

N. Wettels is with the Biomedical Engineering Department, University of Southern California, 1042 Downey Way, Suite 140, Los Angeles CA 90089, USA (e-mail: nick.wettels@gmail.com).

A.R. Parnandi is with the Electrical Engineering Department, University of Southern California Los Angeles, CA 90089, USA (e-mail: parnandi@usc.edu).

J.H. Moon is with the Computer Science Department, University of Southern California Los Angeles, CA 90089, USA (e-mail: iihyunmo@usc.edu)

G.E. Loeb is with the Biomedical Engineering Department, University of Southern California Los Angeles, CA 90089, USA (phone: 213-821-5311, e-mail: gloeb@usc.edu).

G.S. Sukhatme is with the Computer Science Department, University of Southern California Los Angeles, CA 90089, USA (phone: 213-740-0218 e-mail: gaurav@usc.edu).

adjustment prior to, and during, object slippage. This is evidenced in clinical cases where patients who suffer peripheral nerve damage to their hands are able to initiate, but not maintain stable grasp due to lack of sensory feedback from cutaneous sensors [1]. Furthermore, it is clear that humans adjust grip force on objects relative to normal and shear forces at the contact surface [2, 3]. Brittle objects like eggs do not offer additional sensory cues such as visual compression before they break, so tactile sensing must be incorporated.

Much work has been done on algorithms for planning and control of grasp (e.g. [4-10]); most solutions either involve minimizing a cost function based on object-gripper parameters, or are based on a set of heuristics (or a combination of the two). As more parameters are estimated, the algorithms become more complex, but generally closer to optimal. Shimoga and Buss provide a summary of algorithms and also note that many of the grasp control processes are very complex and are only implementable off-line.

Our approach is to create a simple grip control algorithm that can be calculated quickly "on-line" consistent with the short latencies needed in grasp management without object or plant knowledge. We present a proof-of-concept implementation of a biomimetic tactile sensor [11] in grasping exercises. The sensor is compliant to support grip and its design is such that simple algorithms can be implemented in real-time to calculate normal and tangential forces regardless of point of contact. To test the system, we performed pinchgrasp tasks with a mechatronic prosthesis and sensor using minimal force necessary to maintain a stable grip in a constrained environment (described further below).

The minimal grasp force to hold an object is determined by ensuring that the ratio of normal to tangential reaction forces multiplied by the static coefficient of friction  $\mu_F$ , exceeds one:

$$1 < \mu_F \times F_{Norm} / F_{Tan} \tag{1}$$

This maintains objects within the force-cone [4, 12] and precludes slippage. Since coefficients of friction are often difficult to determine "on-the-fly" in unstructured environments, our algorithm assumes a conservative estimate of 0.5. In prior work other groups have seen the value in making this simplifying assumption, and pursued strategies that do not require complex calculations for off-line analysis. For example, Gunji *et al* implemented normal force sensing tactile sensors on to a gripper to detect slip and adjust grasp using a PD position controller/ proportional force controller without *a priori* knowledge of object coefficient of friction or weight [13]. Stansfield controlled a pinch grabber using a 6-

axis strain gauge sensor and a safety margin based on Johansson's work [14]. Yussof controlled a pinch grabber using a custom tactile sensor based on an optical signal [15]. Tangential force sensing was not available or limited for these, so the control algorithms could not directly calculate a tangential to normal force ratio. Further reviews of strategies can be found in [4-6, 16].

# II. METHODS

Stable grasp of objects by a robotic or prosthetic gripper is a complex subject that involves many factors: gripper kinematics and dynamics, sensory feedback, object geometry, gravitational and translational acceleration forces, and environmental relationships between the gripper and object (e.g. static coefficient of friction, fingertip deformation) [17].

Our goal is to utilize the Otto Bock Michelangelo 2 (M2) anthropomorphic robotic hand to grasp a Styrofoam coffee cup without crushing or dropping it. The cup will be rapidly filled with water and tangential and normal force feedback to the hand motors will be relayed from the DigiTac<sup>TM</sup> biomimetic tactile sensor array [11] (below).



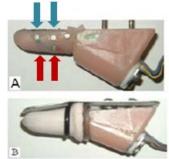


Figure 1) Left: Otto Bock M2 Hand, Right: Tac prototype sensor array: A) Skin removed and platinum electrodes visible; blue arrows point to tangential force sensing electrodes, red arrows point to normal force sensing electrodes on gripping surface B) Skin and nail installed

The M2 hand possesses 2 degrees of freedom: thumb ad/abduction and grip, in which all four fingers simultaneously open and close to the palm. The digits operate at a maximum speed of 408 mm/sec and maximum force of 60N. The hand operates under digital proportional-differential position control and proportional force control. We operate the hand in proportional positional control mode only (described further below) with a fixed velocity. The digits are covered in a soft silicone (Shore A durometer 15). The hand has a span of about 114mm when the fingers are open and slightly less when closed. The hand resembles a normal human left hand and is designed for prosthetic applications.

