Experiments with Proprioception in a Self-Organizing System for Haptic Perception

Magnus Johnsson[1,2] **Christian Balkenius**[2]
[1]Dept. of Computer Science and [2]Lund University Cognitive Science
Lund University, Sweden

Abstract

We have experimented with proprioception in a bio-inspired self-organizing haptic system. To this end a 12 d.o.f. anthropomorphic robot hand with proprioceptive sensors was developed. The system uses a self-organizing map for the mapping of the explored objects. In our experiments the system was trained and tested with 10 different objects of different sizes from two different shape categories. To estimate the generalization ability the system was also tested with 6 new objects. The system showed good performance with the objects from both the training set as well as in the generalization experiment. In both cases the system was able to discriminate the shape, the size and to some extent the individual objects.

1. Introduction

Haptic perception, i.e. active tactile perception, is of outmost importance in the field of robotics since a well performing robot has to interact with its environments. However, haptic perception is also important in supporting and sometimes also substituting the visual modality during the recognition of objects. Like humans, robots must be able to perceive shape and size as well as to discriminate between individual objects by haptic exploration.

The modelling of haptic perception as well as the implementation of haptic perception in robots are two neglected areas of research. Robot hand research has mainly focused on grasping and object manipulation (Dario et al, 2003; DeLaurentis & Mavroidis, 2000; Rhee et al, 2004; Sugiuchi et al, 2000), and many models of hand control have been focused on the motor aspect rather than on haptic perception (Arbib et al, 2000; Fagg & Arbib, 1998), although there are some exceptions (Allen & Michelman, 1990; Caselli et al, 1994; Dario et al, 2000; Erkmen et al, 1999; Heidemann & Schöpfer, 2004; Hosoda et al, 2006; Jockusch et al, 1997; Natale & Torres-Jara, 2006; Petriu et al, 2004; Stansfield, 1991; Taddeucci et al, 1997).

Our previous research on haptic perception has resulted in the design and implementation of a number of versions of two different working haptic systems. The first system (Johnsson, 2004; Johnsson et al, 2005a; Johnsson et al, 2005b; Johnsson & Balkenius, 2006a) was a system for haptic size perception. It used a simple three-fingered robot hand, the LUCS Haptic Hand I, with the thumb as the only movable part. The LUCS Haptic Hand I was equipped with 9 piezo electric tactile sensors. This system used self-organizing maps, SOMs, (Kohonen, 1988) and a neural network with leaky integrators and it successfully learned to categorize a test set of spheres and cubes according to size.

The second system (Johnsson & Balkenius, 2006b; Johnsson & Balkenius, 2006c; Johnsson & Balkenius, 2006d; Johnsson & Balkenius, 2007) was a system for haptic shape perception and used a three-fingered 8 dof robot hand, the LUCS Haptic Hand II, equipped with a wrist for horizontal rotation and a mechanism for vertical re-positioning. This robot hand was equipped with 45 piezo electric tactile sensors. This system used active explorations of the objects by several grasps with the robot hand to gather tactile information. The LUCS Haptic Hand II was not equipped with any proprioceptive sensors. Proprioception is the perception of the relative positions of different body parts. Suitable proprioceptive sensors are sensors that register joint angles. Instead of proprioceptive sensors the system used the positioning commands to the actuators, which is less accurate than real proprioceptive sensors since the wanted positions are not necessarily the same as the actual positions. Depending on the version of the system, either tensor product (outer product) operations or a novel neural network, the Tensor Multiple Peak SOM, T-MPSOM, (Johnsson & Balkenius, 2006c; Johnsson & Balkenius, 2006d, Johnsson & Balkenius, 2007) was used to code the tactile information in a useful way and a SOM for the categorization. The system successfully learned to discriminate between different shapes as well as between different objects within a shape category when tested with a set of spheres, blocks and cylinders.

The current paper explores a somewhat different approach which is based on proprioception. Using the position of each joint as the only input, we have designed an anthropomorphic robot hand, which can discriminate objects and categorize them according to shape and size.

