A Cortical Architecture for Parallel Anticipation of Sensorimotor Sequences*

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Abstract

The basic idea of our anticipatory approach to perception is to avoid the common separation of perception and generation of behavior and to fuse both aspects into a consistent neural process. Our approach is based on the prediction of the consequences of hypothetically executed actions. In this sense, perception of space and shape is assumed to be a generative process of anticipating the course of events resulting from different sequences of actions. We present a biologically motivated computational model that is able to anticipate and evaluate hypothetical sensorimotor sequences. Our Model for Anticipation based on Cortical Representations (MA-COR) allows a completely parallel search at the neocortical level using assemblies of rate coded neurons for grouping, separation, and selection of sensorimotor sequences.

1 Introduction

Based on findings for the sensorimotor character of perception [1, 7], we have developed an alternative approach to perception that avoids the common separation of perception and generation of behavior and fuses both aspects into a consistent neural process [6]. In this approach, perception of space and shape in the environment is regarded to be an active process which anticipates the sensory consequences of alternative hypothetical interactions with the environment, that could be performed by the sensorimotor system, starting from the current sensory situation. This point of view emphasizes the generative and anticipative character of perception considering both sensory and motor aspects of the action-perception-cycle.

In the following, we turn to the question of where in the brain anticipating sensorimotor systems may be expected. Based on these findings, in Section 3, we present MA-COR. This model allows a completely parallel search at the neocortical level using assemblies of rate coded or spiking neurons for generation, grouping, separation, and selection of sensorimotor sequences. It is intended as a general scheme for sensorimotor anticipation in a neural architecture. It does not attempt to provide a detailed description of a specific cortical or subcortical structure, but we try to capture some general properties of architecture and processing that are relevant to our "perception as anticipation"-approach in brain-like systems (for details see [3]).

2 Biological evidence

Figure 1 provides an overview of the main cortical structures used in our model including the brain regions involved and their connections. The visual information about an actual situation is carried from the retina to the cerebral cortex and reaches also the posterior parietal cortex (PPC). The PPC effects the integration of different sensory in-

puts, thereby processing afferent inputs not only from visual cortex (V4, V5, etc.), but also from the primary somatosensory cortex (SI) and limbic cingulate gyrus. This sensory information enables PPC to generate an activity distribution describing the current status of the animal and forming the basis of successive motor planning. Such planning of motor actions could be shown to take place in the secondary motor areas, e.g. the premotor cortex (PMC) and the supplementary motor area (SMA) (see Figure 1) [9, 10].
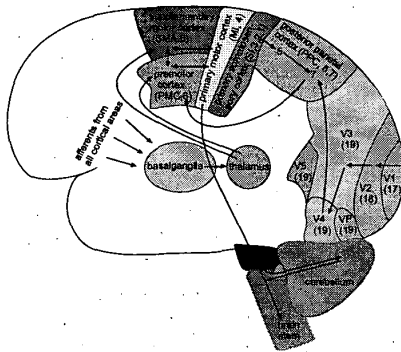

Figure 1: Schematic illustration of the essential cortical and subcortical systems that may be involved in sensorimotor anticipation based on internal simulation.

Thach (1996) found that the premotor parts of the brain are active both in planning movements to be executed and in thinking about movements that shall not be executed. Thus, these areas may play a role in anticipating or rehearsing a movement without actually performing it. The SMA also appears to be crucial in temporal organization of movements, especially in sequential performance of multiple movements. The outputs of the PMC and SMA are sent to regions of the primary motor cortex (MI) that control proximal and axial limb movements or body movements via the brainstem and the medial cerebellum for fine tuning of movements [4].

Another subcortical area, the basal ganglia (BG) is of great importance because they are implicated in motor habit learning or might play a role in interfacing many cerebral cortical areas to systems for behavioral output. Especially the striatum receives inputs from all parts of the cerebral cortex, including PMC, MI, SI and has outputs directed strongly towards the premotor and prefrontal cortex via which they could influence movement selection and initiation [8]. Besides these cortical inputs, the striatum receives afferent inputs from dopamine neurons in the midbrain [11]. This way, striatal neurons are able to learn an association between the sensorimotor context and the dopaminergic afferents, which allows to evaluate sensory situations without external reinforcement [11].

3 Model for Anticipation

Observable behaviors are the only indicators to evaluate and compare the perceptual performance of sensorimotor systems as a whole.