The DigiTac biomimetic sensor is a compliant, variable impedance tactile sensor array that is designed to be robust enough to withstand the everyday human environment while overcoming the limitations of commercially available sensors and those limited to the laboratory (discussed further in surveys of tactile sensing [18-20]). It meets the requirements of an effective tactile sensor [21] in a compliant, anthropomorphic fingertip. It has the appropriate dynamic

range and negligible hysteresis [11, 22] for prosthetic grasp control usage.

# A. Determination of Forces

The DigiTac sensor has been well characterized with regard to normal forces. As forces are applied to the elastomeric skin, it deforms the conductive path for the fluid that makes up the sensor. This causes an increase in impedance, which is read as a drop in voltage (due to the particular voltage divider measurement circuit arrangement). For our constrained task, some electrodes are arranged to sense normal forces, and some to sense tangential forces (Fig 2).

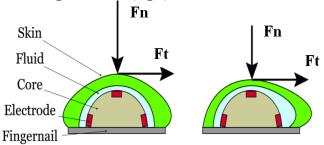


Figure 2: The effect of normal and tangential forces on different electrodes. Left) A large normal force and small tangential force causes bulging of fluid on both sides. Right) A comparatively small normal force and large tangential force causes bulging of the skin and fluid on one side

In realistic scenarios, the hand and tactile sensor will be changing posture, so the relative contribution of each electrode's impedance to the estimation of normal and tangential forces will depend on that posture and point of contact with the object.

Because some electrodes have higher resting impedances compared to others, the voltage values are normalized to one another for relative comparison. For the prototype used in our experiment, the voltage vs. force plot is shown below; normal force characterization, measurement and signal conditioning are explained in [11].

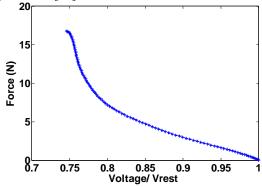


Figure 3:  $V_N = Voltage/Voltage$  Rest (when no forces are applied) vs. NormalForce for DigiTac Electrode

Because we operated over relatively light forces, we linearized the behavior of the sensors from 0 to 6 N, using the following equation (R-squared = 0.9948):

$$F_{\text{Norm}} = -31.31 \text{ x V}_{\text{N}} + 31.35$$
 (2)

where V<sub>N</sub> is the normalized resting voltage from the impedance sensors. In the tests performed here, normal force was estimated from the mean of the normalized signals from two electrodes under the region of contact with the object.

# A.1 Kalman Filter for Tangential Force Calculation

To calculate a force from the voltages in Figure 3, we developed a simple Kalman filter (KF) for state estimation [23], with initial state being zero tangential force when no forces are being applied. A Kalman filter was chosen because this particular sensor configuration produces noisy signals and Kalman filters act as low-pass IIR filters. This sensor noise has since been mitigated by refining the texture applied to the internal surface of the skin [22]. Furthermore, the KF integrates signals from a population of sensors to a produce a force output. This is necessary because the voltage to force relationship calculation cannot be direct like the normal force case; each of the relevant electrodes will have a different sensitivity to a given amount of tangential force due to the irregular deformation of the finger on a given side combined with the fact that the deformation is not uniform between the two sides.

The filter has five inputs: the voltages from two "left" electrodes, two "right" electrodes (Figure 1a) and the past tangential force value. The signals for the right electrodes (the increasing voltage electrode values) were correlated to the left (decreasing voltages) during exposure to tangential forces and related using the following linear fit with an R-squared value of 0.9166:

$$V_{\text{Left}} = -2.85 \text{ x } V_{\text{Right}} + 3.852$$
 (3)

The KF has a measurement equation based on the linear range of forces (0-6 N) from Figure 3 and Equation 3 and no control equation. The values of the filter coefficients for the measurement equation and past tangential force value were determined by performing pinch-grasp tasks with an Advanced Mechanical Technology- HE6X6-16, 6-axis forceplate (described further below).

## B. Algorithms and Constraints

Our method favors a set of heuristics and biological inspiration, (much like the work in Bekey et al [7, 26]) as opposed to complex calculations, to make the problem tractable in real-time. Grasp planning is constrained in this experiment, as the object is placed into a predetermined grasp pose chosen by the human programmer based on cup size – in this case it is a precision pinch grasp so the ring finger and thumb of the M2 hand serve as the primary contact points..

