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Using Higher Order Synapses and Nodes to Improve the Sensing Capabilities of Mobile Robots

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Abstract

In this paper we present three types of higher order artificial neural networks that may be included in heterogeneous ANN architectures to improve the perceptual performance of mobile robots. Two of the networks are based on synaptic processing, with the advantage that this type of processing works with the raw data and not an average, as is the case of nodes. The first one of the structures is designed for handling temporal relations using synaptic delays. The second one, through gaussian functions in the synapses, endows the networks with the capacity of recognizing particular objects in images independently of the background. By integrating these gaussian synapse networks in a global visual architecture, this detection becomes independent of position, orientation and scale. Finally, the third network presented is based on the use of persistence by means of the implementation of habituation neurons as input nodes of networks.

1. Introduction

Mobile Robots are very good examples of systems that can be autonomous. They interact with their environment performing actions in order to achieve objectives as a function of perceptions and previous actions. Obviously, as Van de Velde [12] indicates, for a system to be autonomous it must organize its own internal structure in order to behave adequately with respect to its goals and the world, that is, it must learn. Learning involves several aspects that affect the cognitive and physical structure of a robot. It must be carried out all the way from the organization of perceptual information to the synchronization of the actuation of the robot.

Several approaches have been employed for the implementation of learning structures in robot cognitive systems, but the most successful paradigm in this area has been that of artificial neural networks. Many systems, specially in the realm of behavior based robotics, implement artificial neural networks that can be trained for perceptual tasks, control tasks, actuation tasks or, more often, for a combination of these in the form of some type of complete behavior that directly links perception and actuation. In general, the ANN systems governing the behaviors have been

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homogeneous in nature and usually based on multilayer perceptrons. Sometimes, recurrences were added in order to handle time dependent phenomena.

In this paper, we argue for the introduction of heterogeneous higher order ANN architectures in robot perceptual and control systems. That is, we introduce higher order artificial neural networks in order to better adapt them to the particular behaviors or tasks they must perform within the robot cognitive architecture. In addition, different types of networks collaborate joining their strengths to better achieve the tasks in hand. In particular, here we are going to concentrate on three types of higher order architectures applied to the perceptual systems of three robots. The first two are based on higher order synapses and the third one on a higher order node.

Synapses have often been the poor brother in terms of the processing carried out by most ANNs applied to robotic circuits. In fact, in most instances they have been used as simple relay elements, with no intrinsic function other than weighing values that traversed them. Some works, such as [2], have introduced some processing ideas in the synapses of ANNs, but mostly in the field of signal prediction. In general, for robot control or sensing circuits, especially in autonomous evolutionary robotics, neural networks have concentrated their processing capacities in their nodes. This situation actually limits the discriminating capabilities of networks, inducing a large number of nodes for certain tasks. Obviously, if the function being applied by each network node is over an average of its inputs, the capacity of filtering out noisy or irrelevant information can only be acquired through the pooling of many nodes. One realm where this is more noticeable is that of the detection of objects in images, where noise or different backgrounds, illumination or other artifacts lead to the need for very large networks in order to obtain acceptable results.

From another point of view, the capacity of handling temporally related events is something that is very important in the case of autonomous robots. Usually, the perception of something relevant to the robot is not given by a single event, but by a given temporal pattern of events. In fact, adding the capability of making use of time makes robots much “smarter” in what they can achieve and in their regular operation.

Within this Special Session we find other papers that emphasize the use of higher order networks. Fernandez, Echave and Graña in their paper have used a Self Organizing Map to adaptively obtain a vector quantization over color image sequences, filtered by a VQ Bayesian filter. Through the application of a correlation method on the isolated pixels they finally obtain the optical flow. Panerai, Metta and Sandini present an application where an ANN that controls the eye movements of a binocular robot learns the adequate compensatory movements for the stabilization of the image. Two motion related cues are used as inputs to a *Growing Neural Gas – Soft Architecture*, which provides the eye velocity command to counter-rotate the camera so as to stabilize the image of the outside world. Finally, Fernández-Delgado, Iglesias and Barro uses the model known as "Supervised Reinforcement Learning" (SRL) through a MART network with the aim of minimizing the effects of the design of a suitable action selection strategy in a reinforcement learning approach. Their paper shows the efficiency in the learning and the high stability obtained using this methodology in the design of a wall following behavior by a mobile robot.