2. LUCS Haptic Hand III

The LUCS Haptic Hand III is a five fingered 12 dof anthropomorphic robot hand equipped with 11 proprioceptive sensors (Fig. 1). The robot hand has a thumb consisting of two phalanges whereas the other fingers have three phalanges. The thumb can be separately flexed/extended in both the proximal and the distal joints and adducted/abducted. The other fingers can be separately flexed/extended in their proximal joints whereas the middle and the distal joints are flexed/extended together. All this is similar to the human hand. The wrist can also be flexed/extended as the wrist of a human hand. The phalanges are made of plastic pipe segments and the force transmission from the actuators, which are located in the forearm, are handled by tendons inside the phalanges in a similar way to the tendons of a human hand. All fingers, except the thumb, are mounted directly on the palm. The thumb is mounted on a RC servo, which enables the adduction/abduction. The RC servo is mounted on the proximal part of the palm, similar to the site of the thumb muscles in a human hand. The actuators of the fingers and the wrist are located in the forearm. This is also similar to the muscles that actuate the fingers of a human hand. The hand is actuated by in total 12 RC servos, and to get proprioceptive sensors the internal potentiometers in the RC servos, except the RC servo that actuates the wrist, have been included in the sensory circuit. The resistances of these potentiometers are proportional to the angle of the different joints.

The software for the LUCS haptic hand III is developed in C++ and runs within the Ikaros system (Balkenius, & Morén, 2003; Balkenius et al, 2007; http://www.ikaros-project.org/). Ikaros provides an infrastructure for computer simulations of the brain and for robot control.

Movies and additional pictures of the LUCS Haptic Hand III can be found on the web site http://www.lucs.lu.se/People/Magnus.Johnsson.