In order to prevent drastic hunting around a set-point and to compensate for small perturbations, we incorporated a grip force overage similar to human levels. When humans grasp an object, Johansson has shown that they apply a 10 to 40% safety margin (depending on the dexterity of the individual) [28]. In order to initiate grasp, an object is placed in the M2 and a preshape is chosen by the human programmer. The algorithm is started and when the weight of the object is no longer supported, the algorithm adjusts its grip to maintain stable grasp (Fig. 4).

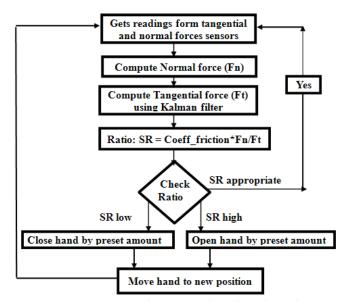


Figure 4: Grip Adjustment Algorithm Flow Chart

The hand functions in proportional position control mode for our experiments; position changes of the hand in response to tangential to normal force ratio are shown in Table 1. The controller is set to achieve a safety factor of 1.20 (based on Johansson's values).

Table 1: Grip State Action Table

| Ratio Value (R) | Grip State                    | Action                   |  |
|-----------------|-------------------------------|--------------------------|--|
| R <.95          | No/ Poor Grip<br>or Hand open | Close: 2 x position unit |  |
| .95<= R <1.25   | Loose Grip                    | Close: one position unit |  |
| 1.25=< R <=1.45 | Stable Grip                   | No change needed         |  |
| R >1.45         | Tight Grip                    | Open: 2 x position unit  |  |

One position unit corresponds to 0.53 mm lateral for the thumb and 0.37 mm for the finger over the range of our experiments.

# C. Description of Equipment and Experiments

The hand was connected to a PC via a USB port and powered externally. The sensor was mounted to the thumb only and connected to the computer via an NI USB-6218 data acquisition block. Programming of the hand as well as data collection from the sensor was done via Matlab in a soft-real time format [27]: here Matlab captures the data in discrete intervals, but due to software priorities, there are delays, in our case approximately 750 msec.

Calibration of sensor data to forces was performed by suspending the force-plate from spring mounts and performing pinch-grasp tasks: the sensor contacted the active side of the force plate while grasp was initiated by the M2 hand; this causes an increase in measured normal force. The grasp control algorithm was then started and the force-plate was depressed manually causing an increase in tangential force along the sensor surface. The normal and tangential forces of the force-plate were recorded and the Kalman filter was

calibrated to these data. The measurements were made to calibrate the sensor to the forces on the active surface of the force-plate, not to the actual weight of the plate itself.

Experiments were conducted to evaluate the ability of the hand-sensor interface and algorithm to adjust grasp reliably to changes in cup volume; trials were repeated five times. The hand grasped the Styrofoam cup and was then filled with 250 mL of water at various rates (Fig. 5, Table 2).

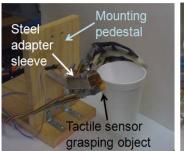




Figure 5: Hand/Sensor assembly: the thumb of the hand is removed and a shore A 60 rubber socket is placed over the stump and hard-bolted to the sensor via a steel adapter

Table 2: Cup Fill Rates

| Tubic 2. Cup I til Rules         |      |      |      |     |  |
|----------------------------------|------|------|------|-----|--|
| Time to Fill (sec)               | 4    | 6    | 10   | 57  |  |
| Average Loading<br>Rate (mL/sec) | 62.5 | 41.7 | 24.6 | 4.4 |  |

#### III. RESULTS

#### A. Calibration

Post-calibration normal and tangential force plots are presented in Figures 6 and 7 below.

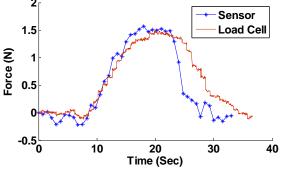


Figure 6: Above) Normal force sensor vs. force-plate output after calibration trials

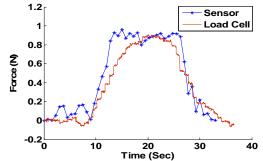


Figure 7:Tangential force sensor/ Kalman filter vs. force-plate. output after calibration trials

Cross-correlation coefficients for the normal and tangential force plots are 0.9751 and 0.9376, respectively.

# B. Grasp Adjustment

Grasp trials where the cup was held, filled and not dropped or crushed for all fill rates were only achieved after proper calibration of the system as shown in Figures 6 and 7. A plot of normal and tangential forces of the sensor is shown for such a trial in Fig. 8.

