CONTEXT-SENSITIVE GENERATION OF GOAL-DIRECTED BEHAVIORAL SEQUENCES BASED ON NEURAL ATTRACTOR DYNAMICS

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Introduction

Autonomy in robotic systems makes it possible for a human user to define goals for the robot in relatively macroscopic terms, while the robotic system figures out the details. In addition to the considerable problem of providing all the component perceptual and motor behaviors, interactive scenarios require principles for behavioral organization and sequence generation. Behavioral organization must ensure that at each moment in time all behavioral constraints are satisfied. Sequence generation must achieve the goal by assembling in the correct order the component behaviors that lead to the goal.

Techniques to address both kinds of problems have been developed in a variety of different fields. What is not well understood is how to combine the two demands under the boundary conditions of interactive behavior. First, the constraints to be integrated may change in time as interactive scenarios are naturally dynamic. Second, the user may change goal or behave inconsistently, to which an interactive system must react meaningfully.

Behavioral organization has been an important topic in behavior-based robotics [3] because in that approach to autonomous robotics competence and flexibility arise from the activation and deactivation of elementary behaviors. A number of schemes have been proposed, of which the one by Pattie Maes [7] is probably closest in spirit to our approach.

We have based our ideas on the attractor dynamics approach to autonomous robotics [8, 9]. In this framework, a nonlinear dynamical system generates the temporal evolution of behavioral variables, such that desired behaviors are fixed-point attractor solutions while un-desired behaviors are repellors. Unlike the potential field approach for trajectory formation [5], the behavioral variables are at all times in an attractor, which they track as the attractor shifts. This provides the motion plan with stability properties, a particular advantage when time varying inputs or changing task demands perturb the system.

This approach has been extended to address behavioral organization by introducing activation variables that represent whether a particular behavior is activated or not. A competitive attractor dynamics of such variables then stabilizes states of behavioral organization [1, 6, 8, 11]. External and internal constraints imposed on the behavioral system are contributions to the dynamics. Quantitative changes in these contributions arising, for instance, as sensory inputs change, may lead to qualitative changes of the dynamics, e.g. an attractor disappearing or a new attractor appearing. This happens at bifurcations at which attractors go through an instablity. The system relaxes to another stable state that represents a solution that satisfies all constraints. Nonlinear effects like bistability and hysteresis that depend on the history of the system can be exploited for decision making under uncertainty in order to avoid oscillations or to prolongate the influence of a source no longer present.

The fact that attractor dynamics are at work throughout the system, both to generate movement plans and to organize behaviors, makes system integration particularly robust. Attempts to extend this framework to the planning of behavioral sequences [10] have remained limited exactly because the serial order problem was solved algorithmically.

This paper extends the attractor dynamics approach to address sequence generation as well as behavioral organization. To do so, we need to drastically simplify and rebuild the mathematical framework on which previous attractor dynamics systems for behavioral organization [1, 6, 8, 11] were built. We replaced the particular mathematical setting of the degenerated pitchfork bifurcation in this prior work by a piece-wise linear dynamics inspired by the dynamic field framework of Amari [2]. The crucial step in extending the approach is to introduce a second layer of activation variables, a “motivation” layer, with different coupling structure. While at the level of behavioral organization coupling expresses logical constraints (behavior A is a prerequisite for behavior B, or excludes behavior B, or is independent of behavior B), at the motivational level the coupling matrix back-channels activation from the goal to the component behaviors required to reach the goal (somewhat reminiscent of dynamic programming).

In the following paragraphs, we first explain how behavioral organization works within our neural architecture and then describe our implementation of the neural architecture on the miniature robot Khepera. After that the results of some exemplary scenarios are presented which illustrate the ability to organizee the implemented behaviors on the Khepera particularly with regard to goal-directedness and context-sensitivity of behavioral sequences, and we finish with our conclusions.

Neural attractor dynamics for behavioral organization

On a rather abstract level, the attractor dynamics approach is neurally inspired: elementary behaviors are modelled as neurons that possess a certain value of activity. These neural activities are evolved over time by a dynamical system with attractors at stable patterns of activation. Behavioral interactions like logical preconditions or contradictions as well as contextual appropriateness of behavioral execution are constraints on the behavioral system as a whole; these constraints are modelled as interneural connections and external stimuli which provide exciting or inhibiting contributions to the evolving neural dynamics.

All single neurons together with their neural interconnections make up a dynamic neural network, and the state of the behavioral system is at any point in time described by the activity pattern of all neurons. Input into the neural architecture is provided by external stimuli coming from the physical world. Neural output is directly fed into motor control. This sensor-motor closed-feedback loop serves to couple the effected changes on the environment back into the behavioral organization.

The neural architecture includes two dynamic neural networks: one at an executive level and one at a planning level. For each elementary behavior there exist one behavioral neuron at the executive level and one motivational neuron at the planning level. The behavioral layer models the executive activity, whereas the motivational layer models the planning activity within the behavioral system. A connection between the two layers is established by coupling the motivational activity evolved by the motivational dynamics into the behavioral dynamics insofar as positive motivation acts as one necessary positive contribution to the activation of the corresponding neuron. In the other direction, behavioral activity is coupled into the motivational dynamics for certain motivational neurons as sufficient for deactivation.

We designed the neural attractor dynamics based on a discretization for single neurons of Amari's neural field equation [2], a continuous model for neural activity in cortical structures. The discrete Amari equation describes the temporal evolution of the activity of all single neurons considering positive and negative contributions from external input and internal neural interactions. Since only activated neurons can have an impact on other neurons, the neural attractor dynamics is nonlinear, and effects of bistability and hysteresis can be used for low-level memory and neural competition.

The behavioral dynamics. The neural attractor dynamics of behavioral activity (1) describes the temporal rate of change of the dynamical variable u_i of neural activity und is parameterized for all behavioral neurons i by

- τ, the constant relaxation rate, i. e. the time scale on which the dynamics reacts to changes;
- h, the constant negative resting level of neural activation;
- $\sigma(.)$, a sigmoidal function (2), which maps the value of neural activity onto [0,1];
- $s_i^{\mathtt{beh}}$, the adequate stimulus provided by sensory input of a certain duration;
- u_i, activity of behavioral neuron i, i. e. activity of behavior i;
- m_i, activity of motivational neuron i, i. e. motivation of behavior i;
- $c_{\mathtt{mot}}$, a constant for weighting the motivational contribution, $c_{\mathtt{mot}} < |h|$;
- $\alpha^{\mathtt{beh}}_{\mathtt{selfexc},i}$, excitatory contribution of neuron i's own activity u_i;
- $\alpha^{\mathtt{beh}}_{\mathtt{exc},i}$, all excitatory contribution of active neurons connected to neuron i;
- $\alpha^{\mathtt{beh}}_{\mathtt{inh},i}$, all inhibitory contribution of active neurons connected to neuron i.

