A Robot Hand with T-MPSOM Neural Networks in a Model of the Human Haptic System

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Abstract

We have developed an 8 d.o.f. robot hand, which has been tested with two computational models of haptic perception. Each model uses a variant of the novel self-organizing neural network, the Tensor-Multiple Peak Self-Organizing Map (T-MPSOM). One of the models uses a variant of the T-MPSOM that multiplies the activity corresponding to each of the two input vectors, while the other uses a variant that sums them. The computational models were trained and tested with a set of objects consisting of hard spheres, blocks and cylinders. Both models were capable of shape categorization, and in addition, one of the models was able to discriminate individual objects.

1. Introduction

Haptic perception is the ability to interpret tactile sensory information gathered by active exploration with the hands. One way to research haptic perception is to design and implement artificial organs for haptic perception based on cognitive and neurophysiological knowledge. Models of the involved neural systems can be implemented as computational models while the hands are best to implement physically as robot hands. There has been surprisingly little research aimed at haptic perception. One reason might be the scarcity of well-working tactile sensors of a limited cost. Another reason might be that a lot of attention has been focused at visual perception. Most models of hand control deals with motor aspects rather than haptic perception (Arbib, Billard, Iacoboni & Oztop, 2000; Fagg & Arbib, 1998). This is true also for most robotic hand research has focused on grasping and object manipulation rather than haptic perception (DeLaurentis & Mavroidis, 2000; Sugiuchi, Hasegawa, Watanabe & Nomoto, 2000; Dario, Guglielmelli, & Laschi, 2001; Laschi, Gorce, Coronado, Leoni, Teti, Rezzoug, Guerrero-Gonzalez, Molina, Zollo, Guglielmelli, Dario & Burnod, 2002; Dario, Laschi, Menciassi, Guglielmelli, Carrozza & Micera, 2003; Rhee, Chung, Kim, Shim & Lee, 2004).

There are some exceptions though. Dario et al (2000) developed a system for haptic object classification, and Coelho et al (2001) developed a system that integrates vision and haptics. A cost effective artificial fingertip with force/position sensors and slippage detection have been developed by Jockusch, Walter and Ritter (1997). The fingertip was integrated with the TUM robot hand developed at the Technical University of Munich. An anthropomorphic robot finger with a soft fingertip with randomly distributed embedded receptors has been developed by Hosoda, Tada and Asada (2006). A system for haptic object identification, which uses a low-cost 2D pressure sensor with coarse resolution has been developed by Heidemann and Schöpfer (2004). The sensor is mounted on a PUMA-200 industrial robot arm. The haptic system collects information by repeated contacts with the object, where after the information is combined to a vector. This vector is used as input to a three-step processing architecture for automatic feature formation.

Previously, we have designed and implemented a three-fingered robot hand, the Lucs Haptic Hand I, together with a series of computational models (Johnsson, 2004, 2005; Johnsson et al., 2005a, 2005b; Johnsson & Balkenius, 2006a). The purpose of these systems was to identify important principles of design for our future haptic systems, and to gain experience and knowledge before designing more potent versions. The Lucs Haptic Hand I together with its haptic models was able to learn to categorize the test objects according to size.

To take the next step in our research, we have developed a second robot hand, the Lucs Haptic Hand II (Johnsson & Balkenius, 2006b). The first aim of the Lucs Haptic Hand II was to develop haptic systems capable of shape perception. So far we have successfully developed haptic models for the Lucs Haptic Hand II that combine tactile and proprioceptic information using the tensor product in one or several steps (Johnsson & Balkenius, 2006c). This paper describes a couple of successful haptic models for shape perception that are based on our novel T-MPSOM neural network and the Lucs Haptic Hand II. The T-MPSOM is a variant of a self-organizing neural network. For excellent texts on self-organizing neural networks, see e.g. (Fritzke, 1997; Kohonen, 1988, 1990, 2001). The first model in this paper has been previously described in (Johnsson & Balkenius, 2006c). The second model differs from the first in that it uses a more biologically plausible variant of T-MPSOM.