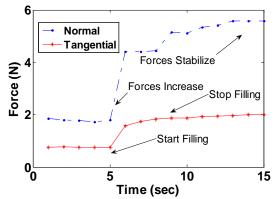


Figure 8: Sensor output during 41.7 mL/sec (avg.) fill trial

#### IV. DISCUSSION

The calibration produced reasonable representations of normal and tangential forces with relatively high cross-correlation coefficients. This calibration was done against a flat force plate, however. e We know that the tactile sensor responds with different impedance vs. force profiles for objects with different radii of curvature [11]. A richer set of contacts should permit simultaneous extraction of contact location and curvature as well as normal and tangential forces.

The range of forces was also limited to the 6N linearization performed. The force versus impedance curve is non-linear; if full range of this device is to be utilized, an extended-Kalman filter would have to be implemented.

There was an initial normal force due to the grasping of the cup; the tangential force was small due to the cup's light weight. The tangential force quickly rises due to the splash of the water into the cup, then steadily increases as the skin of the sensor sags down, indicating the increased load. Our controller responded as intended by reducing the grip opening, resulting in increased normal force to stabilize grasp. A more general approach to impedance control would allow the measured normal and tangential forces to be integrated with the position feedback.

The tangential force was much smoother than normal force due to the low-pass filtering effect of the KF. The tangential and normal force values were lower than expected for 250 mL of water, probably because the sensor was calibrated on a flat, stiff force-plate but it was tested with curved, compliant objects. Significantly though, the ratio of normal to tangential forces was preserved.

It should also be noted that the system was unable to handle very rapid perturbations. In a qualitative experiment, the users attempted to pull a water bottle out of the hand of the system. It was able to adjust to slow tugs, but failed under fast movements that humans may encounter in their environments. The "soft-real time" system in Matlab was providing force updates after mechanical movements with a delay of approximately 750 msec. This is much slower than the 70 msec biological latencies observed in humans in adjusting grasp [28]. Rewriting the code in C and operating in an xPC real-time environment would speed the system up significantly.

# V. CONCLUSION

We have shown a proof-of-concept for a force-minimizing and grip adjustment algorithm in a constrained environment. The algorithm uses a Kalman filter for its tangential force estimation, which boosts its robustness to noisy signals. Making the sensor tacky for grip affords us the ability to make conservative assumptions about the coefficient of friction due to the rubbery skin. This information can be difficult to obtain in unstructured environments.

We attribute part of the success of this experiment to the very constrained environment. The algorithm is designed to sense slip in the downward direction with the hand in a fixed horizontal position, but this is not very realistic in the context of a functional prosthesis. As previously mentioned, the electrodes designated to interpreted tangential forces and normal forces will depend on the posture of the hand. A more sophisticated algorithm could select which electrodes to use for normal and tangential force estimation based information about the orientation of the hand. More general solutions such as artificial neural networks are being explored to extract force vectors as well as center of pressure, which will also be necessary in small object manipulation tasks. Presumably the human brain performs a similar generalized solution to extract the information it needs from the ensemble of individual cutaneous receptors in biological skin.

# **ACKNOWLEDGEMENTS**

We would like to thank Dian-Hua Lin for work with the motor control coding and Andy Chu for his assistance in fabricating the sensor-to-hand adapter and the hand mounting pedestal.

# REFERENCES

- [1] J.C. Rothwell *et al.* "Manual motor performance in a deafferenated man," *Brain* 105 pp. 515-542, 1982.
- [2] I. Birznieks, P. Jenmalm, A. Goodwin, R. Johansson, "Encoding of Direction of Fingertip Forces by Human Tactile Afferents," *J. Neurosci.*, pp. 8222-8237October, 2001
- [3] G. Cadoret and A. Smith, "Friction, Not Texture, Dictates Grip Forces Used During Object Manipulation," J. Neurophys., Vol. 75, No. 5, pp. 1963-1969 May, 1996.
- [4] K.B. Shimoga "Robot Grasp Synthesis Algorithms: A Survey" *The International Journal of Robotics Research*; 15; 230 1996.
- [5] A. Grupen and C. Thomas R. Henderson "A Survey of Dextrous Manipulation." *Technical Report UUCS-TR-007: The University of Utah, Department of Computer Science*, July, 1986.
- [6] S. Venkataraman, T. Iberall. "Dextrous Robot Hands", Springer-Verlag, NY NY, 1990.
- [7] G. Bekey, H. Liu, R. Tomovic, W. Karplus, "Knowledge-Based Control of Grasping in Robot Hands Using Heuristics from Human Motor Skills" *IEEE Transactions on Robotics and Automation*, Vol. 9, No. 6,