Therefore, we are investigating our anticipatory concept within the framework of a simple local navigation behavior with the goal of obstacle avoidance and fast and straight movement. To provide sensory inputs $\underline{x}(t)$, the simulated system was equipped with 8 IR-sensors arranged in a circle. The range of the IR sensors is the twice as far as the diameter of the simulated robot. A motor command $\underline{m}$ consists of a steering angle $\phi \in [-45°, 45°]$ and a velocity $v \in [0, 1]$. The reinforcement is chosen depending on the motor command selected such that a maximum reinforcement r of 1.0 is only delivered for $\phi = 0$, $v = 1$ without collisions. The reinforcement decreases up to a minimum value of $r = 0.3$, for greater steering angles and lower velocities. Collisions are always punished by $r = -1$.

Of great importance for a successful navigation behavior is the evolution of a general understanding of space and shape, independent of specific visual details of the objects in the scene. In our view, the evolution of such a general understanding must be based on the capability to continuously simulate, evaluate, and select sensorimotor alternatives. This requires a generative process of anticipating the course of events resulting from different sequences of actions.

3.1 Architecture

In the MACOR-architecture a *parallel* generation of sequences of sensorimotor hypotheses is assumed. It is realized by a spread of activity through corticocortical connections within our cortical model that is supposed to correspond to SMA/PMC. These connections, thus, allow the direct prediction of subsequent sensorimotor situations as well as an evaluation (w^r) and competence (w^c) for each transition. Learning of these action-values is thought to proceed involving the value-system of the brain, particularly the basal ganglia. The values of a sensorimotor transitions mediated by the basal ganglia are stored directly in the synaptic weights of the respective corticocortical connections.

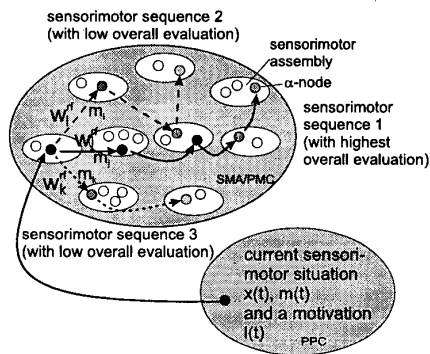MACOR is composed of sensorimotor assemblies of processing nodes (prediction map, see Figure 2).

Figure 2: Basic structure of MACOR modeled at the level of associative cortices. Each node, called α-node, encodes a sensory situation specified by the motor context that resulted in the respective sensory situation. This figure schematically illustrates three short sequences. Each of the generated sequences may have a different length and cumulative evaluation. The connections between the α-nodes encode the motor commands (m) along with their evaluations (w^r) and competence (w^c) for the corresponding sensorimotor transition. Different grey levels were used to symbolize different activities of sensorimotor nodes.

The nodes (α-nodes, pyramidal cells) in each sensorimotor assembly represent alternative motor commands serving to bring the system into the respective sensory situation.

Thus, initiated by a real sensorimotor situation, a certain α-node in our model is activated which propagates its activity y_j^α to all other α-nodes connected to it by corticocortical connections w_{ij}^c (see Equation 1, where n is the number of assemblies and m is the number of nodes in each assembly).

$$y_i^\alpha(t+1) = \max_{j \in [0, n \cdot m - 1]} w_{ij}^c(t) \cdot y_j^\alpha(t) \qquad (1)$$

The hereby activated α-nodes may in turn activate further α-nodes, thus generating whole sequences of sensorimotor hypotheses. Since the maximal value of the competence weights is lower than 1.0 (see Equation 7), a subsequent α-node will always be lower activated than its predecessor. Also, a node will only be activated if its input activity exceeds a threshold. This also supplies a stopping criterion for the propagation of sequences.

While the parallel generation of sequences of sensorimotor hypotheses is achieved by the α-nodes, the model assumes that the selection of the best evaluated sequence is realized by pyramidal cells called β-nodes (see Figure 3).
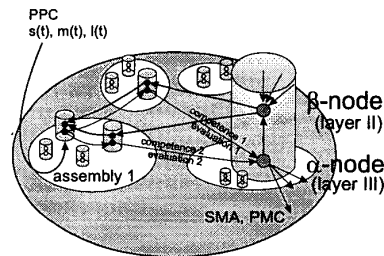

Figure 3: Backpropagation of local sequence evaluations onto the β-startnode in assembly 1.

These pyramidal cells exist in cortical layer II of SMA/PMC with extensive reciprocal projections to both MI and PMC [2]. Thus, each β-node is associated with a corresponding α-node in the same cortical column. The β-nodes may select a sequence for actual execution at any point in time as the local evaluations (w^r) for the generated sequences are projected back onto the β-start node. The activity of a β-node i is determined by the activity of its corresponding α-node $(y_i^\alpha(t+1)$, see Equation 1), the evaluation weight $(w_{ij}^r(t))$ from the preceeding α-node j

and added by the output activity of the other β-nodes propagated back (only from successor in sequence).

$$y_i^\beta(t+1) = w_{ij}^r(t) \cdot y_i^\alpha(t+1)$$
$$+ \max_{k \in [0, n \cdot m - 1]} y_k^\beta(t) \quad (2)$$

Intersections of sequences in the same sensory situation as shown in Figure 2 between sequence 1 (solid line) and sequence 2 (dashed line) may be partially avoided utilizing the motor context to reach this situation. Thus, a number of sequences may project onto the same assembly, where different nodes will be activated due to the disparate motor context of the trajectories.