For behavioral activity, the neural attractor dynamics is formulated as the following differential equation:

$$\tau \dot{u}_i = -u_i + h + s_i^{\mathtt{beh}} + c_{\mathtt{mot}} * \sigma(m_i) + \alpha^{\mathtt{beh}}_{\mathtt{selfexc},i} + \alpha^{\mathtt{beh}}_{\mathtt{exc},i} - \alpha^{\mathtt{beh}}_{\mathtt{inh},i} \tag{1}$$

All elementary behaviors with positive behavioral activity are executed. Therefore, the constraints on the dynamics for a behavioral neuron must be designed such that it relaxes into a positive attractor only if the execution of this behavior is desirable. These behavioral constraints consist of two aspects that must be satisfied: first, the behaviorial and sensorial context, i. e. all active behaviors and all present external stimuli must allow the execution of the considered behavior, and second, the execution of this behavior is contributory to the execution of the goal behavior. The first aspect, the appropriateness of a behavior, is for its behavioral neuron determined by the contributions of the stimulus (if it is sensitive to external stimuli) and the overall positive and negative influences of other neurons, $s_i^{\texttt{beh}} + \alpha_{\texttt{exc},i}^{\texttt{beh}} - \alpha_{\texttt{inh},i}^{\texttt{beh}}$. The second aspect, the goal-orientedness of the behavior, is specified by its motivation, $c_{\texttt{mot}} * \sigma(m_i)$. Both aspects must necessarily by fulfilled, and no aspect may outweigh the other.

We consider motivation as a property of an elementary behavior which indicates the readiness of its execution. Although the context of a behavior may be given, it will not be executed without being motivated. If several behaviors share the same current context, the ones which lead to the goals will be activated. And if several behaviors lead to the goals, the ones which are contextually appropriate will be activated.

We chose the sigmoidal function as in (2), where β parameterizes the slope of the resulting function; we define $\beta = 100$.

$$\sigma(u) = \frac{1}{1 + e^{-\beta u}} \tag{2}$$

Neural coupling. The excitatory and inhibitory contributions from interneural interactions, including self-excitation, which are coded by combined α in (1), are computed as expressed in (3), (4), and (5). We will now explicate these computations.

The coupling of a neuron's own activity into its neural dynamics implements one form of the nonlinear concept of hysteresis, because the same amount of excitation which does not suffice to change the neuron's state from inactive to active may persist without deactivating it when the neuron is active. Moreover, if the amount of self-excitation is greater than $|h|$ (plus the absolute amount of inhibition, if present), the once activated neuron will stay active, even if all external excitation ceases. With fluctuating input, neural self-excitation also leads to an effect of low-pass filtering. Self-excitation can thus serve to stabilize a decision once it is brought about.

The amount of a neuron's self-excitation is coded in the main diagonal of the square matrix **A** of interneural excitation among all neurons; as expressed in (3), the value in A_{ii} is multiplied by the sigmoidal output of neuron i's activity in order to establish this contribution.

$$\alpha_{\texttt{selfexc},i}^{\texttt{beh}} = A_{ii} * \sigma(u_i) \tag{3}$$

In behavioral sequences, the activating context of a behavior is defined by the activity of all other behaviors, which are necessary for the execution of the considered behavior or are not contradictory to it. For instance, in order to execute the behavior *drive to the red object*, a behavior *find the red object* has to be executed beforehand; and a behavior *drive to the blue object*, which is executed at the same time, may prevent the approach to the red object; a behavior *open the gripper*, in contrast, may be executed in parallel.

Therefore, we can distinguish between behaviors as precondition for another behavior, behaviors as competition for another behavior, and behaviors as neutral or concurrent for another behavior. We code these logical conditions for the execution of behaviors in square matrices.

Matrix **A** contains in each entry A_{ij} for each behavior i, which behaviors j have to be active at the same time in order to activate behavior i with their combined contributions; it is also called the AND-matrix, because the influencing behaviors have to be active in logically conjunctive combination.

Matrix **H** contains in each entry H_{ij} for each behavior i, which behaviors j must be active alternatively to execute their influence on behavior i; this matrix is also called the OR-matrix, because one of the necessary behaviors may be, depending on its amount of contribution, sufficient to activate behavior i; behaviors j form a logically disjunctive combination.

The third matrix, γ, contains in each entry γ_{ij} for each behavior i, which behaviors j may not be active at the same time and exclude i's execution by a certain amount; here, one of the necessary behaviors j being active may suffice to prevent the activation of i by its contribution. Since the individual inhibitory contribution matters, mutual inhibition is not excluded.

The overall excitatory influence in (1) is computed by considering whether all necessary neurons in **A** and **H** are active and calculates their combined contribution. The product in (4) denotes the logic conjunction $\forall j \neq i : A_{ij} \wedge \sigma(u_j)$, which can only become true iff A_{ij} is true and $\sigma(u_j)$ is true, i. e. there are necessary contributions, and all contributing neurons are active. Only if this product does not equal 0, the sum of all active contributions in **A** is effective. In contrast, the active contributions in **H** are only added, because they are disjunctive. In order to prevent false negative results by non-contributing neurons, all considered entries A_{ij} must be greater than 0.

$$\alpha^{\mathtt{beh}}_{\mathtt{exc},i} = \sum_{j\neq i}[A_{ij} * \sigma(u_j)] * \prod_{j\neq i}[sign(A_{ij}) * \sigma(u_j)] + \sum_{j\neq i}[H_{ij} * \sigma(u_j)], \forall A_{ij} > 0 \tag{4}$$

The overall inhibitory influence in (1) considers whether at least one necessary neuron in γ is active for each neuron i and calculates the resulting inhbitory contribution to the dynamics of i, as expressed in (5).

$$\alpha^{\mathtt{beh}}_{\mathtt{inh},i} = \sum_{j\neq i} \gamma_{ij} * \sigma(u_j) \tag{5}$$

The above mentioned neutral interactions are realized insofar as concurrent neural activity is implicit in missing interneural connections or entries of 0 in the interaction matrices. The interaction matrices may not be contradictory in their entries: $\forall i, j : (A_{ij} + H_{ij}) * \gamma_{ij} = 0$. Furthermore, there does not exist any selfinhibition, so $\forall i : \gamma_{ii} = 0$.

Neural excitation. By considering one interactive neuron, the evolution of its activity with change in contributions to the dynamical system is illustrated in fig. 1.

Without any input, the dynamical system is in a stable state at the negative attractor in $u_i = h$ with all non constant contributions equal to zero. This means that neuron i is inactive and cannot exert any influence on other neurons or on the motor control. The corresponding phaseplot can be seen in fig. 1a.

When the inactive neuron receives input from excitation by a stimulus or by connected excitatory or inhibitory active neurons, the attractor moves towards the positive regime, if the positive contributions outweigh the negative ones, or it moves towards more negative values in the opposite case; the dynamics is lifted or lowered respectively by the amount of the overall input.

Small forces or short durations of forces will only perturb the system to small extend; after few time steps it will be again stable within the attractor.

