# LUCS Haptic Hand I 

Magnus Johnsson<br>Dept. of Computer Science and Lund University Cognitive Science<br>Lund University, Sweden


#### Abstract

This paper describes a robotic hand, LUCS Haptic Hand I, that has been built as a first step in a project at LUCS aiming at studying haptic perception. In the project, several robotic hands together with cognitive computational models of the corresponding human neurophysiological systems will be built. Grasping tests with LUCS Haptic Hand I were done with different objects, and the signal patterns from the sensors were studied and analyzed. The results suggest that LUCS Haptic Hand I provides signal patterns that are possible to categorize. It should be possible to base the categorization on certain properties that can be derived from the raw data.


## 1 Introduction

The ability to identify materials and objects with the aid of touch in our hands is an ability that we often take for granted, and normally we hardly think about it. But to be possible, this ability demands a hand with a very sophisticated ability to manipulate grasped objects, and receptors for several submodalities, especially cutaneous and proprioceptive mechanoreceptors. In addition, neuro-physiological systems are needed, that actively can choose a way to manipulate the object in question in a beneficial way and then control the execution of these manipulations, while at the same time receiving and categorizing sensory data.

One way to learn more about how such an ability works and to find applications for that knowledge by reversed engineering, is to try to build an artificial system capable of what have been mentioned above, i.e. capable of haptic object categorization. Such a system should take the human hand and brain as a prototype.

To build such a system is our ambition.
There are several reasons why it should be interesting to build a system capable of haptic object categorization modeled on the corresponding human system. From a pure scientific viewpoint it is interesting because the model can constitute support for the cognitive and neuroscientific theories that it is founded on. It might also provide new insights into the modeled neurophysiological systems. From an applications perspective it is interesting because it might provide new knowledge about robotic haptics and artificial intelligence. Since the system will be founded in the workings of the corresponding human systems, it might also be used to simulate the effects of, for example, nerve injuries between the hand and the brain and the cortical reorganization that follow these kinds of injuries (Johnsson, 2004).

So far robotic haptics is not a very well researched area, and that means only a few haptic perception systems have been built. One example is a system capable of haptic object classification (Dario et al., 2000). This system has obtained object classification with the aid of touch and vision, by replicating the human ability to integration of sensory data from different modalities into one low-level perception, so that object recognition can be obtained without any interference from high-level cognitive processes. The system consists of two levels of neural networks: the first level for feature extraction from the tactile and dynamic signals, and the other, that is fed with output from the previous level of neural networks, output from a visual recognition module and with direct thermal sensor output, aims at recognition.

Two antropomorfa robotic manipulation platforms (Laschi et al., 2002; Dario et al., 2003) based on neurophysiological models of grasping includes both a visual and a haptic sensory system. These robotic human-like manipulation systems consist of a robotic arm with a
hand and a head with a binocular vision system. The hands are equipped with tactile sensors Software modules implement basic human-like sensory data processing. Preliminary experiments have yielded encouraging results.

DeLaurentis and Mavroidis (2000) have designed a prototype of a five-finger biomechanical robotic hand that imitates the shape of the human hand. Each finger is actuated by four shape memory alloy artificial muscle wires, which are connected to both sides of the superior and the inferior part of the body of the finger.
Sugiuchi, Hasegawa, Watanabe and Nomoto (2000) have developed a robotic hand together with a control system. The robotic hand has five fingers and 22 degrees of freedom. Each finger has four joints, each actuated by a RC servo. The surface of the robotic hand is covered with a distributed touch sensor that has more than 500 points of measurement. The system is able to control the position, the orientation, the velocity, and the force at multiple points of the robotic hand simultaneously. The distributed touch sensor consists of 64 x 16 lines of electrodes placed on both sides of a pressure sensi-tive rubber-sheet. The whole surface is scanned within 20 ms , which yields the pressure on each point with a resolution of 12 bits.

As a beginning to our project to explore haptic perception and build a system capable of it, we have built LUCS haptic hand I, which is a very simple robotic hand equipped with push sensors.
At least three fingers, each with three degrees of freedom are needed to enable a robotic hand to manipulate an arbitrarily shaped object so that it can be relocated in a arbitrary and appropriate way, without any rolling or slipping contacts (Bicchi, 2000). This means that Lucs Haptic Hand I wont be capable of very sophisticated manipulation, but this is not the aim of it. Mechanisms for hand movements and dexterous finger maneuver are complicated aspects of robotic hands. For example the grasp has to be analyzed and an optimal set of contact forces have to be selected. In practice, this is done by the formulation of the dexterous manipulation problem (Okamura, Smaby \& Cutkosky, 2000). The solution of these problems we postpone until later versions of haptic systems.