- December 1993.
- [8] M. Buss, H. Hashimoto, J. Moore, "Dexterous Hand Grasping Force Optimization", *IEEE Transactions on Robotics and Automation* Vol., 12. No 3. June 1996.
- [9] S. Chiaverrini, B. Siciliano, L. Villani "A Survey of Robot Interaction Control Schemes with Experimental Comparison," *IEEE/ASME Trans.* on Mechatronics, Vol. 4, No. 3, pp. 273-285. 1999.
- [10] G. Liu, Z. Li "Real-Time Grasping-Force Optimization for Multifingered Manipulation: Theory and Experiments" *IEEE/ASME Transactions on Mechatronics*, Vol. 9, No. 1, pp. 65-77 March 2004.
- [11] Wettels N., Santos V.J. Johansson R.S., and Loeb G. E., "Biomimetic tactile sensor array." Advanced Robotics, vol. 22, no. 7, pp. 829-849 June 2008
- [12] G. Puchhammer, "The Tactile Slip Sensor: Integration of a Miniaturized Sensory Device on an Myoelectric Hand," *Orthopadie-Technik Quarterly*, English, edition I/2000, pp. 7-12
- [13] Gunji, D. et al. "Grasping Force Control of Multi-fingered Robot Hand based on Slip Detection Using Tactile Sensor," *Proceedings of SICE Annual Conference* Tokyo, Japan, August, 2008.
- [14] S. A. Stansfield "Experiments in Robotic Sensorimotor Control During Grasp" *IEEE Transactions on Systems, Man and Cybernetics*, Vol. 23, No. 3, pp. 23-33 May/June, 1993.
- [15] H. Yussof, M. Ohka, H. Suzuki, N. Morisawa, "Tactile Sensing-Based Control Algorithm for Real-Time Grasp Synthesis in Object Manipulation Tasks of Humanoid Robot Fingers" Proceedings of the 17th IEEE International Symposium on Robot and Human Interactive Communication, Munich Germany, pp.377-382 August, 2008.
- [16] A. Bicchi and V. Kumar. "Robotic grasping and contact: A review," Proc. IEEE Conf. on Robotics and Automation, pp 348 – 353, San Francisco, CA, April 2000.
- [17] M.R. Cutkosky, "On grasp choice, grasp models and the design for manufacturing tasks," *IEEE Transactions on Robotics and Automation*, 5(3) pp.269-279, 1989.
- [18] R.D Howe,, "Tactile Sensing and Control of Robotic Manipulation," in *Journal of Advanced Robotics*, Vol.8,No.3, pp. 245-261, 1994.
- [19] M. H. Lee and H. R. Nichols, "Tactile sensing for mechatronics—a state of the art survey," *Mechatronics* 9, pp.1–31, 1999.
- [20] C. Melchiorri, "Tactile Sensing for Robotic Manipulation," Ramsete: Lecture Notes in Control and Information Sciences Vol. 270 Springer Berlin, 2001.
- [21] C. De Silva, "Mechatronics: An Integrated Approach," CRC Press, Boca Raton, FL, Ch. 6, 2005.
- [22] N. Wettels, L.M, Smith, V.J. Santos, G.E. Loeb "Deformable Skin Design to Enhance Response of a Biomimetic Tactile Sensor," Proc. of International Conference on Biomedical Robotics and Biomechatronics, Scottsdale, Arizona, October, In press, 2008.
- [23] S. Thrun, W Burgard. D Fox, "Probabilistic Robotics," MIT Press, Cambridge, MA, 2006.
- [24] M. A. Wilkin, W. J. Manning, D. A. Crolla, M C Levesley, "Use of an extended Kalman filter as a robust tyre force estimator," *Vehicle System Dynamics*, 44:1, pp.50-59,2006.
- [25] S. Dutre, H. Bruyninckx, S. Demey, J. De Schutter, "Solving Redundant Contact and Grasp Uncertainties," *Proceedings of the IEEE/RSJ International Conference on Robotic and Automated Systems*, pp. 3478-3483 November, 1996
- [26] D Beattie, T. Iberall, G. S. Sukhatme, and G. A. Bekey, "EMG Control for a Robot Hand Used as a Prosthesis," In *International Conference on Rehabilitation Robotics*, Wilmington, Jun 1994.
- [27] http://www.mathworks.com/products/daq/description1.html
- [28] R.S. Johansson, J R. Flanagan, "Tactile sensory control of object manipulation in humans." *Handbook of the Senses. Vol.: Somatosensation*. Edited by Kaas J. and Gardner E. Elsevier, 2007.