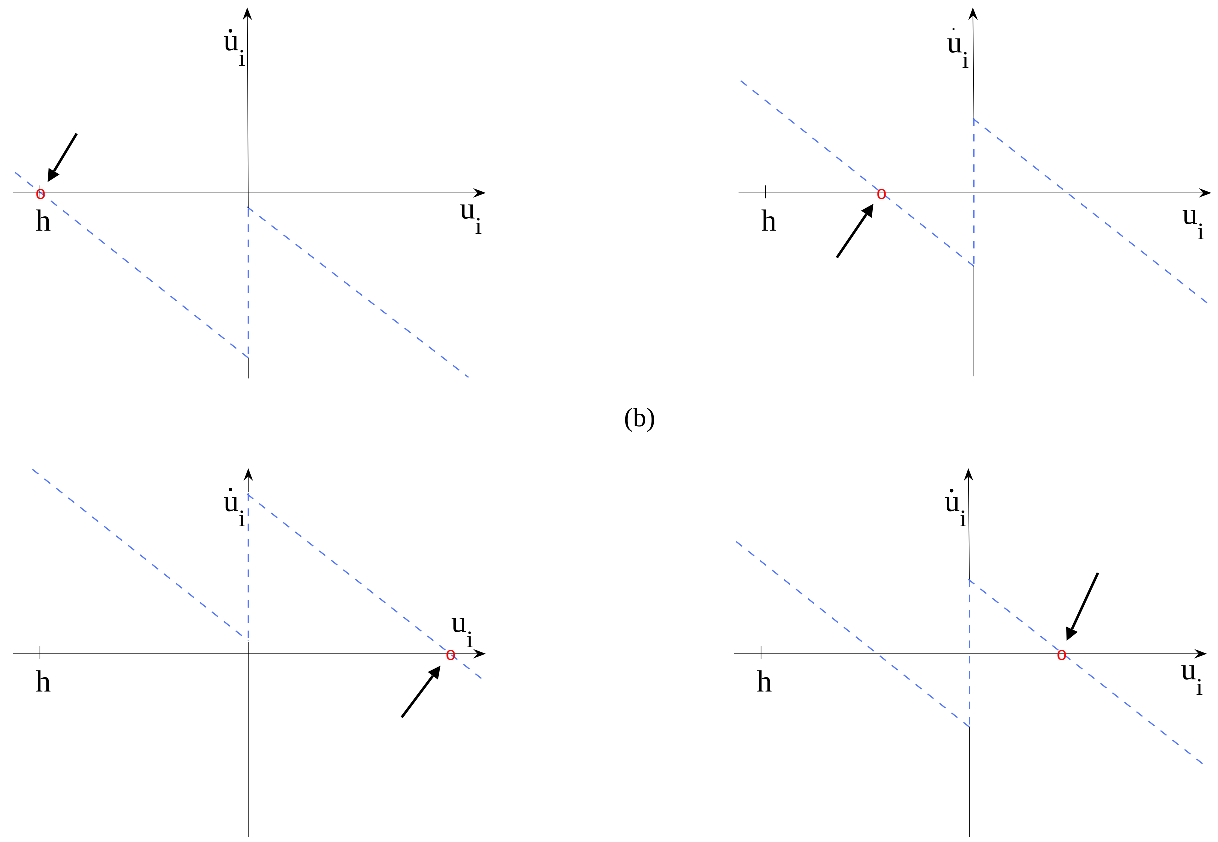
If the positive contributions acting on the negative neuron are strong but not stronger than $|h|$, the distance to $u_i = 0$, the dynamics bifurcates and a new attractor arises in the positive regime. The dynamics has become bistable; since the state of the system cannot leave the regime of the current negative attractor, the other attractor is not reachable and the state of the system remains inactive (see fig. 1b).

Otherwise, if the resulting forces are stronger than $|h|$ the quality of the dynamics changes again by a bifurcation permitting the positive attractor to be the only one. Now the state of the system is attracted by this single attractor in the positive regime and the behavior is “switched on” with positive neural activity (see fig. 1c). Now the neuron is enabled to influence other neurons by inhibition or excitation, excite itself, or parameterize motor control.

When the positive contributions to a self-excitatory neuron cease to apply and the negative ones are not significant, the dynamics bifurcates and becomes bistable again without changing the state of the behavioral system (see phaseplot in fig. 1d). This is caused by the constraint that only active neurons can execute influence including self-excitation. This effect can be described as hysteretic, because under the same conditions the current state depends on the history of the system.

Since the absence of beforehand activating forces does not deactivate this self-exciting neuron, the active neuron can only be “switched off” by adding negative input into the system, e.g. by a competing neuron. This inhibition will lower the dynamics again, causing a bifurcation and a relaxation of the system into the newly generated negative attractor at negative neural activity. If these negative force ceases only the constant influence of the negative resting level remains as a contribution and the system has reached the state without input again (see again fig. 1a).

The stability analysis of the neural dynamics is straightforward because it is piece-wise linear. Stable fixed points are found



(a) (b)

(c) (d)

Figure 1: Snapshots of the continuous qualitative change of the neural dynamics with respect to number and regime of the attractors. It depends on input and history which attractor the system is in (indicated by the red circle). The rate of change (the temporal derivative) of the neural activity, $\dot{u}$, is plotted against the neural activity itself, u, for one neuron i; h denotes the negative constant resting level of the neural activity. An attractor as a stable fixed point is indicated by a zero-crossing with negative slope, representing a value of activity without change over time. The system can be "switched on" (evolving from state (a) via (b) to state (c)) by adding enough positive input (i. e. input must exceed $|h|$) into the system and causing a bifurcation to a bistable system and another bifurcation to a monostable system when an attractor reaches the activity value of 0. Once the system is "switched on", a self-exciting neuron may remain active even if the external input has died away (state (d)) because the amount of activity is coupled with its own evolution. In order to switch the system off in this case, negative input has to be added to the system evolving then from state (d) through a bifurcation to state (a). It is easy to see that the system will always be in or just moving into an attractor.

for solutions of the dynamical system $\dot{u} = 0$, because, as this equation expresses, then the rate of change of the dynamical variable equals zero.

In the negative regime, where the dynamical variable is less than zero, $u < 0$, a fixed point can be found by the solution $0 = -u + h + s + c^{\texttt{mot}} * \sigma(m) + \alpha^{beh}_{\texttt{selfexc}} + \alpha^{beh}_{\texttt{exc}} - \alpha^{beh}_{\texttt{inh}}$ at the value of u if $h + s + c^{\texttt{mot}} * \sigma(m) + \alpha^{beh}_{\texttt{selfexc}} + \alpha^{beh}_{\texttt{exc}} - \alpha^{beh}_{\texttt{inh}}$ is less than 0.

In the positive regime, where $u > 0$, a fixed point can be found for $0 = -u + h + s + c^{\texttt{mot}} * \sigma(m) + \alpha^{beh}_{\texttt{selfexc}} + \alpha^{beh}_{\texttt{exc}} - \alpha^{beh}_{\texttt{inh}}$ at u if $h + s + c^{\texttt{mot}} * \sigma(m) + \alpha^{beh}_{\texttt{selfexc}} + \alpha^{beh}_{\texttt{exc}} - \alpha^{beh}_{\texttt{inh}}$ is greater than 0.

An example for a bistable neural dynamics is given in the case of two competing neurons: If two neurons, i and j, are mutually coupled by inhibition, then for the activity of neuron i, u_i, there is a fixed point in the negative regime if $u_j > 0$ and $u_i = h + s + c^{\texttt{mot}} * \sigma(m) + \alpha^{beh}_{\texttt{selfexc}} + \alpha^{beh}_{\texttt{exc}} - \gamma_{ij} * \sigma(u_j)$ is less than 0, and there is also a fixed point in the positive regime if $u_j < 0$ and $u_i = h + s + c^{\texttt{mot}} * \sigma(m) + \alpha^{beh}_{\texttt{selfexc}} + \alpha^{beh}_{\texttt{exc}} - \gamma_{ij} * \sigma(u_j)$ is greater than 0.

Categories of neurons. The behavioral neurons can be categorized by their connectivity into five types: Purely perceptual neurons only receive stimuli from sensory input and only couple into the dynamics of other neurons, whereas the activity of those neurons which are connected to the actuating hardware, is coupled into the motor control dynamics – these motor neurons only receive contributions from other neurons and provide the overall output of the behavioral system. Motor neurons are self-excitatory in order to stabilize their contribution by perceptual neurons which might be active only very shortly because they depend strongly on the stimulus frequency.