2. Biological Background

There is a need for several neural mechanisms to enable grasping (Castiello, 2005). For example the forces and movements of the individual fingers have to be controlled. Somatosensory information is gathered by different kinds of receptors in the skin, the joints and the muscles. This information is used in the locomotion of the hand, to enable an adequate grasp and in the process of identifying an object. There are tactile receptors for several submodalities, including cutaneous and proprioceptive mechanoreceptors (Gentaz, 2003). When an object is grasped the sensory information is conveyed from the receptors to the central nervous system by the dorsal-medial leminiscal system (Gardner & Kandel, 2000; Gardner, Martin & Jessell, 2000). The dorsal root ganglion neurons have axons that are split into two branches, whereof one is ascending trough the dorsal column and synapses in a nucleus in the medulla, and the other branch ends in the skin, a joint or a muscle where its terminal constitutes the receptor. In many cases the terminals are provided by an end organ, called a corpuscle, that modifies the mechanical properties of the receptor. The neurons in the nucleus in the medulla send out axons that synapse in a nucleus in the contralateral thalamus. The somatosensory information is processed both sequentially and in parallel (Saper et al, 2000). This is clear since the axons from the neurons in the thalamic nucleus ascend and synapse in the primary somatosensory cortex (S1), in the secondary somatosensory areas (S2), and in the posterior parietal areas and in the motor cortex (Gentaz, 2003).

It is possible to identify objects with passive touch. The object identification is then based on information gathered by receptors sensitive to pressure, heat, touch and pain (Millar, 2006). A better discrimination of the objects is possible if the objects are actively explored which has been shown in studies with monkeys and humans (Millar, 2006). In addition, it is impossible to identify large objects without active exploration. When actively exploring an object much more sensory and proprioceptic information can be gathered.

There is a considerable grasping network in the human brain that includes prefrontal cortex, primary motor cortex, premotor cortex, supplementary motor area, primary somatosensory cortex, the inferior parietal lobule, superior parietal lobule, anterior intraparietal area (AIP), and subcortical areas like the basal ganglia and cerebellar circuits (Castiello, 2005). The activity in the AIP and the premotor cortex seem to code for grasping actions related to the shape and the type of the intended object (Castiello, 2005). The AIP seems to represent the whole action of reaching and grasping and it also seems to be tuned for precision grips. In contrast, the premotor cortex seems to represents only a part of the action. The AIP also seems to contain neurons that visually code for three-dimensional objects.

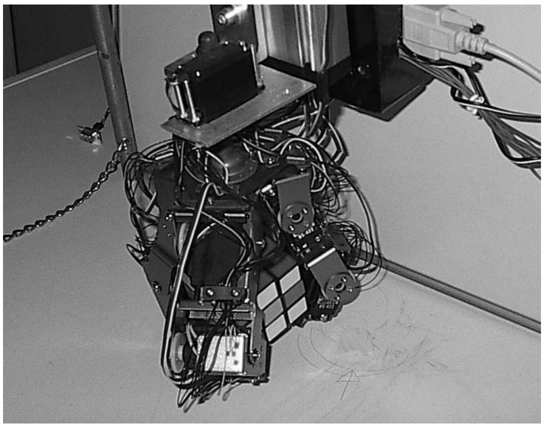

Figure 1: The Lucs haptic hand II while grasping Rubikś cube.

3. Lucs Haptic Hand II

The Lucs Haptic Hand II (Fig. 1), developed at Lund University Cognitive Science (Johnsson & Balkenius, 2006b), is a three-fingered robot hand equipped with 45 pressure sensors. The robot hand has totally 8 d.o.f. The fingers consist of a distal and a proximal segment. Each segment contains an actuator (RC servo) and a sensor plate (Fig. 2) is mounted on the inner side. The distal segments are articulated against the proximal segments, which in turn are articulated against a triangular plastic plate. The triangular plastic plate is in turn mounted on a wrist consisting of a bearing and a stick connected to a RC servo for force transmission. The wrist enables horizontal rotation of the robot hand. The wrist is in turn mounted on a lifting mechanism that consists of a splint and another RC servo.

All software and computational models for the Lucs Haptic Hand II were developed as Ikaros modules (Balkenius & Morén, 2003). In Fig. 3 an example of the reactions of the 45 sensors during a grasping movement is shown. A movie of the Lucs Haptic Hand II in action is available on the web site (Johnsson, 2005).

4. T-MPSOM

The novel Multiple Peak Self-Organizing Map (T-MPSOM) is a variant of the Self-Organizing Map (SOM) (Kohonen, 1988, 1990, 2001) with multiple activation, that takes two input vectors.