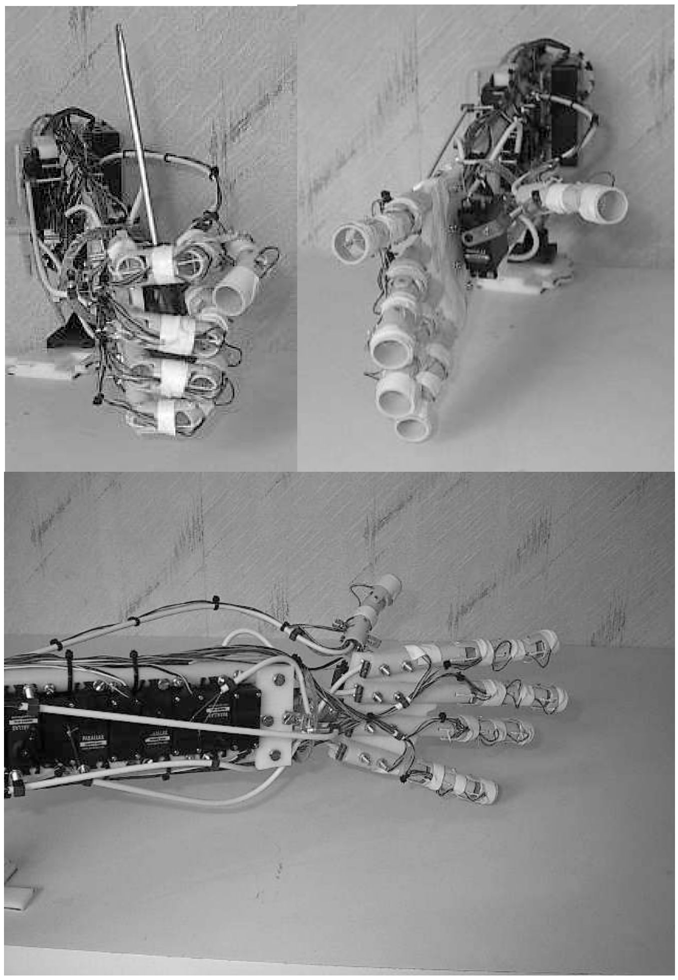

Figure 1: *The LUCS Haptic Hand III while holding a screw driver, in open position seen in a front view and in a side view. Some of the actuators in the forearm can also be seen in the side view. The 12-dof robot hand has five fingers, is of the same size as a human hand and all its parts have approximately the same proportions as their counterparts in a human hand. Each finger can be separately flexed/extended in the proximal joint, whereas the medial and distal joints are flexed/extended together as real human fingers. As a human hand the thumb has only a proximal and a distal phalang. These can also be separately flexed/extended. In addition the thumb can also be adducted/abducted in a way similar to the human thumb. The wrist is capable of flexion/extension. The actuators of the LUCS Haptic Hand III are controlled via a SSC-32 (Lynxmotion Inc.). The proprioceptive sensors are scanned with a MAX396CPI multiplexor chip and digitalized using a NiDaq 6008 (National Instruments). The NiDaq 6008 converts multiple analog input signals to digital signals, which are conveyed to the computer via a USB-port. The robot hand is equipped with two multiplexor chips, which means it is prepared for 21 additional sensors.*

3. A Proprioception Based Model

3.1 Model Design

The single grasp model consists of the LUCS Haptic Hand III, sensory and motor drivers, a self-organizing map, SOM, (Kohonen, 1988), and a commander program that executes the grasping movements. The sensory driver scans the proprioceptive sensors when requested to do so by the commander program, while the motor driver translate high level motor commands from the commander to commands appropriate for the robot hands servo controller board. When the commander exe-

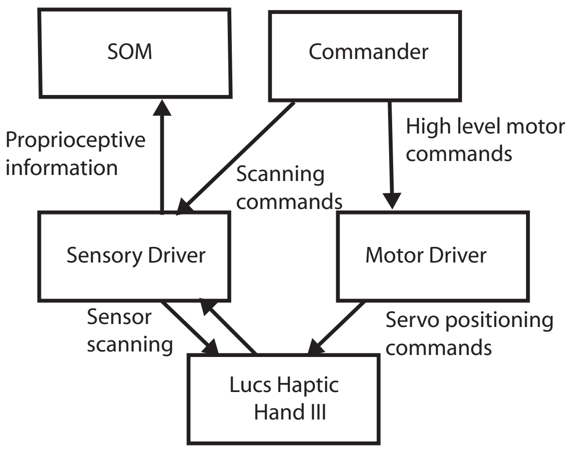

Figure 2: *Schematic depiction of the single grasp model. The commander program executes the grasps by sending high-level motor commands to the motor driver, which translates and conveys the information to the servo controller board of the robot hand. When the robot hand has become fully closed the commander program request a scanning of the registers of the 11 proprioceptive sensors of the robot hand. The sensory information is conveyed as a vector to the self-organizing map.*

cutes a grasp the robot hand is closed around the object. When the robot hand is fully closed the sensory driver samples the registrations from the 11 proprioceptive sensors and conveys the information as an eleven-elements vector to the SOM, which is activated and adapts its weights if the model is in the learning phase.

The self-organizing map is a 225 neuron dot product SOM with plane topology, which uses softmax activation with the softmax exponent equal to 10 (Bishop, 1995). The use of softmax activation is a way to reinforce the activation in the central part of the activated area and attenuate the activation in the peripheral parts.

3.2 Grasping Tests

We have tested the single grasp model with 10 objects, see Table 1 objects a-j. These objects are either cylinder shaped or block shaped. There are five objects of each shape category. All objects are sufficiently high to be of a non-variable shape in those parts grasped by the robot hand, e.g. a bottle used is grasped on the part of equal diameter below the bottle neck.

During the grasping tests the test objects were placed on a table with the open robot hand around them. If the objects were block shaped we always placed the longest side against the palmar side.

To simplify the testing procedure each object was grasped 5 times by the robot hand, i.e. in total 50 grasps were carried out, and the sensory information were written to a file. Then the SOM were trained and tested with this set of 30 samples. The training phase lasted for 2000 iterations, then the weight adaptation was turned of and each sample was input to the SOM again and the activation recorded.

