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Neural network models of haptic shape perception

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Abstract

Three different models of tactile shape perception inspired by the human haptic system were tested using an 8 d.o.f. robot hand with 45 tactile sensors. One model is based on the tensor product of different proprioceptive and tactile signals and a self-organizing map (SOM). The two other models replace the tensor product operation with a novel self-organizing neural network, the Tensor-Multiple Peak Self-Organizing Map (T-MPSOM). The two T-MPSOM models differ in the procedure employed to calculate the neural activation. The computational models were trained and tested with a set of objects consisting of hard spheres, blocks and cylinders. All the models learned to map different shapes to different areas of the SOM, and the tensor product model as well as one of the T-MPSOM models also learned to discriminate individual test objects.

Keywords: Haptic perception; Robotic hand; Tensor product; Self-organizing map

1. Introduction

To explore an object using touch, it is necessary to actively move the hand over the object to determine its shape. With passive touch, information is gathered by receptors sensitive to pressure, heat, touch and pain [24], but a more active exploration of the object enables cutaneous information from the skin and proprioceptive information from the joints to be combined, to allow larger amounts of information about shape and size to be collected. It also makes the perception of texture possible. Together, these processes are called haptic perception and involve sensory as well as motor systems.

The modeling of haptic perception and the implementation of haptic perception in robots are neglected areas of research. Robot hand research has mainly focused on grasping and object manipulation [8,10,27,29], and many models of hand control have been focused on the motor aspect rather than on haptic perception [2,11]. There are exceptions, though [1,6,7,12–14, 25,26,28,30].

We have previously researched haptic perception by designing and implementing a three-fingered robot hand, the LUCS Haptic Hand I, together with a series of computational models of haptic size perception [15–19].

Here, we describe our second haptic robot hand, the LUCS Haptic Hand II [20], together with three models of haptic shape perception. The LUCS Haptic Hand II (Fig. 1) is an 8 d.o.f. three-fingered robot hand equipped with 45 piezoelectric touch sensors developed at Lund University Cognitive Science (LUCS). A movie that shows the LUCS haptic hand II in a grasping task is available on the web site [16]. Each finger consists of two segments, which consist of a RC servo and a bracket together with a sensor plate mounted on the palmar side. The two segments of a finger are articulated against each other and the three fingers are articulated against a triangular plastic plate where they are mounted symmetrically. The sensor plates are equipped with 7 or 8 pressure sensitive sensors depending on whether the plate belongs to a proximal or a distal finger segment. An example of the status of the sensors during a moment in a grasping movement can be seen in Fig. 2. The triangular plastic plate is mounted on a wrist consisting of a bearing, and an actuator connected to a rod for force transmission. The wrist enables horizontal rotation of the robot hand, and is in turn mounted on a lifting mechanism, which consists of an actuator and a splint.

The first haptic model described in this paper uses the tensor product (or outer product) to combine cutaneous and

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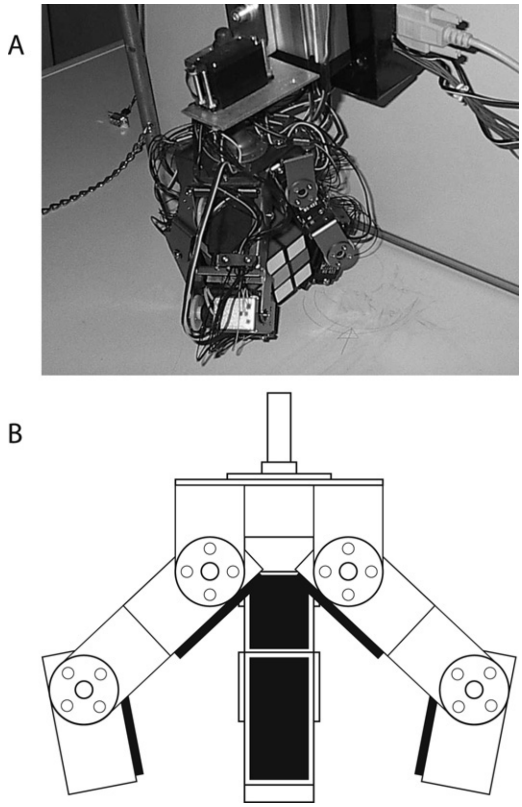