The aim of building LUCS haptic hand I and to, later, implement computational brain models to enable a more simplistic ability to haptic object categorization is to get experiences that will enable us to build a more advanced and elaborate version later. Therefore the technical level of LUCS haptic hand I has been kept
elementary. However, the robotic hand has been built with the aim to generate tactile signal patterns, while grasping objects that are differentiated enough to enable categorization with respect to, at least, hard-ness and size and possibly even shape.

In humans, what kinds of procedures are used depend on the age. The haptic procedures used by young children are simpler than those used by adults. In fact, already a few weak old fetuses are sensitive to tactile stimulation, and newborns respond differently dependent on how elastic or stiff an object is (Streri, 2003). A 3-4 year old child has an exploratory procedure for shape discrimination, but it is not optimal (Hatwell, 2003). The hand namely stays immobile on the object. Such static contact provides, besides information on temperature, also approximate information on shape, texture, size, and hardness. At adulthood, on the other hand, the explorative procedures have become closer to optimality (Hatwell, 2003).

Adults use several haptic procedures. The choice of procedure depends on the kind of property explored. When texture is explored of, lateral motion is used, and indeed, movements seem to be necessary for the perception of texture (Gentaz \& Hatwell, 2003). Unsupported holding is used for the estimation of weight, and pressure to explore the hardness of the material (Hatwell, 2003). By the aid of contour following, more precise information on shape and size is provided. Unsupported holding is used for the estimation of weight (Hatwell, 2003). In weight estimation, it is first and foremost the arms and shoulders that are most sensitive, while the fingers also have some sensitivity to gravitational constraints (Hatwell, 2003).

In haptic object identification it is not only information extracted from stimulus that influence the identification, but also expectations based on the context or previous experiences, i.e. there is top-down processing involved (Klatzky \& Lederman, 2003).

The rest of this report will consider the technical construction of LUCS haptic hand I, and an analysis of the signal patterns received from it while it is grasping objects.

## 2 LUCS Haptic Hand I

LUCS haptic hand I (Fig. 1) has three fingers and one of them, the thumb, is moveable with one degree of freedom. The fingers, that are of a plastic material, are straight and rigid and of a rectangular shape. The two


Figure 1: The LUCS haptic hand I, while grasping a clementine. The robotic hand has three fingers equipped with three pressure sensors each. Only the thumb is moveable with one degree of freedom. The thumb is mounted on a metal joint, connected to a RC servo. As an interface to the computer, we have used a Basic Stamp II together with a mini SSC II.
fixed fingers are mounted so that their superior sides are slanted inwards. The thumb is mounted on a metal joint that in turn is mounted on a RC servo. The point of using the metal joint is, besides transmitting torque from the RC servo to the thumb, to stabilize sideway movements, so that the movement of the thumb becomes more accurate. When the thumb moves to close the robotic hand, it ends up right between the two fixed fingers.
Each finger is equipped with three pressure sensors, attached to the fingers with equal distance in between, i.e. one sensor is placed at the outermost part of the finger, one sensor at the innermost part, and one in between. To keep track of the signals, the sensors have been numbered, and (Fig. 2) shows the correspondence between the sensors number and the sensors. There are tiny plastic plates mounted on top of the pressure sensors. The size of the plastic plates is such that they fit within the borders of the pressure sensors. These plastic plates are necessary to distribute pressure over the sensors.
Every pressure sensor is, together with a capacitor and a resistor, part of a RC-time circuit (Fig. 3), which generates a pulse with a frequency that depends on the pressure applied to the pressure sensor. The pressure


Figure 2: The figure shows what sensor number correspond to what sensor on LUCS haptic hand I. The view of the open robotic hand is to be considered as seen from above.


Figure 3: A RCTime circuit.
sensors have a resistance that varies with the pressure applied, so the time for the capacitor to become fully loaded is therefore dependent on the pressure on the sensor.

LUCS haptic hand I communicates with the computer via the serial port, and as an interface a Basic Stamp II is used. The Basic Stamp executes a loop that in every iteration reads a message, coming from the computer, about whether the position of the thumb is going to be changed, and to what position. If the position is going to be changed, then a signal is sent to another board, a mini SSC II, which generates a pulse to the RC servo which then moves to the desired position. In every iteration of the loop the frequency of each RCtime circuit is also read and sent to the computer. (Fig. 4) shows the circuits involved in the communication between Lucs Haptic Hand I and the computer.

All software for LUCS haptic hand $I$ is developed and


Figure 4: The circuits involved in the communication between Lucs Haptic Hand I and the computer.
will continue to be developed in the future as Ikaros modules (Balkenius \& Morén, 2004). Ikaros provides a kernel and an infrastructure for computer simulations of the brain and for robot control.
The current software consists of an Ikaros module that handles the communication on the serial port. In addition it orders a grasping movement of the robotic hand and receives information about the status of the sensors. As output a matrix is generated that represents the status of the sensors at different discrete points in time during the grasping movement.