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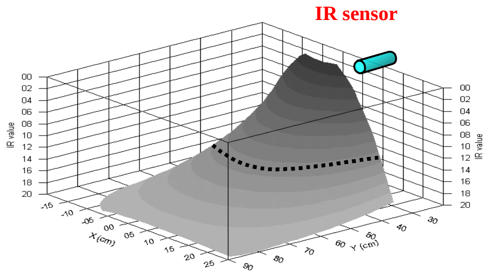

Figure 1: Response of IR sensor depending on the position of an object. Dashed line indicates positions that return the same IR value.

2. Time in robotics

The direct physical connection between sensors and actuators that has been emphasized throughout the behavior based robotics literature [1] and, in particular, in the evolutionary robotics field, has tended to create mostly static representations for the control of behavior based robots, generating purely reactive behaviors without any explicit consideration of time. In addition, most of the sensing was carried out by introducing the values directly from the physical sensors to the behavior controllers or through some standard non learnable preprocessing stages expecting the control structure to handle all the problems of sensor integration and/or learning associated with the required task in the environment.

In order to obtain a better interaction with the dynamics of the real world, processing structures that can take into account this dynamicity should be employed whether in the sensing apparatus, the control structure or the actuation mechanisms. In the case of ANNs there are several possible solutions that take into account past information. The first possibility is to use recurrent artificial neural networks that encode a summary of past information received by the inputs, that is, a “state”, encoded in some nodes through recurrences. In the behavior based or evolutionary robotics field we find several groups that have made use of this approach. For instance, the Sussex Group [7], used complex recurrent neural networks for visually guided robots. A recurrent ANN with a memory unit in the hidden layer that receives and provides information only to the hidden nodes was considered in [11] in order to generate wandering behavior in the Khepera robot. Gallagher et al. [5] employed Hopfield networks in the controllers of each leg of a simulated hexapod. In [9] the authors made use of RANNs obtained through a developmental process for simulated insects for quick walking and following an odor gradient while avoiding obstacles. Lund and Miglino [10] employ an Elman type network in order to evolve detour behavior in a Kephera robot. Jakobi [8] evolves arbitrary recurrent neural networks, with a pre-specified number of nodes, for negotiating a T-maze with the Khepera robot in the direction indicated by a light. And in [6] Gomez and Miikkulainen make use of a recurrent neural network evolved through incremental evolution of the different nodes for a prey-capture task in a simulated agent.

3. Synaptic delays for considering time

Our approach has been to incorporate trainable delays to the synapses of a feedforward ANN and obtain a new training algorithm that was able to adapt them to the temporal aspects of the problem in hand. This algorithm was called Discrete Time

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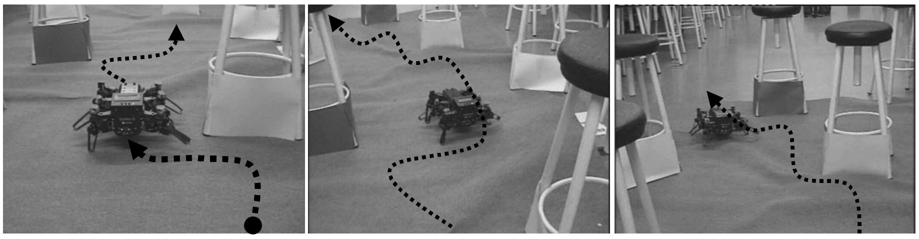

Figure 2: Hermes II avoiding tree-like obstacles using just the front left IR sensor

Backpropagation (DTBP) [3]. These structures were employed to generate virtual sensors where a range of individual sensings of regular sensors was temporally correlated to obtain a more useful representation of the world.

To test the approach, we have made use of a hexapod robot, our Hermes II, which has 6 infrared sensors mounted on top of its legs. Obviously, moving the shoulder joint of the legs can change their field of sensing. In figure 1 we display the response of the left front IR sensor. It can be clearly seen in this figure that by obtaining the response from a single sensor in a single leg position there is no way of knowing where the object is, we can only say that there is an object within a given arch and we have very little clue on its distance. There are many points where the object could be that for the sensor imply the same IR reading. This is shown in the figure by means of the black line (and any parallel to it) that indicates positions of objects that would produce the same IR value in the sensor.