Each neuron in the two-dimensional grid that con-

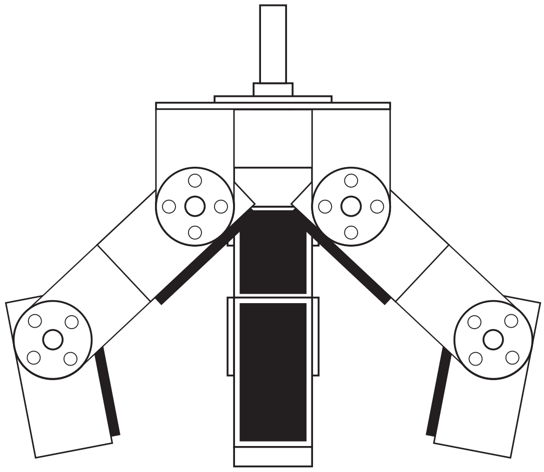

Figure 2: Schematic overview of the Lucs Haptic Hand II. The three-fingered robot hand has 8 d.o.f. Each finger consists of two segments symmetrically mounted on a triangular plastic plate. The plastic plate is mounted on a wrist, which in turn is mounted on a lifting mechanism. Each finger segment is built with a RC servo and a servo bracket. The actuators of the Lucs haptic hand II are controlled via a SSC-32 (Lynxmotion Inc.). Each finger segment is equipped with a sensor plate (black) containing 7 or 8 piezo-electric touch sensors.

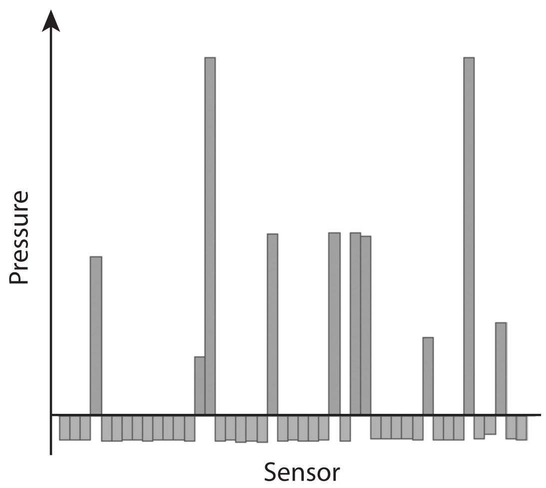

Figure 3: Snapshot of the signal pattern from the Lucs Haptic Hand II during a grasp of an object.

stitutes the T-MPSOM has two weight vectors corresponding to the dimensionality of the two input vectors received in every iteration. The sum of each input element is multiplied with an arbor function (Dayan, 2000), which corresponds to the receptive field of the neuron, and the result is further multiplied with the connection weights. Since there are two input vectors, there will be two sums and depending on the variant of the T-MPSOM these sums are then multiplied (Johnsson & Balkenius, 2006c) or added. This yields the activity of the neuron.

There is a contribution from every neuron in the neural network when updating the weights of a neuron. The degree of contribution from a single neuron is dependent on the activity of the neuron and a Gaussian function of the distance between the contributing neuron and the neuron whose weights are updated. The input vectors as well as the weight vectors are normalized in each iteration.

In mathematical terms, the T-MPSOM consists of a $i \times j$ matrix of neurons. In each iteration every neuron n_{ij} receives the two input vectors $a \in \Re^m$ and $b \in \Re^n$. n_{ij} has two weight vectors ${w_a}^{ij} \in \Re^m$ and ${w_b}^{ij} \in \Re^n$. The activity in the neuron n_{ij} is given by

$$x_{ij} = \sum_m A(i,m){w_a}^{ij}{}_m a_m \sum_n A(j,n){w_b}^{ij}{}_n b_n$$

in the variant with multiplied activations, and by

$$x_{ij} = \sum_m A(i,m){w_a}^{ij}{}_m a_m + \sum_n A(j,n){w_b}^{ij}{}_n b_n$$

in the variant with added activations, where

$$A(\alpha, \beta) \propto e^{-\left(\alpha - \frac{max\alpha}{max\beta}\beta\right)^2/2\sigma^2}.$$