Another type of neuron, the inter neurons, are not connected to structures outside the behavioral system – they only receive input from other neurons and also only act on other neurons; they serve to converge the countributions of two or more neurons. Low-level inter neurons extend the function of the matrices of excitatory interaction because they can e. g. form groups of alternatively (OR)-coupled neurons as AND-coupled connections. High-level inter neurons represent the achievment of a behavioral goal and are called intentional neurons.

A special category of behavioral neurons is, like a combination of perceptual and inter neuron, receptive to external stimuli but also to motor neuron activity. These neurons are called success neurons, because they temporally bind an incoming specific stimulus to the activity of a motor neuron and represent thus the success of the motor activity, when they get activated. After a success neuron has become active, it inhibits the motor neuron in order to stop the motor action. Success neurons also excite themselves, so that they represent the memory of the successful action for a longer period than the activity of motor and perceptual neuron.

The motivational neurons are all inter neurons except for the motivational neurons of the high-level intentional neurons: these motivational neurons receive the specific goal stimulus, when a goal is set by the user, and serve as sources of motivation, because the spreading of motivation begins there. After the corresponding intentional neuron got activated, this activity is coupled inhibitorily with the activity of the source of motivation, so that it is deactivated after the goal has been achieved. This stops the spreading of motivation and therefore all possible neural activities concerning the achieved goal. The motivational source neurons are the only motivational neurons with self-excitation, which they use to prolongate their activity after the exciting stimulus has died away, and the only ones sensitive to inhibition.

Behavioral goals. When a behavioral goal is established by the user, a stimulus is applied to the motivational neuron of the success neuron which represents the achievement of the desired goal. Starting from this source of motivation, motivation spreads over all neural connections to all reachable motivational neurons. The neural interactions of the motivational dynamical network are parallel to the excitatory ones of the behavioral dynamical network – inhibitory connections are not considered. The idea behind the motivational connections is to allow for a pre-activiation of the predecessors of a behavioral neuron, if this neuron shall become excited by one or more of its predessors. Since motivation starts from the behavioral goal, all motivated neurons represent possible behaviors leading to the goal.

The motivational dynamics. The neural attractor dynamics for motivational activity as stated in (6) shows the same underlying characteristics as the neural attractor dynamics for behavioral activation in (1).

$$\tau \dot{m}_i = -m_i + h + s_i^{\texttt{mot}} + \alpha^{\texttt{mot}}_{\texttt{selfexc},i} + \alpha^{\texttt{mot}}_{\texttt{exc},i} - \alpha^{\texttt{mot}}_{\texttt{inh},i} \tag{6}$$

Contributions concerning motivational neural interaction are retrieved from the same matrices of excitatory interaction as for the behavioral dynamics, **A** and **H**, only without taking the main diagonal into account. There is one additional matrix used just for motivation, **M**, which contains the amount of self-excitation of the sources of motivation in the main diagonal. Self-excitation is computed (cf. (7)) by multiplying its amount by the activity of the same neuron, filtered by the sigmoid (2).

$$\alpha^{\texttt{mot}}_{\texttt{selfexc},i} = M_{ii} * \sigma(m_i) \tag{7}$$

For the computation of the excitatory contributions of motivational neuron i, $\alpha^{\texttt{mot}}_{\texttt{exc},i}$, the entries of the excitatory interaction matrices are now read out with respect to the columns of **A** and **H**: as (8) expresses, a motivational neuron i is excited if at least one of the motivational neurons k is active, the corresponding behavioral neurons of which are excited by behavioral neuron i.

$$\alpha^{\texttt{mot}}_{\texttt{exc},i} = 1 - \prod_{k \neq i} [1 - (sign(A_{ki}) * \sigma(m_k))] * \prod_{k \neq i} [1 - (sign(H_{ki}) * \sigma(m_k))] \tag{8}$$

The inhibitory contribution is again only relevant to the motivational source neurons, and it is established by coupling their self-excitation with the activity of the correspondent intentional neuron (cf. (9)). Doing so, the self-excited motivational source neurons receive inhibition equal in amount to their self-excitation and are thus “switched off”.

$$\alpha^{\texttt{mot}}_{\texttt{inh},i} = M_{ii} * \sigma(u_i) \tag{9}$$

The robotic implementation

The neural architecture has been implemented to make a Khepera II (K-Team, Lausanne) miniature robot perform manipulation tasks with colored building bricks. Our Khepera was equipped with a color camera and a gripper (cf. (2)) and acted in a 1 m^2 arena in which colored manipulation objects, obstacles and colored areas were spread (cf. (2)).

As sensory input, we used the video image for color-based object segmentation and recognition, the distance and angle to detected objects estimated from the image and the camera geometry, the eight radial IR-proximity sensors for obstacle detection, the left and right wheel encoders for odometry, and feedback from the gripper concerning arm and gripper position. Motor output was supplied to the left and right wheel motors, the arm and the gripper.

Figure 2: The employed Khepera II robot and its arena.

The three processes for behavioral organization, image processing und robot control were running with PVM on Gentoo-Linux. Inter-process communication was carried out through the exchange of messages by reading from and writing to dedicated channels.

Image processing. The grabbed video images were segmented by the hue- and saturation values of the object and ground colors. From a segmented object region, the central moment was calculated for the horizontal angle between center of object and heading direction of the robot. The lower bound of a segmented region was used to estimate the distance to the object in the real world, considering height and incline of the camera, its vertical flare angle and the vertical image resolution.

Robot control. We implemented the dynamical systems approach to path planning (e. g. [11]) for robot motion control: A dynamical system of the robot's heading direction used the angles to targets from image processing and the angles to obstacles detected by the IR sensors, and a dynamical system of the robot's path velocity applied the absolute positions of robot and targets, which were retrieved from the estimated distance to the targets and the encoder values, to provide the desired robot speed. Together with the temporal difference of heading direction, the speed commands for the left and right wheel motors were directly sent to the Khepera. By the neural activity of the motor neuron "obstacle avoidance", the consideration of obstacles was switched on or off within the dynamical system of heading direction. For turning in exploration, the dynamical system of heading direction just followed an attractor moving on a circular arc.
The dynamical system of the arm position used two attractors for the raised and the lowered arm, switched on or off by the activities of the according motor neurons, and the temporal difference of the arm position was sent to the Khepera. Though the gripper position can be read out continuously between open and closed, it is only possible to give a closing or opening command to the Khepera, so that a discrete solution was used for gripper control.

Behavioral organization. Although about 71 behaviors were implemented, the programming code for the behavioral organization is extremely sparse because all relevant information is coded in the interaction matrices containing the neural couplings. Additional coding is only necessary for mapping sensory input to stimuli.
In order to obtain some interesting object manipulation and path planning behavior, we defined the following elementary behaviors.