3.2 Learning within the map

For learning within the prediction map, special attention must be paid to the structure of the sensorimotor situations and the learning of the competence and evaluation weights. In our model, learning may occur simultaneously or sequentially. In our investigations, we first preferred sequential learning and used SOFM and Neural Gas [5] for clustering of the sensorimotor situation (see Figure 4).

For the learning of the corticocortical connections it is essential that all possible transitions are explored a number of times, as only this will ensure the learning of meaningful competences and evaluations as the basis for correct predictions. This exploration may be realized as random action selection or by optimistic initialization of the evaluation weights and the selection of the maximally evaluated transition (see Equations 3, 4, where r_{max} is the maximally achievable reinforcement).

$$w_{ij}^C(t=0) = \frac{1}{n \cdot m} \quad (3)$$
$$w_{ij}^r(t=0) = 2 \cdot r_{max} \quad (4)$$

High optimistic evaluation weigths w_{ij}^r yield rather high sequence evaluations at the beginning of training. For actually experienced transitions, the competence weights are increased (see Equation 5), yet their evaluation weight must be decreased from the optimistic initial value (see Equation 8). The selection of the sequence with the highest cumulative

evaluation thus results in a choice biased towards sequences featuring transitions not yet explored. Only after a transition has been experienced a number of times (high competence weight), the transition can achieve a higher local sequence evaluation than not yet explored transitions. This serves to realize an exploration of the environment depending on the knowledge already gained about sensorimotor transitions. During the exploration only actually executed transitions cause an adaptation of the competence and evaluation weights. As a result of the adaptation, the competence weights for actually experienced transitions are increased (see Equation 5) and decreased for wrongly predicted ones (see Equation 6). After the adaptation of the weights all efferent competence weights of node j are normalized to the value 1 (see Equation 7). This allows the determination of the probability of a transition into a subsequent situation. The adaptation of the evaluation weights w_{ij}^r computes a moving average over all (z) experienced reinforcements r (see Equation 8).

$$w_{ij}^C(t+1) = w_{ij}^C(t) \cdot 1.5 \quad (5)$$
$$w_{ij}^C(t+1) = w_{ij}^C(t) \cdot 0.99 \quad (6)$$
$$w_{ij}^C(t+1) = \frac{w_{ij}^C(t+1)}{\sum_{k \in [0, n \cdot m - 1]} w_{kj}^C(t+1)} \quad (7)$$

$$w_{ij}^r(t+1) = w_{ij}^r(t) + \frac{r - w_{ij}^r(t)}{z} \quad (8)$$

3.3 Results

An essential goal of our first investigations was to demonstrate that the anticipative system leads to a better local navigation than a reactive one. Only the anticipative system is able to predict badly evaluated system states, yet it can also handle with such states to pursue an overall better evaluated sequence. The basis for the results to follow is the prediction map shown in figure 4. The clustering of the sensorimotor situations and the learning of the corticocortical connections proceeded sequentially.

To generate the prediction map shown in figure 4, a random action selection within the

first 2.500 time steps was used to structure the clusterers of the prediction map. After that, further 60.000 time steps of random and reactive action selection were used to explore the sensorimotor transitions during which only 18% of the connections were explored (the main part of the unexplored connections will remain so due to the given range of motor commands). After learning, the Euclidean distance between the predicted and the actually experienced sensory situation was computed as a prediction error, which has the averaged value of 23% of a maximum value. The reason for this high value might be a too small prediction map. In small maps only typical situations are represented. Situations, in which a motor command establishs a strong change of the sensory situation, are not represented.
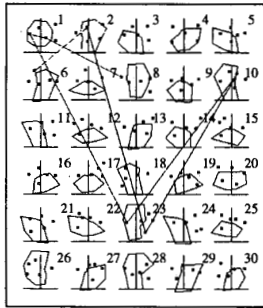

Figure 4: To structure the prediction map, the sensory situations were clustered by a Neural Gas. Each neuron of the clusterer contains 5 neurons to code the motor context. The sensory situation represented by a neuron is depicted by an octagon, where the distance of each vertex from the middle corresponds to the reading of an IR-sensor (top two vertices correspond to the forward sensors). Motor actions are shown as little squares. The greater their distance to the horizontal line, the greater the velocity a neuron represents. Their position with regard to the vertical line characterizes their steering angle, which produces turns to the left up to $-45°$(left of the vertical) or $45°$.