The updating of the weight vectors are given by

$${w_a}^{ij}(t+1) = {w_a}^{ij}(t) - \alpha(t)\beta_{ij}(t)\left[a(t) - {w_a}^{ij}(t)\right]$$

and

$${w_b}^{ij}(t+1) = {w_b}^{ij}(t) - \alpha(t)\beta_{ij}(t)\left[b(t) - {w_b}^{ij}(t)\right],$$

where $0 \leq \alpha(t) \leq 1$, and $\alpha(t) \to 0$ when $t \to \infty$. The learning in each neuron is controlled by

$$\beta_{ij}(t) = \frac{\beta'_{ij}(t)}{max\beta'_{ij}(t)}$$

where

$$\beta'_{ij}(t) = \sum_k \sum_l x_{kl}(t) G(n_{kl}, n_{ij})$$

and $x_{kl}(t)$ is the activity in n_{kl} at time t and $G(n_{kl}, n_{ij})$ is a Gaussian function.

5. Multiple Peak SOM Models

5.1 Designs

We have implemented two variants of haptic models based on the T-MPSOM neural network. They are similar in all aspects but one, that the T-MPSOMs in one variant multiply the activations while the other adds them. The haptic models consist of the Lucs Haptic Hand II, the sensory and motor drivers and five common Ikaros modules described below (Fig. 4).

Grasping Module: This module corresponds to the motor areas involved in the human haptic system. Its responsibility is to carry out individual grasping movements. The movements of the wrist and vertical displacement of the hand is done elsewhere, i.e. at a higher level of the model. The module starts a grasping movement by moving the proximal finger segments. During the movement the sensors status of each finger segment are measured and if the summed sensors registrations exceeds a certain threshold or the finger segment reaches a maximal position, then the segment stops moving. Then a proximal segment has stopped, the distal segment starts moving until its sensors summed registrations exceeds a threshold or the distal segment reaches a maximal position. The idea of this procedure is to let the robot hand take a shape that is in accordance with the grasped object. The Grasping Module controls the motor driver and receives information about the sensors registration from the sensory driver. It communicates upwards in the model with the STM Module and the Commander Module.

T-MPSOM: There are three instances of the module that implements the T-MPSOM. All of them take information about the configuration of the robot hand, the wrist or the lifting mechanism (i.e. proprioceptic information) as input from the Motor Driver. The first instance of the T-MPSOM takes as input the vectors that represent the configuration of the wrist and the lifting mechanism. This instance corresponds to the somatosensory areas in the human brain that receive proprioceptic information and code for the localization and orientation of the hand. The output from the first T-MPSOM Module is conveyed to a second instance of the T-MPSOM Module. The second instance of the T-MPSOM Module also receives as input the vector that represents the current configuration of the robot hand. This instance corresponds to the somatosensory areas in the human brain that receive proprioceptic information about and code for the localizations and orientations of the hand and the fingers. The second instance of the T-MPSOM Module conveys its output to a third instance of the T-MPSOM Module that in addition takes as input a vector that represents the current state of the tactile sensors from the Sensory Driver. The result of this chain of recoding is to make the final activity depend on all the joint angles as well as the sensor response. This establishes a code that depends on the three dimensional shape of the grasped object during a single grasp. This instance corresponds to the somatosensory areas that integrate information from the proprioceptic submodality with cutaneous information. The output from the third T-MPSOM Module is conveyed to the STM Module.

Commander Module: This module takes care of the exploration of the object by grasping it nine different times, at two different heights and five different angles. There is no profound thought behind the number of exploring grasps. We wanted to make use of the robot hands ability to grasp the object at different heights and at different wrist angles and so collect more information about it than is possible with a single grasp. Our estimation, without any thorough investigation, were that about nine grasps at two different heights and five different wrist angles would be enough to make a reasonable use of the robot hands capacity. The exploration of the objects in this way emulates the manipulation done by a human being when trying to identify an object by haptic exploration. This is done by relocation of the object in the hand and at the same time collecting tactile information. This is implemented in the model by letting the Grasping Module receive instructions about at what wrist angle and at what height the grasping movements should take place. The Commander Module receives signals from the Grasping Module about whether the grasping movement is completed or not. After the completion of nine grasps the Commander Module decides that the exploration is completed. This module corresponds to areas in the frontal lobes.