Perception (12 behaviors)
- object of red/green/blue/any color is determined (by an internal stimulus)

- ground of green/blue/yellow color is determined (by an internal stimulus)
- gripper is open/closed/between open and closed (by gripper position)
- arm is up/down (by arm position)

Action (20 behaviors)
- determine color of current object/ground (sets an internal stimulus)
- search a object/ground of current color (visual search)
- explore for a object/ground (turn around during visual search)
- approach the found object/ground (approach position)
- pursue the object/ground (visual search during approach)
- avoid obstacles (use IR information for repulsive forces in path planning)
- lower/raise the arm (set arm position)
- open/close the gripper (set gripper position)

Success (18 behaviors)
- color of the current object/ground is determined
- ready to work (state with open gripper and raised arm)
- object/ground is found
- object/ground is approached
- object/ground is pursued
- arm is lowered/raised
- gripper is opened/closed

Intention (21 behaviors)
- color of the current object/ground is determined
- object/ground is found
- object/ground is approached
- arm is lowered/raised
- gripper is opened/closed
- object is grasped/put down (goals with approach)
- object is picked up/deposited (goals without approach)
- object is delivered/pushed (goals with approaches to object and ground)

In the neural architecture, each behavior is modelled by its activity through a behavioral neuron and by its motivation through a motivational neuron. For the neural representation of the above mentioned elementary behaviors, a number of neurons bigger than the number of behaviors had to be implemented, because in the current architecture, it was not possible to re-excite a motor neuron that has been active before, although it is inactive. The reason for this is that an excited motor neuron is inhibited by the corresponding success neuron, which represents the successful accomplishment of the motor activity and stays active further on. For instance, for every raising of the robot arm during one behavioral sequence, a seperate motor neuron and the corresponding success neuron for the identical motor activity had to be added. Further, 27 additional low-level inter neurons were used for converging connections (AND/OR), and also a default neuron had to be inserted as behavioral context for always applicable neurons (e. g. the determination of the object color: one of the related motor neurons, one for each color, is motivated and if all of them are excited, only the motivated of them gets active). This amounted to a complete number of 106 neurons.
The behavioral neural connections are given by the described three matrices of all excitatory and inhibitory influences. fig. 3 gives a compressed color-coded view of a combined 106 x 106 matrix, which includes all three matrices.
The complete system of the neural architecture and the robotic system together with their interfaces is shown in fig. 4.

In order to set behavioral goals and to visualize motivation and activation of behavioral neurons, we used a graphical user interface, which is shown in fig. 5. The readability of the display depends on the number of portrayed neural connections.

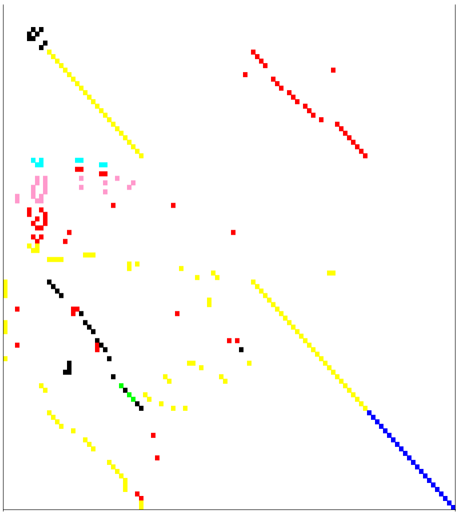


Figure 3: Combined color-coded diagram of all interaction matrices of behavioral neurons. Color-codes: black: -0.5, green: -0.3, cyan: 0.15, pink: 0.2, red: 0.25, yellow: 0.5, blue: 0.75

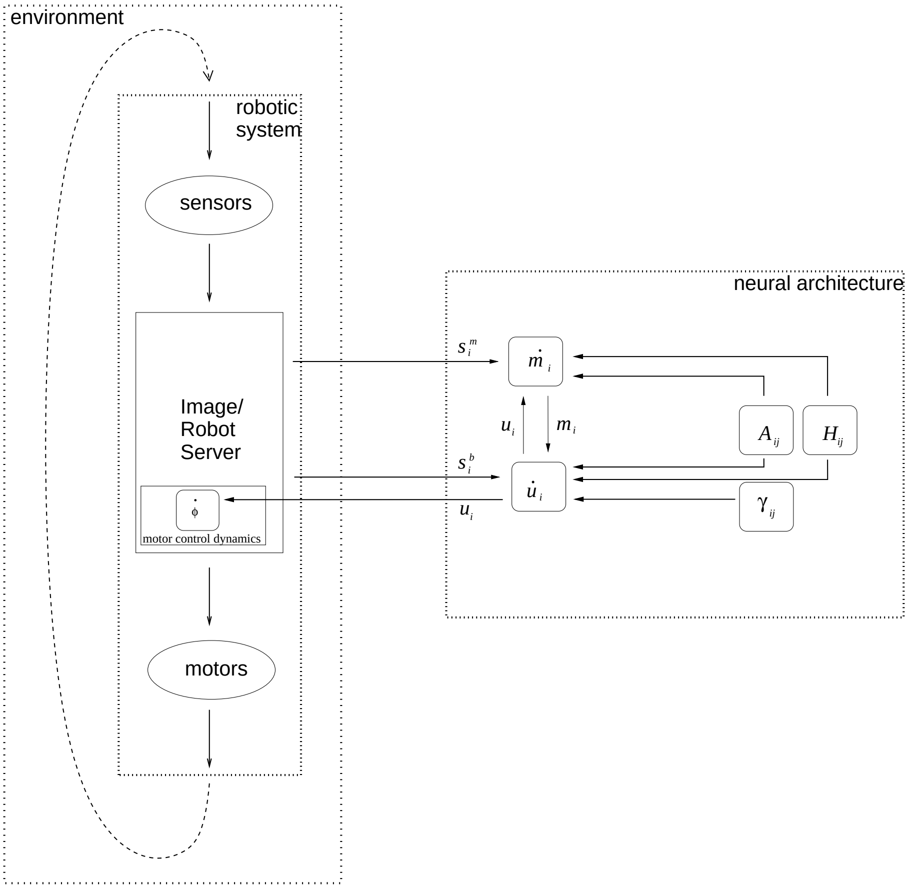


Figure 4: The neural architecture and the robotic system.

Results

With the implementation described above, we let the Khepera act out several tasks like searching and grasping an object, first grasping an object and then delivering it to a certain ground etc. In order to present the system's capability concerning the generation of context-sensitive and goal-directed behavioral sequences, two scenarios in two variations are described now. In the subsequent diagrams (figs. 6 – 13), the time courses of motivation starting from the respective sources of motivation and the time courses of activation starting from the contextual appropriate behaviors are shown for all task variations