One way to disambiguate the position of the object is to use more than one partially overlapping IR reading through the inclusion of previous information. To achieve this we have made use of a synaptic delay based neural network and the Discrete Time Backpropagation training algorithm. Training was carried out starting from several examples of real readings and the network employed consisted of two input neurons, two hidden layers with 15 neurons each, and two output neurons. The network incorporated synaptic delays in every layer. The inputs consisted of the IR value returned by the sensor and the shoulder angle we commanded the leg. The outputs consisted of the distance and angle of the object from the IR sensor.

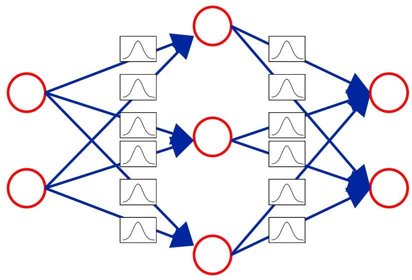

Figure 3: Structure of the Gaussian Synapses Network

Only 20000 training steps were required for the network to be able to discriminate, with sufficient accuracy, the exact position of the object with respect to the robot using just the left front IR sensor. In figure 2 we display the Hermes II robot provided now only with the sensory information of the synaptic delay neural network in the front left IR sensor, walking through an obstacle field (the color of each obstacle is different to complicate the IR perception of the environment). The trajectory followed by the robot is indicated by means of a dashed line. The only information used by the robot was coming from the aforementioned IR sensor so it can be clearly seen that the accuracy in detection has been highly increased. Without

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incorporating this virtual sensor through a higher order network the robot would not be able to distinguish where an object was located and thus avoid it efficiently.

4. Gaussian synapses and the visual system of robots

The power of a MLP network lies, almost exclusively, in its high connectivity. The components of the network do not display enough complexity for them to individually handle an important part of the information processing. One option to compensate for this is to increase the processing power of synaptic weights. In typical MLP architectures, the weight is a numerical value, which, once the network has been trained, will have the same effect on any value that circulates through this synapse. On the other hand, the use of functions, converts the synapses into active elements,

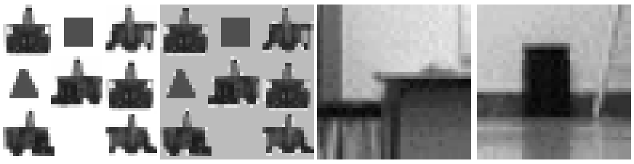

Figure 4: Some of the 48x48 pixel images used for training. The first and second frames are both positive and negative detection examples, the others are only negative cases.

whose outputs depend not only on the higher or lower intrinsic importance of the connection, but also on the value that reaches it each moment of time. This is the approach we have followed to develop trainable detectors for the visual system of a generic robot. The structure of the network used is shown in figure 3 and the training algorithm employed, GSBP (Gaussian Synapses BackPropagation), is explained in detail in [4]. The connections now have a synaptic function with three parameters for the GSBP algorithm to adjust: the amplitude of the gaussian, its center and its variance.

As an example of the use of gaussian synapses networks in developing a virtual sensor for a mobile robot´s visual system, we present a robot detector. For a mobile

Figure 5: Beginning (left) and end (center) of a moving robot path. In the right picture we display the results provided by the detector in four discrete instants of time; the dot size means proximity to robot camera. The arrows are only a guide to the eye.

robot it is very important to detect another robot that appears in its visual field, both for predator-prey purposes or robot finding for collaboration. The network used for this detector consists of 256 input neurons, 1 output neuron and two 8 neuron hidden layers. We have trained the network sweeping the 16x16 pixel input window of the network across 48x48 pixel images, with different robot views and false shapes with simple backgrounds, as shown in figure 4. Additional negative images -without any robot in them- were presented to the network in the same sweeping mode.

After 5000 epochs of training, we tested the ability of the network to discriminate images of the robot in real environments (see figure 5). The test images are frames of a moving robot movie. We display the results of the application of the network to the images in the right picture of figure 5. The black pixels represent null detection and white pixels represent positive detection in the 16x16 pixel window in which the white dot is centered. It can be observed that the sizes of the detection images are different. This is due to the additional sweep in scale that is carried out to take into account the fact that the robot may appear in the image with different size from the one used in training.

To reduce the amount of computation required to sweep the images, we are developing an attention selection module that allows the network to be faster in detecting what is relevant in the visual field.

5. Habituation neurons

Finally, a better adaptation to the problems the perception apparatus of a robot may encounter is achieved through specific purpose neural networks with unconventional nodes. We include in this paper an example of the increased ability to perform a wall following task achieved by a Rug Warrior robot. This is a small, circular robot with two wheels and several very low quality sensors.