STM (Short-Term Memory) Module: The output from the third T-MPSOM Module is in every iteration conveyed to the STM Module where it is superimposed during the whole exploration of an object. In this way the tactile and proprioceptic information from the whole exploration of an object is integrated into a single code. The sensory information of a haptically explored object should, in some form, be temporarily stored in the brain before the recognition of the object can happen after some active exploration.

SOM Module: The matrix that represents the sensory information from the completed exploration is used as input to a module that implements a Self-organizing Map (SOM) (Kohonen, 1988, 1990, 2001). The SOM Module has 225 neurons in the models. This module corresponds to recognition areas in the inferior temporal lobe.

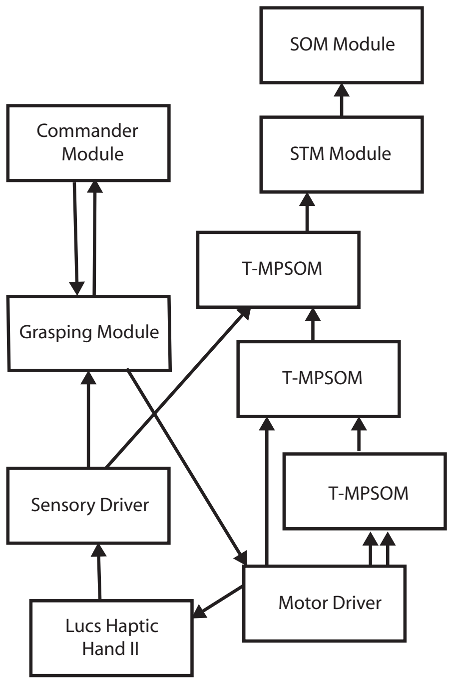

Figure 4: The model of haptic perception using the T-MPSOM model.

6. Grasping Tests

To simplify, the tactile and proprioceptic information from the explorations of the test/training objects, presented in table 1, were written to files. The haptic systems carried out 5 explorations of each of the test/training objects, i.e. in total 30 explorations, to create a test/training set. The models were trained in two phases as explained below. The reason for this was to avoid a lot of programming when adjusting the system to work with explorations read from files. Both models were trained with randomly chosen explorations from the test/training set for, in total, 5000 iterations. This training phase was done to let the three instances of T-MPSOMs in a model organize. Following this the model was exposed to each example of the training set, i.e. each of the 6 different objects were explored 5 times, i.e. in total 30 times and the output from the STM Module were written to files. The resulting sets of 30 files were then used as training/test sets for the models SOM Modules. The SOM Modules of the models were trained with 1000 randomly chosen samples from these training/test sets. Finally the trained models were tested with each of the 30 samples in these training/test sets.

7. Results

The grasping tests with the model that used the T-MPSOM variant with multiplied activations (Fig. 5A) gave that the model was capable of categorization of the objects according to shape, i.e. the cylinders, the spheres and the blocks were categorized in different parts of the SOM. This model was also capable of separating the individual objects in the training/test set from each other, with one exception. The exception was that a boccia sphere was mistaken as a boule sphere. We have carried out some experiments were we varied the relationship between input vectors and the size of the T-MPSOMs in x direction and y direction. We found that when the relationship between the numbers of elements in input vector a and the number of neurons in the y direction was similar to the relationship between the number of elements in input vector b and the number of neurons in x direction the performance was superior. The reason for this is probably that the activity is otherwise smeared out in a destructive way. We also found that the models worked best if the sigma of the Arbor functions were kept small. The three instances of the T-MPSOM used 25, 90 and 1058 neurons and the SOM used 225 neurons.

The grasping test with the model that used the T-MPSOM variant with added activations (Fig. 5B) went out slightly worse than the previous model. However, it performed quite well. The reason for adding the activations instead of multiplying them was that it yields a model with increased biological plausibility.

This model was able to categorize the objects according to shape with one exception. The exception was that the boccia sphere was confused with the cylinder. Unlike the model with T-MPSOMs that multiplies the activations, this model was not able to discriminate between objects within the same shape category. It might be that the slightly worse performance of this second model could be improved if neural networks containing more neurons were used. Another thing that perhaps would improve the performance is the use of softmax activity. However, this needs further investigation.