3.3 Generalization Tests

We have also tested if the model is able to generalize its knowledge to new objects, i.e. to objects not included in the training set. To this end we used 6 new objects, Table 1. 1-6, 3 cylinder shaped object and 3 block shaped objects. The new objects were of variable sizes. The fully trained model was fed by input from grasps of the new objects under the same conditions as the objects in the training set. Each object in the new set was grasped once and the activity in the SOM was recorded.

3.4 Results and Discussion

The mapping of the test objects in the SOM is depicted in fig. 3. In fig. 3A the mapping of individual grasps have been grouped. Each group encloses the mapping of grasps of a single test object. One grasp of the olive oil bottle, one grasp of the tube and one grasp of the plastic bottle 2 have been excluded from the grouping since they are not mapped together with the other grasps of the same object and they are also mapped in the wrong shape category (they are mapped at a proper place when considering size though). As can be seen in fig 3A the model is able to discriminate between individual objects, although not perfectly.

The SOM seems to be organized according to shape, as can be seen in fig. 3B. Four groups of objects can be distinguished in the map. The same three objects as in fig. 3A have been excluded, and for the same reason. One of the groups encompasses large block shapes, one group encompasses small block shapes, one group encompasses large cylindrical shapes, and one group encompasses small cylindrical shapes. Thus the model seems to be able to discriminate between shapes, and it also groups the shapes according to whether they are bigger or smaller.

The SOM also seems to have become organized in a way so that the mapping of the test objects are ordered in a clockwise manner according to size from smaller to larger. It seems as the extension of the surface turned against the palmar side of the hand during grasping has precedence when the SOM organizes according to size and the extension of this surface is also what we consider when we say that the SOM is ordered according to size. That the surface turned at the palmar side has precedence is also what would be expected since this

Table 1: *The 16 objects used in the experiments with the single grasp model. The objects a-j were used both for training and testing, whereas the objects 1-6 were used in the generalization test.*

Label	Object	Shape	Size (mm)	Size (mm)
a	Tube	Cylinder	Diameter = 58	-
b	Beer Can	Cylinder	Diameter = 64	-
c	Wood Block	Block	Length = 75	Width = 47
d	Wine Bottle	Cylinder	Diameter = 70	-
e	Plastic Block 1	Block	Length = 63	Width = 63
f	Plastic Bottle 2	Cylinder	Diameter = 72	-
g	Olive Oil Bottle	Block	Length = 65	Width = 65
h	Plastic Bottle 1	Cylinder	Diameter = 80	-
i	Plastic Block 2	Block	Length = 80	Width = 63
j	Coffee Package	Block	Length = 97	Width = 67
1	Card Board Package 1	Block	Length = 77	Width = 66
2	Card Board Package 2	Block	Length = 84	Width = 62
3	Card Board Package 3	Block	Length = 95	Width = 62
4	Spice Bottle	Cylinder	Diameter = 57	-
5	Treacle Bottle	Cylinder	Diameter = 63	-
6	Plastic Bottle 3	Cylinder	Diameter = 79	-

information should in some way be coded by the proprioceptive information from all the fingers but the thumb, whereas the perpendicular surface (in the case of a block shape) is only coded by the proprioceptive information from the thumb. There is one exception to the size ordering in the SOM though, namely plastic bottle 1, as can be seen in fig. 3C. However, within a shape category the test objects are mapped clockwise from smaller to larger according to size without exceptions. This could be interpreted as a precedence of shape over size when the SOM is organized, i.e. the shape information has a heavier influence on the organization than the size information.

The results are interesting because they reveal that the proprioceptive information encompasses information about both the shape and the size of the grasped objects, and in addition information that enables discrimination of the individual objects to some extent.

The result of the generalization experiment is depicted in fig. 3D. As can be seen each of the objects is mapped so that it can be identified as the most similar object in the training set, i.e. if the test object is block shaped then it is mapped in the same area as the most similar block shaped object in the training set, and if the test object is cylinder shaped then it is mapped in the same area as the most similar cylinder shaped object in the training set. This also means that all test objects are mapped so that they are ordered according to size in the same way as the objects in the training set, and that they are correctly mapped according to shape. Thus the models ability for generalization is total for the tested objects.