The only sensors the Rug Warrior can employ to perform the wall following task are its two infrared sensors. These sensors are binary; they return 1 when detecting something and 0 when there is no detection. There is no information about the distance between the object and the robot. To overcome this problem it is necessary to use some kind of temporal information processing in the controller. We have achieved

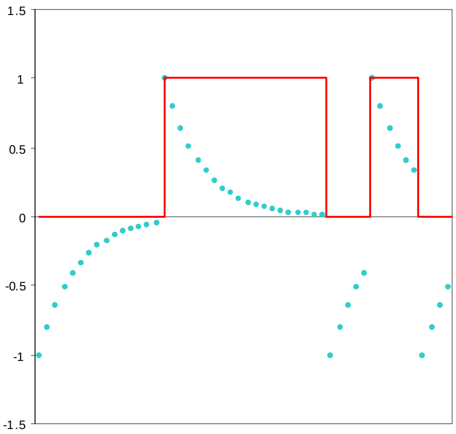

Figure 6: Output from a habituation neuron (dotted line) for a given input (continuous line) and c=0.8.

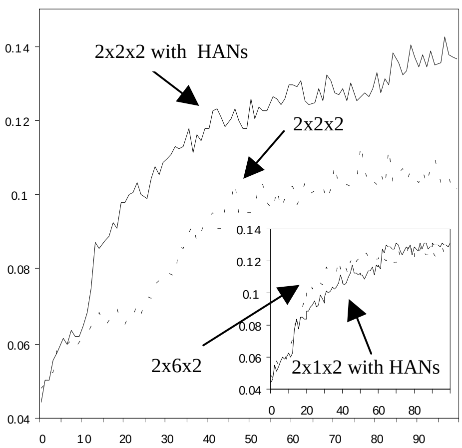

Figure 7: Evolution of fitness of the best individual for the wall following controller. Dotted lines indicate evolutions employing linear input neurons. Continuous lines are evolutions using habituation input neurons.

this employing ANNs with synaptic temporal delays. The synaptic weights, synaptic temporal delays, bias and sigmoid's slopes are obtained through evolution. But the computational capabilities of the Rug Warrior are very limited and, if we want to have several controllers running simultaneously on it, these controllers must be as small as possible.

This objective is met by employing habituation neurons (HAN) as input neurons. These neurons work as shown in figure 6. This kind of neuron has a given output value whenever its input changes, but if the input remains constant the neuron becomes "habituated" to this input, its level of activity decreases ($O_{t+1} = c * O_t$ where $c \in [0..1]$) and, therefore, its output goes progressively to zero.

If we employ habituation neurons as input neurons (each input neuron is connected to a sensor), a hidden layer and an output layer with two neurons (each one connected to one motor) the number of neurons in the hidden layer and connections decreases noticeably. As we can see in figure 7, a controller with habituation input neurons performs much better than one without it for the same number of hidden layer neurons. In fact, as displayed in the inset, a controller with input HANs and only 1 neuron in the hidden layer (4 connections) is equivalent in performance to a controller with linear input neurons and 6 neurons in the hidden layer (24 connections). This is a great improvement in terms of computational requirements, which allows us to run more complex global behaviors in the Rug Warrior.

In figure 8 we can see the real robot with a controller containing habituation input neurons and two neurons in the hidden layer. The controller was evolved to perform a wall following behavior taking into account the different environmental and noise conditions the robot could be faced with.

Figure 8: Rug Warrior performing wall following with habituation input neurons and two neurons in the hidden layer.

6. Conclusions

In this paper, we argue for the introduction of heterogeneous higher order ANN architectures in robot perceptual and control systems. That is, we introduce higher order artificial neural networks in order to better adapt them to the particular behaviors or tasks they must perform within the robot cognitive architecture. In particular, we have presented three types of higher order architectures applied to the perceptual systems of three robots. The first two are based on higher order synapses containing delays in one case and gaussian functions in the other. The third one

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includes higher order nodes called habituation neurons. The results from using these networks in virtual sensors for the robots clearly indicate that they allow the robot to perform their tasks much better than with regular networks and normally with much smaller networks, something that is really important in the case of mobile autonomous robots. In fact, some of the tasks carried out with these virtual sensors would not be possible with regular feedforward architectures.

Much more research is required in this realm in order to obtain adequate training strategies for networks that adapt much better to the idiosyncrasies of the different tasks a robot cognitive system must carry out.

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