Fig. 1. A: The LUCS haptic hand II while grasping Rubikś cube. B: Schematic overview of the LUCS Haptic Hand II. The three-fingered robot hand has 8 d.o.f. Each finger consists of two segments symmetrically mounted on a triangular plastic plate. The plastic plate is mounted on a wrist, which in turn 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.), which is a controller board that can control up to 32 RC servos. Each finger segment is equipped with a sensor plate (black) containing 7 or 8 piezoelectric touch sensors.

proprioceptive information gathered by the robot hand in several steps. The tensor product is an operation between a n-dimensional column vector $x = (x_1, \ldots, x_n)^{\mathrm{T}}$ and a m-dimensional row vector $y = (y_1, \ldots, y_m)$ resulting in a $n \times m$ matrix M, where

$$\mathbf{M} = \begin{pmatrix} x_1 y_1 & x_1 y_2 & \cdots \\ x_2 y_1 & x_2 y_2 & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}.$$

The second and the third model are similar to the first model but replace the tensor product operations with the Tensor Multiple Peak Self-Organizing Maps (T-MPSOM:s), a novel neural network architecture that combines the computations of the tensor product with the merits of self-organizing maps. These two models differ in the way the activation of the T-MPSOMs is calculated.

2. T-MPSOM

The novel Tensor Multiple Peak Self-Organizing Map (T-MPSOM) is a variant of the Self-Organizing Map (SOM) [21–23] with multiple activation peaks, that takes two input vectors (Fig. 3).

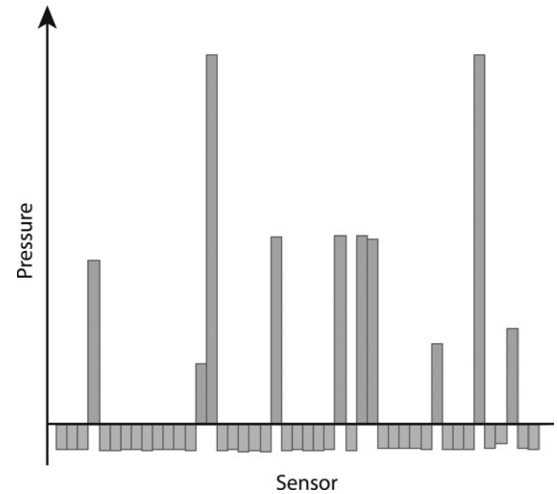

Fig. 2. Registrations from the 45 piezoelectric touch sensors mounted on the finger segments of the LUCS Haptic Hand II during a particular moment when grasping an object.

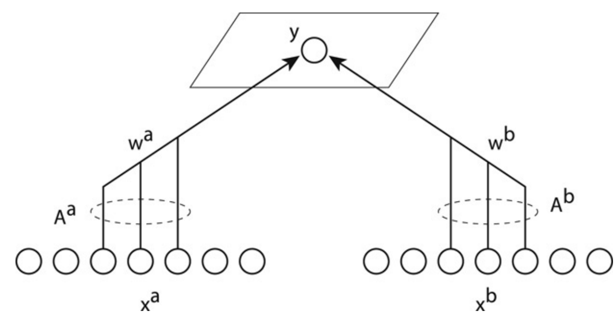

Fig. 3. The connectivity of the T-MPSOM network. See text for explanation.

Each neuron in the two-dimensional grid that constitutes the T-MPSOM has two weight vectors corresponding to the dimensionality of the two input vectors received in every iteration. To calculate the activity of a neuron, two partial activations are first calculated corresponding to each of the input vectors. This activation is calculated by multiplying each element in one of the input vectors with an arbor function [9], and the corresponding element in the weight vector for this input vector. The arbor function corresponds to the receptive field of the neuron. All these products are then summed to obtain the partial activation. The two partial activations for the neuron are then used to calculate the final activation of the neuron. The method employed for this calculation depends on the variant of the T-MPSOM neural network. In the second haptic model the partial activations were multiplied, while in the third they were summed.

Each neuron updates its weight vectors in each iteration. 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 depends on its activity and a Gaussian function of the distance to the weight updating neuron. The input vectors as well as the weight vectors are normalized in each iteration.

In mathematical terms, the T-MPSOM consists of an $I \times J$ matrix of neurons. In each iteration, every neuron n_{ij} receives