## 3 Grasping Tests

We have tested LUCS haptic hand I by letting it grasp a number of objects (Table 1). These objects were selected as test objects, because in preliminary tests the ability of the robotic hand to detect arbitrary shapes turned out to be severely limited. Different kinds of balls turned out to be especially suitable, and therefore such balls were selected to allow studies of the changes to the signal patterns due to hardness and size. To get a comprehension of the impact of the shape on the signal patterns, we also used two different cubes as test object. Both cubes are made of foam rubber, because other objects than those with a spherical shape were hard to detect if they were not of a soft material.

LUCS haptic hand I grasped each object, described in Table 1, 30 times. In each grasping test the object was placed in a similar way in the robotic hand.

The results of the grasping tests are presented in the form of diagrams showing the mean value of the signals, during the grasping, from the 30 grasping tests with an object together with the variance. One diagram
for each sensor for every object was drawn and analyzed. The diagrams are included in the appendix.

## 4 Results

Only sensor 1 reacted when the small cube was grasped, and the maximal strength of the signal was approximately 1400 .

In the case of the big cube, only sensor 7 reacted, and the maximal strength of the signal was approximately 1600 . We can also see that the signal starts earlier and last longer with this cube, than in the case of the smaller one, i.e. the formation in the diagram is broader.

The small ball gave only a reaction of sensor 1, and the maximal strength of the signal was around 3500 . As can be seen in the diagram, there was a reaction of sensor 1 during the whole grasping movement, even when the thumb wasnt pushing against the boll. This is probably due to that the weight of the ball might have been applied directly to the sensor in the case of this object.

In the case of big ball 1 there were reactions of sensor 2 with a maximal signal of approximately 3500 , and sensor 5 with a maximal signal of approximately 4400 . As the case was with the cubes, the signal curve starts earlier and lasts a little bit longer in this case than in the case of the small ball.

The big ball 2 gave reactions of sensor 2 with a maximal signal of approximately 2600 , of sensor 5 with a maximal signal of approximately 2250 , and of sensor 7 with a maximal signal of approximately 4400 . The signal curves for sensor 2 and 5 are of approximately the same width as those for big ball 1 , but the signals are weaker in this case, compared to the case of big ball 1.

Only sensor 1 reacted in the case of the golf ball with a maximal strength of the signal of approximately 3700 . The width of the signal curve is approximately the same as in the case of the small ball, but the signal was a little bit stronger in this case.

## 5 Discussion

In the diagrams for the different objects, that have been tested, it can be seen that the signal patterns from LUCS haptic hand I, are differentiable, to some extent, according to size, shape, and degree of hardness.

The difference in size becomes clear, since the signal patterns, for both balls and cubes, show a signal that starts earlier, lasts longer, and stops a little later during

Table 1: The objects tested by LUCS Haptic Hand I

| Object | Size | Hardness | Material | Sensors |
| :---: | :---: | :---: | :---: | :--- |
| Small Cube | Side 37 mm | Soft | Foam Rubber | S1 |
| Big Cube | Side 55 mm | Soft | Foam Rubber | S7 |
| Small Ball | Circumf. 130 mm | Rather Hard | Plastic | S1 |
| Big Ball 1 | Circumf. 196 mm | Medium Hardness | Rubber | S2, S5 |
| Big Ball 2 | Circumf. 224 mm | Rather Soft | Hard Foam Rubber | S2, S5, S6 |
| Golf Ball | Circumf. 123 mm | Hard | Golf Ball | S1 |

the grasping movement in the case of a bigger object. In the case of balls, it also seems that more sensors are activated if the ball is bigger.
Difference in form, i.e. whether the object is a ball or a cube, also possibly becomes clear from the signal patterns. In the diagrams the curves for the balls seem to have a steeper inclination in their left side, compared to the curves for the cubes.

The degree of hardness is possibly also clear from the signal patterns. This is because the height of the curve seems to indicate a harder material of the object. For example this can be seen by comparing the diagrams for the sensor 2 and for the sensor 5 for the big ball 1 and the big ball 2. In these diagrams one can see that the curves are higher for big ball 1 than for big ball 2 . This tendency can also be seen if the diagrams for sensor 1 for the small ball and for the golf ball are compared, where the little harder golf ball also has a little higher curve. However, this should need further investigations.
One observation that can be done in the diagrams is that the sensors seem to react somewhat asymmetrically, i.e. the sensors on the left finger (sensors 1, 2, 3) seems to react more than the sensors on the right fixed finger (sensors 4, 5, 6). This is probably due to that the angle between the fixed left finger and the thumb is slightly different from the angle between the right fixed finger and the thumb, because of small imperfections in the physical construction. The push sensors and the tiny plastic plates mounted upon them might also be mounted with a slight asymmetry.