4. Conclusions

We have experimented with a system for haptic perception based on our novel anthropomorphic robot hand, the LUCS Haptic Hand III. The system uses a novel approach, i.e. it only uses proprioceptive information, which resulted in a very well performing haptic system. In comparison with our earlier system for haptic shape perception (Johnsson & Balkenius, 2006b; Johnsson & Balkenius, 2006c; Johnsson & Balkenius, 2006d; Johnsson & Balkenius, 2007), the current system has turned out to be much more able to correctly categorize objects according to shape in a much wider size range, and this is done with a less computationally expensive model. The current model was also able to map the sizes of the objects in an ordered fashion, and to discriminate between objects as long as they were not too similar. A human would probably have a similar problem if she was not able to detect the material properties of the objects or expressed differently, if all object were of exactly the same material and weight. We also successfully tested the systems ability to generalize its learning to 6 novel objects.

It would be interesting to compare our systems to self-organizing systems developed by others. Heidemann and Schöpfer (2004) describes a haptic system, which consists of a plate with a touch sensitive array mounted on a robot arm. The system explores an object by sequences of contacts and feeds a self-organizing neural architecture with input. The system was able to learn to recognize 7 different objects when tested.

Natale and Torres-Jara (2006) describes a system consisting of an upper body humanoid robot with a hand