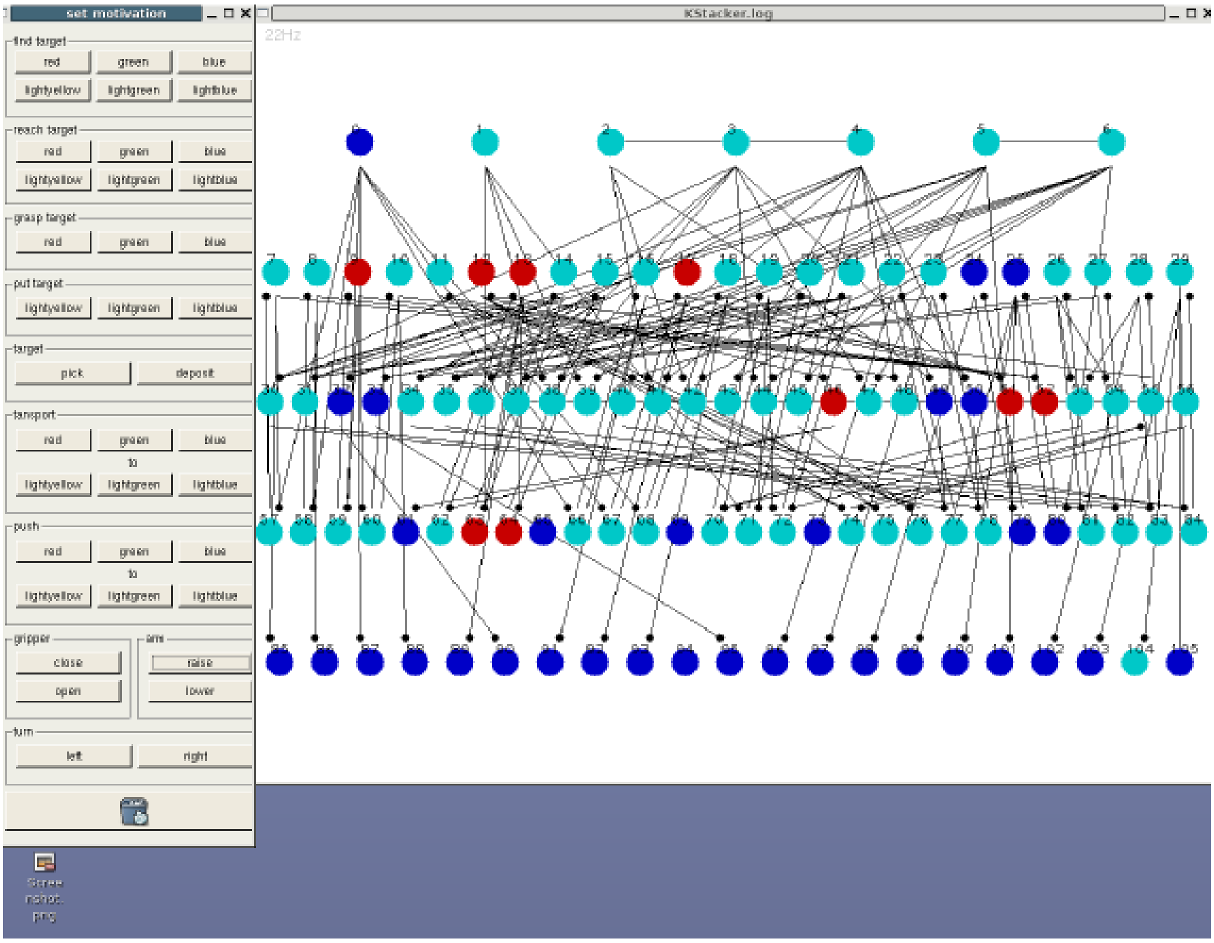


Figure 5: GUI with interactive setting of goals and visualization of current state (inactive (dark blue), motivated (light blue), excited (red) behavioral neurons) of the dynamic neural network. Neural categories from top to bottom: perception, success, low-level inter neurons, motor, and intention neurons.

and for all 106 neurons. One time step corresponds to approximately 45 ms. The alternating activity of the perceptual neurons results from the reduced stimulus frequency in order to reduce message traffic; the stimulus duration was set to 5 time steps. The numbering of the neurons can be mapped to their labeling by means of table 1.

no.	label	no.	label	no.	label
0	default	27	successDropTarget	79	lowerArm
1	targetRemote	28	successSecureTarget	80	raiseArm
2	handsTied	29	successFreeArm	81	encloseTarget
3	handsSpread	30-48	and1-and19	82	dropTarget
4	handsOpen	49-56	or1-or8	83	secureTarget
5	armUp	57	determineAnyTarget	84	freeArm
6	armDown	58	determineRedTarget	85	iDeterminedAnyTarget
7	successAnyTarget	59	determineGreenTarget	86	iDeterminedRedTarget
8	successRedTarget	60	determineBlueTarget	87	iDeterminedGreenTarget
9	successGreenTarget	61	exploreTarget	88	iDeterminedBlueTarget
10	successBlueTarget	62	searchTarget	89	iFoundTarget
11	successDoArmDown	63	pursueTarget	90	iApproachedTarget
12	successReadyToWork	64	approachTarget	91	iDeterminedLightgreenGround
13	successSearchTarget	65	avoidObstaclesTarget	92	iDeterminedLightblueGround
14	successPursueTarget	66	determineLightgreenGround	93	iDeterminedLightyellowGround
15	successApproachTarget	67	determineLightblueGround	94	iFoundGround
16	successLightgreenGround	68	determineLightyellowGround	95	iApproachedGround
17	successLightblueGround	69	exploreGround	96	iOpenedGripper
18	successLightyellowGround	70	searchGround	97	iClosedGripper
19	successSearchGround	71	pursueGround	98	iLoweredArm
20	successPursueGround	72	approachGround	99	iRaisedArm
21	successApproachGround	73	avoidObstaclesGround	100	iPicked
22	successOpenGripper	74	doHandsSpread	101	iDeposited
23	successCloseGripper	75	doArmUp	102	iGrasped
24	successLowerArm	76	doArmDown	103	iPut
25	successRaiseArm	77	openGripper	104	iDelivered
26	successEncloseTarget	78	closeGripper	105	iPushed

Table 1: Numbers and labels of neurons (behavioral and motivational).

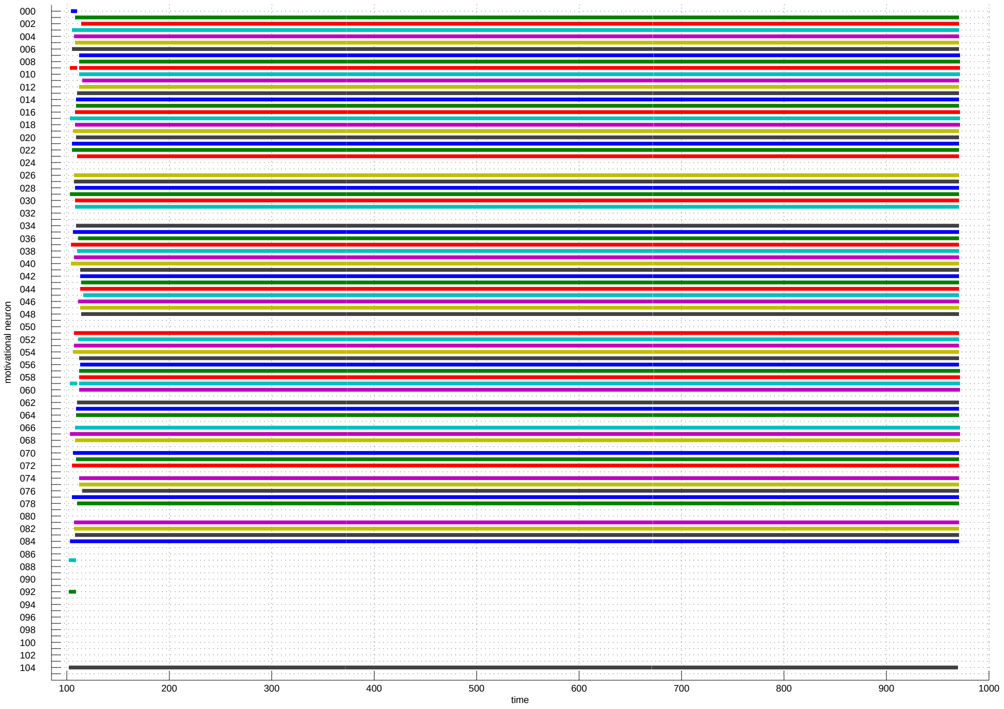


Figure 6: Motivational neural excitation in task 1A.