The results suggest that it should be possible to categorize the objects according to different properties of the signal patterns, i.e. properties like width, slope, height, and so on of the diagrams. This should be more efficient and also more interesting compared to a categorization solely based on the raw data from the sensors. Implementing a mechanism that first extracts these properties from the raw data can do this.

Another lesson from the tests with LUCS Haptic

Hand I is that the next robotic hand we build should be equipped with jointed fingers that closes properly around the grasped object. This will allow a larger amount of sensors to become activated during the grasp of an object, and it will allow the whole capacity of the sensor equipment to be used.

## References

Balkenius, C., \& Moren, J. (2004). Ikaros (2004-1124). http://www.lucs.lu.se/IKAROS/.

Bicchi, A. (2000). Hands for dexterous manipulation and robust grasping: a difficult road towards simplicity, IEEE Transactions on robotics and automation, 16, 6, 652-662.
Dario, P., Laschi, C., Carrozza, M.C., Guglielmelli, E., Teti, G., Massa, B., Zecca, M., Taddeucci, D., \& Leoni, F. (2000). An integrated approach for the design and development of a grasping and manipulation system in humanoid robotics, Proceedings of the 2000 IEEE/RSJ international conference on intelligent robots and systems, 1, 1-7.

Dario, P., Laschi, C., Menciassi, A., Guglielmelli, E., Carrozza, M.C., \& Micera, S. (2003). Interfacing neural and artificial systems: from neuroengineering to neurorobotics, Proceedings or the 1st international IEEE EMBS conference on neural engineering, 418-421.

DeLaurentis, K.J., \& Mavroidis, C. (2000). Development of a shape memory alloy actuated robotic hand. (2004-10-28). http://citeseer.ist.psu.edu/383951.html

Gentaz, E. (2003). General characteristics of the anatomical and functional organization of cutaneous and haptic perceptions. In Hatwell, Y., Streri, A., \& Gentaz, E., (ed.). Touching for knowing, 17-31,

John Benjamins Publishing Company.

Gentaz, E., \& Hatwell, Y. (2003). Haptic processing of spatial and material object properties. In Hatwell, Y., Streri, A. \& Gentaz, E., (ed.). Touching for knowing, 123-159, John Benjamins Publishing Company.

Hatwell, Y. (2003). Manual exploratory procedures in children and adults. In Hatwell, Y., Streri, A., \& Gentaz, E., (ed.). Touching for knowing, 67-82, John Benjamins Publishing Company.

Johnsson, M. (2004). Cortical Plasticity - A Model of Somatosensory Cortex. http://www.lucs.lu.se/ People/Magnus.Johnsson
Johnsson, M. (2005). http://www.lucs.lu.se/People/ Magnus.Johnsson/HapticPerception.html

Klatzky, R., \& Lederman, S. (2003). The haptic identification of everyday objects. In Hatwell, Y., Streri, A., \& Gentaz, E., (ed.). Touching for knowing, 105121, John Benjamins Publishing Company.

Laschi, C., Gorce, P., Coronado, J., Leoni, F., Teti, G., Rezzoug, N., Guerrero-Gonzalez, A., Molina, J.L.P., Zollo, L., Guglielmelli, E., Dario, P., \& Burnod, Y. (2002). An anthropomorphic robotic platform for ex-perimental validation of biologically-inspired sensorymotor co-ordination in grasping, Proceedings of the 2002 IEEE/RSJ international conference on intelligent robots and systems, 2545-2550.

Okamura, A.M., Smaby, N., \& Cutkosky, M.R. (2000). An overview of dexterous manipulation, Proceedings of the 2000 IEEE international conference on robotics \& automation, 1, 255-262.
Streri, A. (2003). Manual exploration and haptic perception in infants. In Hatwell, Y., Streri, A., \& Gentaz, E., (ed.). Touching for knowing, 51-66, John Benjamins Publishing Company.
Sugiuchi, H., Hasegawa, Y., Watanabe, S., \& Nomoto, M. (2000). A control system for multi-fingered robotic hand with distributed touch sensor, Industrial electronics society. IECON 2000. 26th annual conference of the IEEE, 1, 434-439.


Figure 5: Small cube test data.

Sensor 1


Sensor 4


Sensor 7


Sensor 2


Sensor 5


Sensor 8


Sensor 3


Sensor 6


Sensor 9


Figure 6: Big cube test data.

Sensor 1


Sensor 4


Sensor 7


Sensor 2


Sensor 5


Sensor 8


Sensor 3


Sensor 6


Sensor 9


Figure 7: Small ball test data.

Sensor 1


Sensor 4


Sensor 7


Sensor 2


Sensor 3


Sensor 6



Sensor 9


Figure 8: Big ball 1 test data.


Figure 9: Big ball 2 test data.


Figure 10: Golf ball test data.