8. Discussion

We have designed and implemented two working haptic models based on the T-MPSOM neural network together with the Lucs Haptic Hand II. The models are based on knowledge about the neurophysiology of the human haptic system (see section 2). The two models differ only in that the activity of a neuron is calculated by multiplying the activities corresponding to the respective input in one of them, whereas in the other model theses activities are summed. The latter yields a more biologically plausible model. The models consist of a number of software modules that correspond to different systems in the brain. There are modules corresponding to the motor areas, the frontal executive areas, the recognition areas in the inferior temporal lobe and the short-term memory. In addition, the T-MPSOMs correspond to areas that code for proprioceptic information and to an area that

Table 1: The test objects used with the three haptic models for the LUCS Haptic Hand II

Object	Material	Size (mm)	Size (mm)	Size (mm)
Boccia	Plastic	Diameter = 72	-	-
Boule	Metal	Diameter = 82	-	-
Cylinder	Hard Board	Diameter = 62	Height = 121	-
Metal Cylinder	Metal	Diameter = 75	Height = 109	-
Block 1	Wood	Height = 110	Length = 50	Width = 50
Block 2	Wood	Height = 110	Length = 58	Width = 50

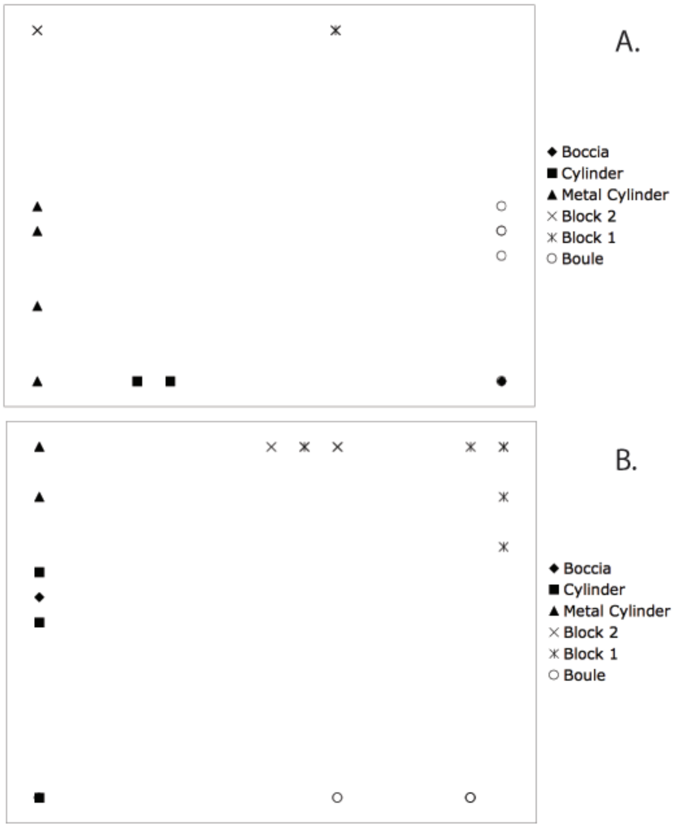

Figure 5: A. Results with the model that uses the variant of the T-MPSOM that multiplies the activations. B. Results with the model that uses the variant of the T-MPSOM that adds the activations. The images show the centers of activity in the SOM during the testing. Both of the models are, more or less, able to categorize the test objects according to shape and the first model identified most of the individual objects.

integrate proprioceptic and cutaneous information.

Both models were able to categorize the test objects according to shape. The model that used T-MPSOMs that multiplied the activities worked best. This model is able to categorize the test objects according to shape, as well as to identify individual objects, with one exception. The exception was that once it categorized a boccia sphere as a boule sphere. The capacities of the models, at least the one that used T-MPSOMs that multiplies the activations should be comparable to that of a human being. If the T-MPSOM model that adds the activations had used a greater number of neurons in the T-MPSOM neural networks it would probably not have made mistakes in any case. However, since we did not carry out these computationally heavy simulations this has to be investigated further. With a hardware implementation of the model, a larger number of neurons would be acceptable.

We also carried out several experiments in which we replaced the SOM Module and the STM Module with a SOM Module with leaky integrator neurons. The idea was to obtain a haptic system consisting of artificial neural networks that self-organize in accordance with the input in all its parts. These experiments did not yield satisfying results.

In the near future we will investigate the potential of the T-MPSOM neural network further, for example it should be possible to generalize the idea to an arbitrary number of input vectors. Another project for the future is to study the interaction between haptics and vision. This would be interesting because these modalities interact to a considerable extent (Castiello, 2005).

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