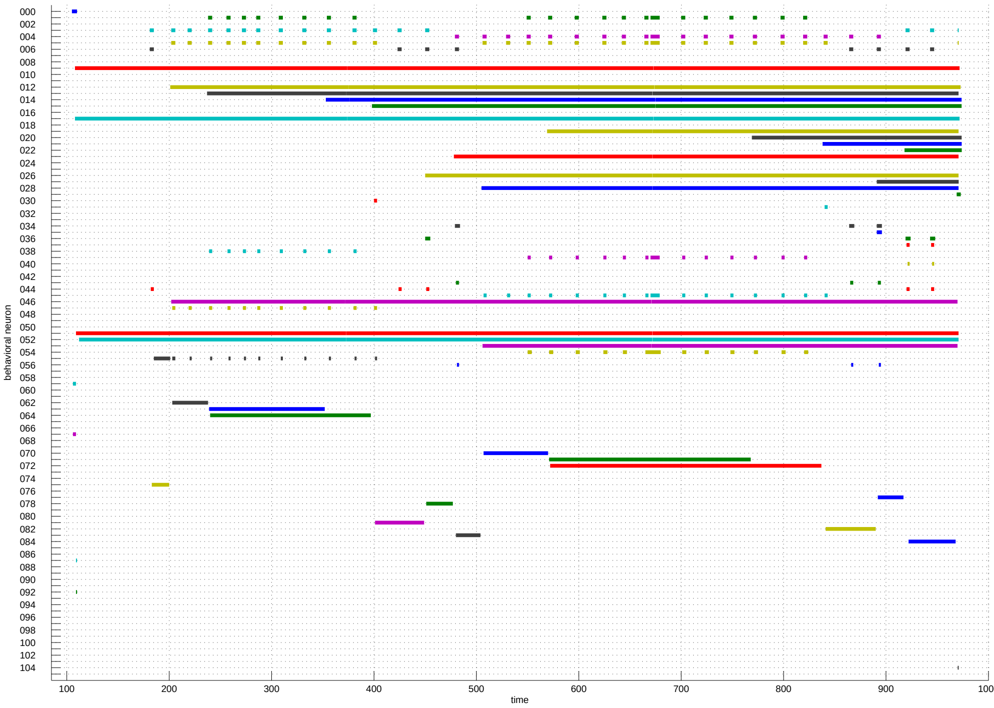


Figure 7: Behavioral neural excitation in task 1A.

Task 1. “grasp the green brick and put it down at the blue ground”
In variation A the initial state of the robot is with empty gripper and low arm. Variation B starts with a different initial state of the robot with a red brick in its gripper and a raised arm. This is a possible state after grasping the red brick or also after an interruption of a longer sequence.

By setting the behavioral goal (“deliver green object to blue ground”) via the GUI, a motivational stimulus is applied to the motivational neuron (source of motivation) of three intentional neurons: for a green object, for a blue ground, and for delivering. After this stimulation has led to neural activation, all reachable motivational neurons are excited by propagating the motivation back against the direction of behavioral excitation; this can be tracked in the corresponding time courses of motivation (figs. 6 and 8). The three sources of motivation are the neurons 87, 92, and 104. As soon as a behavioral neuron is pre-activated by motivation and has a valid context, it is activated and excites or inhibits other behavioral neurons.

In the behavioral time course of variation A (fig. 7), it can be seen that the first excited behavioral neuron is no. 0, “default”: this neuron has always a positive behavioral stimulus, so that it becomes active together with motivation. The default neuron excites the motor neurons nos. 59 and 67, “determine green target” and “determine blue ground”, which set the internal value of the color variables to GREEN and to BLUE, respectively, which are fed as stimuli into the already motivated and pre-activated success neurons, nos. 9 and 17, which are excited next. As soon as the stimuli coming from the robot excite the perceptual neurons of an open gripper and a low arm (nos. 3 and 6, near time step 180), the arm is being raised (no. 75)

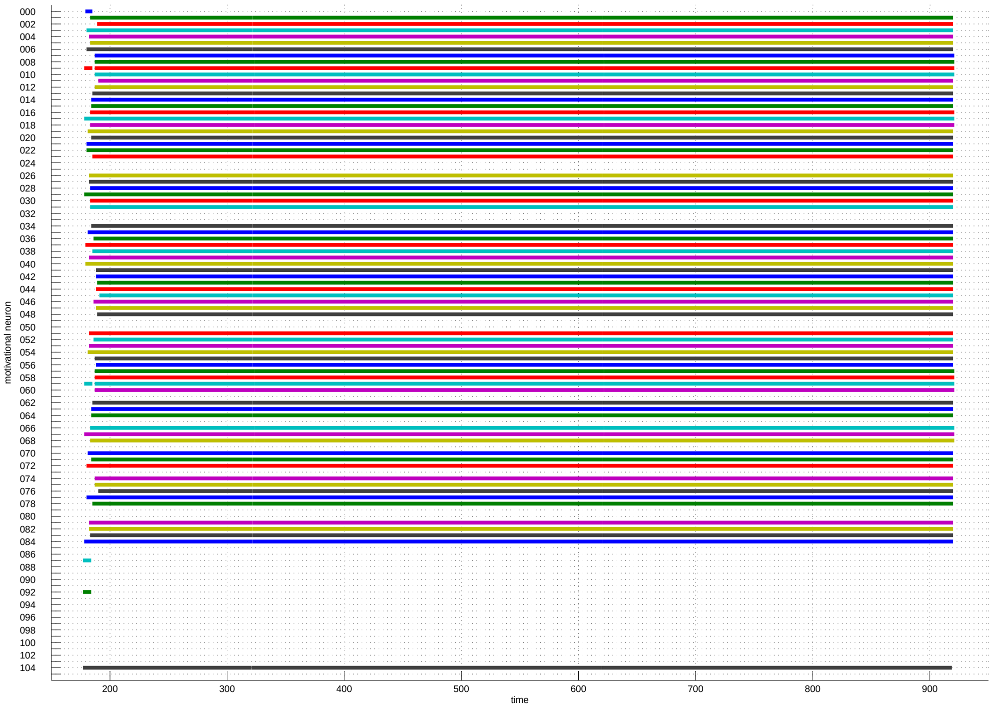


Figure 8: Motivational neural excitation in task 1B.

to reach the starting configuration (cf. success neuron no. 12). Then the current target is being searched for (no. 62 near time step 200) and found (no. 13 at 235). This is the precondition for motor neurons 64 and 63 to approach the object and visually pursue its position. Close to the object, the pursuing (no. 63) stops (time step 355) and its success neuron is excited which immediately inhibits this motor neuron. Then the object is reached (distance equals to 0) (no. 64 at about time step 395) and the corresponding success neuron is excited (no. 15). As can be tracked analogously to the description so far, the sequence proceeds as follows: lowering the arm (81), closing the gripper (78), raising the arm (80), searching for the ground (70), approaching and pursuing the ground (72 and 71), lowering the arm (82), opening the gripper (77) and raising the arm (84).

Since Task 1 varies only in the initial state of the robot, the set goal is identical for A and B, so that the spreading of motivation is equivalent in both variations (figs. 6 and 8), and only the behavioral sequence differs (figs.7 and 9) in the beginning due to the different context of the initial state of the robot.

The behavioral time course of variation B (fig. 9) shows that the different context of the state of the robot leads to the execution of different motivated behaviors in the beginning of the sequence, after the colors of the object and the ground have been determined, in order to reach the starting configuration with an empty gripper and a raised arm: the object in the gripper is being set to the ground and the gripper is being opened. Then, the sequence goes on as in variation A by raising the arm (an action necessary in variation A to reach the starting configuration), searching the target, approaching and pursuing it, and so on.