To provide an example for the parallel hypothesis generation, figure 5 shows all steps for the anticipation of a resulting sequence. The activities of the β-nodes during their propagation are depicted in the gray values arranged in vertical bars (black is high activity, time runs from left, $t=0$ to right, $t=7$). As hypothesis generation progresses, β-nodes are activated stronger, indicating an increasing number of generated sequences with highly

evaluated transitions. The β-startnode is marked by a big square in all hypothesis steps. Figure 5 shows all trajectories, that were best in the several hypothesis steps.
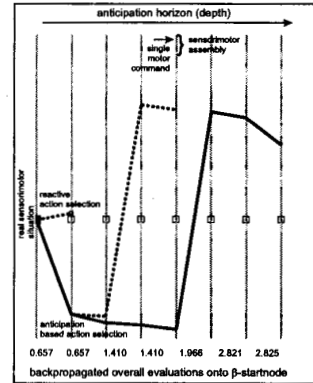

Figure 5: Generation of alternative sensorimotor sequencs of hypotheses, which can change over the time scope of prediction.

The sequence evaluations backpropagated to the β-startnode in the single steps are given below the respective bar. The final resulting trajectory is drawn as a solid line, all others as dotted lines. At $t=1$, the difference in the action chosen between a reactive and an anticipative system is observable: the reactively chosen transition initially has a higher overall sequence evaluation, but with ongoing planing results in a lower one.

Investigations regarding a comparison between anticipative and reactive systems are shown in figure 6.
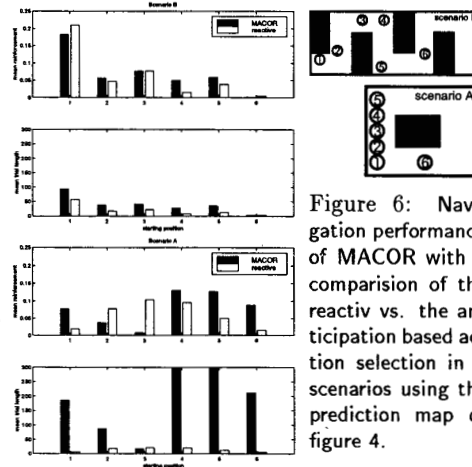

Figure 6: Navigation performance of MACOR with a comparision of the reactiv vs. the anticipation based action selection in 2 scenarios using the prediction map of figure 4.

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Beginning from typical scenario positions in front of a wall, at an angle to the wall, or in a hallway, the trials ended by a collision or after 300 steps. Especially in situations in front of an obstacle the reactive system went some steps straight ahead before it had a collision. In contrast, the anticipation based system had both higher mean trial lengths (2nd and 4th row left, Figure 6) and higher mean reinforcements (1st and 3rd row left, Figure 6), especially in the scenario A (more possible straight movements). In scenario B the mean reinforcements are similar, but the anticipation based system had more collision-free steps (trial length).

4   Discussion and Outlook

A critical point of this architecture is its weak biological correspondence, especially with respect to the evaluation of sequences and backpropagation of the start node. Further, due to the activation functions used, no recurrent loops can be used to form sequences. To solve the binding problem, how a node can encode to which sequence it belongs and thus, to which predecessor it must backpropagate its sequence evaluations, an alternative approach tries to realize MACOR with spiking neurons. The advantage when using spiking neurons rests with the utilization of time as another criterion of sequence constituency. As this feature is already encoded in the phase, a neuron does not need to be told explicitly to which sequence it belongs. First success with Integrate-and-Fire neurons could be achieved synchronizing the spiking phase of all neurons in one sequence while the neurons of other sequences fire out of phase. This neurons also allow to encode the sequence evaluation in the spiking rate, such that the highest frequency marks the best sequence, whose sum of individual evaluations is highest.

Additional research is necessary regarding the presently chosen form of cortical representation of sensorimotor states in sensorimotor assemblies consisting of motor context-nodes. Although the representation of a sensory situation together with its motor context somewhat defuses the superposition problem of hypotheses sequences at the same sensory situ-

ation, it also requires the generation of an entire motor map as motor context for each sensory situation. The number of necessary nodes for a multitude of situations may thus exceed the available resources especially with respect to a biological realization. A separate representation of sensory situations and motor commands, would be comparatively more plausible in biological terms. The binding of sensory and motor assemblies could also be realized by a temporal coding using synchronization between nodes in sensory and motor assemblies belonging together. Considering these problems, we are aware that much work remains to be done to complete this computational model of sensorimotor anticipation as a base for action selection.

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