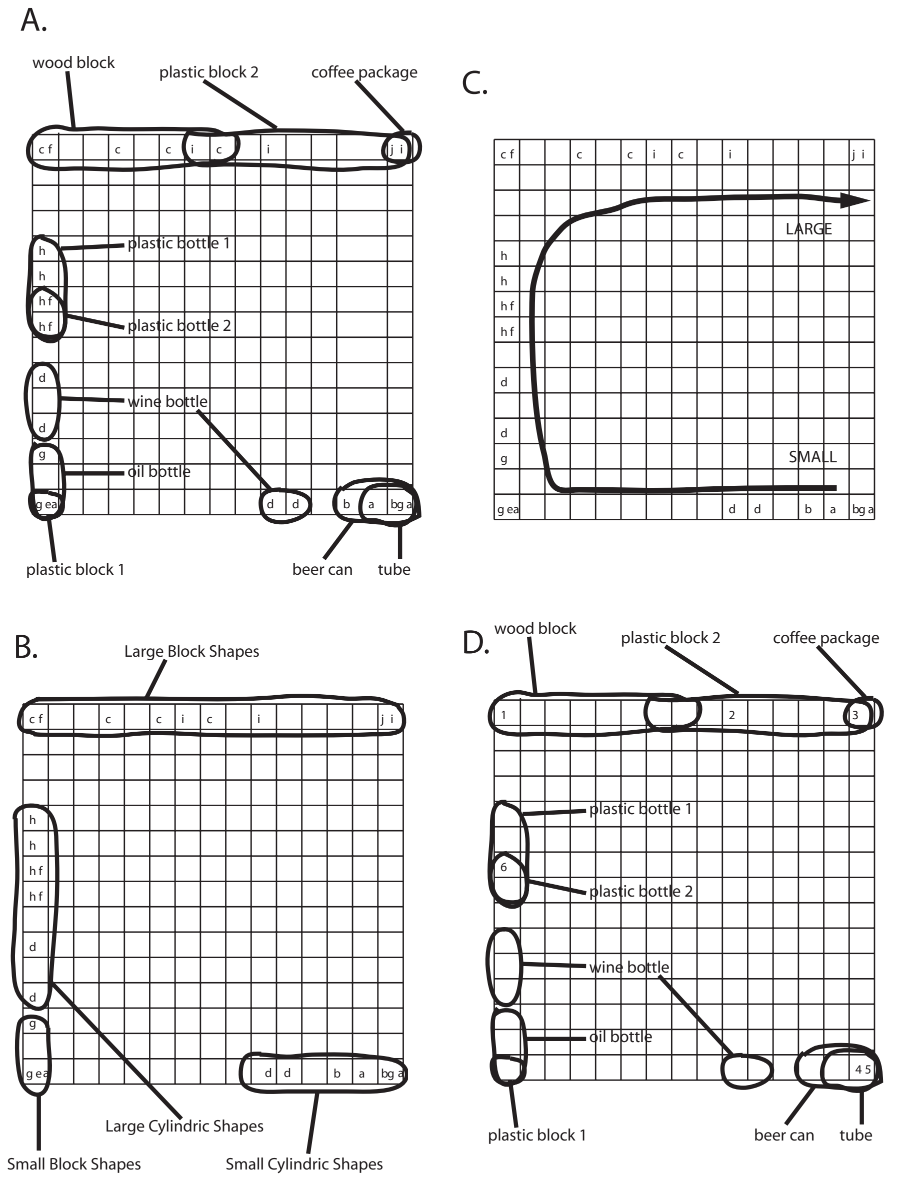

Figure 3: *The mapping of the test objects. The characters a-j and the numbers 1-6 refer to the objects in table 1. Each square represents a neuron in the SOM, which consists of* $15 \times 15 = 225$ *neurons. The presence of a letter in a square indicates a centre of activation in the SOM for the corresponding object. The occurrence of a certain letter in more than one square means that the corresponding object has different centres of activation during different grasps of the same object, i.e. all letters of a certain kind represents all occurring centres of activation in the SOM when the system was tested with the corresponding object. A: The mapping of the individual objects. The mappings of the samples of each training object have been encircled. The mappings of three samples (of the 50 training samples) were excluded when we encircled the areas for each of the 10 training objects (they are included as individual mappings in the figure, though). The reason to their exclusion was that the mappings of these samples deviated a lot from the mappings of the other samples of the same training object, i.e. they are considered outliers. B: Four groups of objects can be distinguished in the map. The same three objects as in A were excluded when we encircled the four areas and for a similar reason. One group encompasses large block shapes, one group encompasses small block shapes, one group encompasses large cylindrical shapes, and one group encompasses small cylindrical shapes. C: The mapping of the test objects are ordered clockwise from small to large according to size with one exception, plastic bottle 1. Within a shape category the test objects are mapped clockwise from small to large according to size without exception. D: In the generalization experiment the test objects are mapped so that they can be identified with the most similar object in the training set. The encircled areas are the same as those in fig. 3A. The test objects are also ordered according to size in the same way as the objects in the training set, and they are correctly mapped according to shape.*

equipped with dome-like tactile sensors, which are sensitive to pressure from all directions, as well as position sensors (proprioception). The system also includes a camera together with a visual system for coarse localization of the object. The information gathered by the system was used as input to a SOM. When evaluated with 4 different objects, a bottle, a box and two cups these objects were mapped differently. However, the cups could not be distinguished from each other.

When compared with the two systems described above our system stands out in that it is able to categorize the objects according to shape, order them according to size as well a recognize individual objects to a large extent.

Because of the successful approach with using proprioceptive information as a base for haptic shape perception as well as size perception we will in the nearest future continue our research in haptic perception with the following tasks: Try to bring the proprioceptive system to its absolute limits, e.g. by exploiting the possibility of the LUCS Haptic Hand III to carry out a more active exploration than simply grasping the objects in only one way. This can be done by adducting/abducting the thumb and by flexing/extending the wrist differently in different grasps; Investigate texture and heat perception and maybe also the perception of hardness and integrate these submodalities to the system to get a system that is able to detect material properties and discriminate between equally shaped and sized objects of different materials.

At a later stage we will study the interaction between haptics and vision. This would be interesting because these modalities interact to a considerable extent (Castiello, 2005). Another issue is to investigate haptic manipulation systems, i.e. systems for manipulation of objects that, in a very bio-inspired way, relies heavily on the haptic feedback received during the manipulation for their performance.

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