Task 2. “transport the blue brick to the yellow ground”
The second task consists of two different goal settings, which demonstrate that activities of behavioral neurons can be shared in different sequences which lead to different goals. This is possible because the decision for a subsequent behavior out of several contextually appropriate ones depends also on the motivation coming from the goal behavior.

In variation A the goal “push the blue brick to the yellow ground” is set and in variation B the goal “grasp the blue brick and put it down at the yellow ground”.

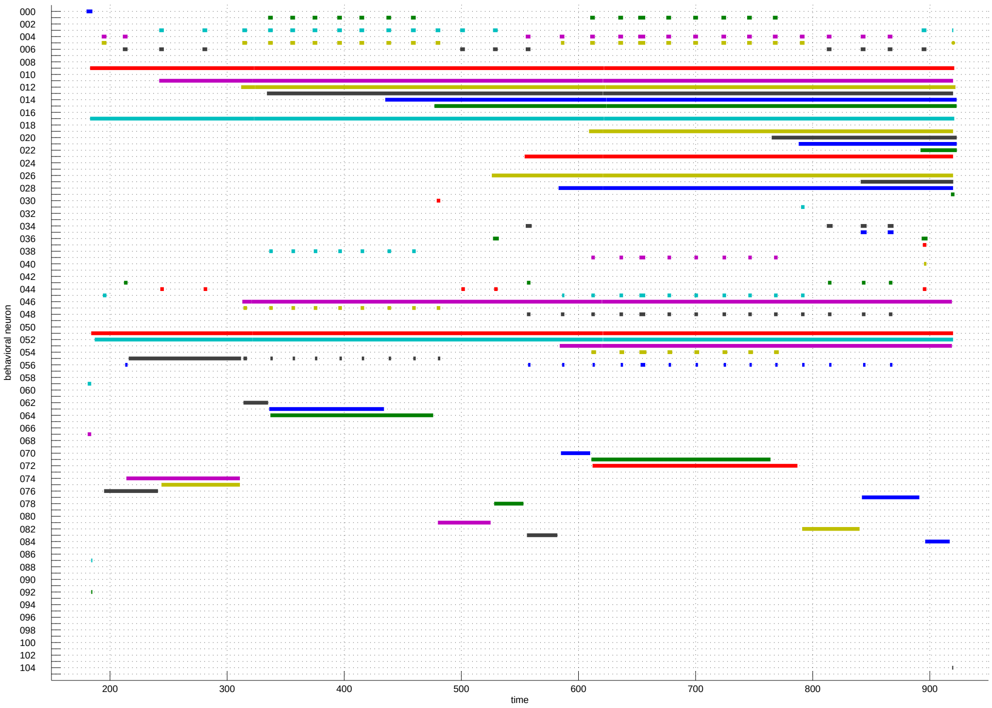


Figure 9: Behavioral neural excitation in task 1B.

The motivation diagrams (figs. 10 and 12) show, that starting from a different intentional motivation, partly different neural connections are included into the spreading of motivation. Since in pushing the object neither gripper movements nor arm movements with an object nor pursuing the ground during its approach (because it will be occluded by the pushed object) are involved, the eleven neurons concerned with these behaviors are not included into the path of motivational spreading.

In both variations, the sequence begins with determining the color of the object and the ground; since variation A was started with the robot arm down, the arm has to be raised to achieve the starting configuration (for safety reasons during driving). Then both sequences are identical: searching, approaching and pursuing the object, and lowering the arm in front of the object ("enclose target"). The success of this behavior is a precondition for closing the gripper and for searching the ground. Since in variation A no closing of the gripper is involved the behavior of searching for the ground in order to push the object there is executed. In variation B, in contrast, the behavior of closing the gripper is executed and the search for the ground is being done after having raised the arm with the object ("secure target").

This task demonstrates that a behavior is executed not only depending on the context but also depending on motivation from the goal.

Conclusions

The neural attractor dynamics approach solves the tasks of generating behavioral sequences from a current sensory and behavioral context to a behavioral goal and of providing stable solutions for goal-directed context-sensitive variations of sequences.

We propose a two-layer dynamic neural network which models the dynamics of the behavioral pattern of temporally continuous behavioral activities and motivations. Logical behavioral relations like precondition, competition and concurrency as well as the current sensory input impose constraints on the attractor dynamics which cause qualitative changes of the dynamics leading to desired stable states of activation patterns. Nonlinear effects like bistablity and hysteresis are exploited to achieve emergent decision-making under uncertainty.

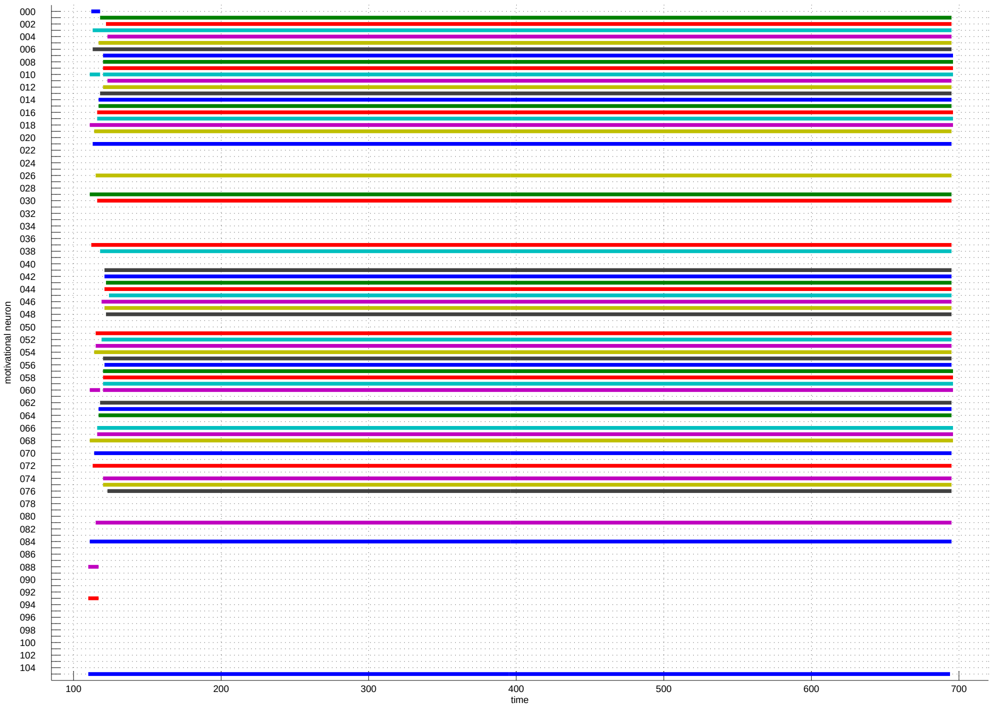


Figure 10: Motivational neural excitation in task 2A.

It is shown that our behavioral organization enables a robot to perform manipulation and path planning tasks acting in real time.

Robust system integration is possible by using attractor dynamics both on the behavioral organization level and on the behavior generating level; the integration of dynamic neural fields for object recognition are currently at work. The approach uses subsymbolic graded state values and is open to learning.

Our implementation of spreading motivation through locally coupled behaviors backwards from the goal and assigning a competitive advantage to contextually appropriate behaviors combines short-term reactivity and long-term planning for behavioral selection and has therefore several concepts in common with the spreading activation network by Maes [7] and the extention of her approach by Dorer [4].

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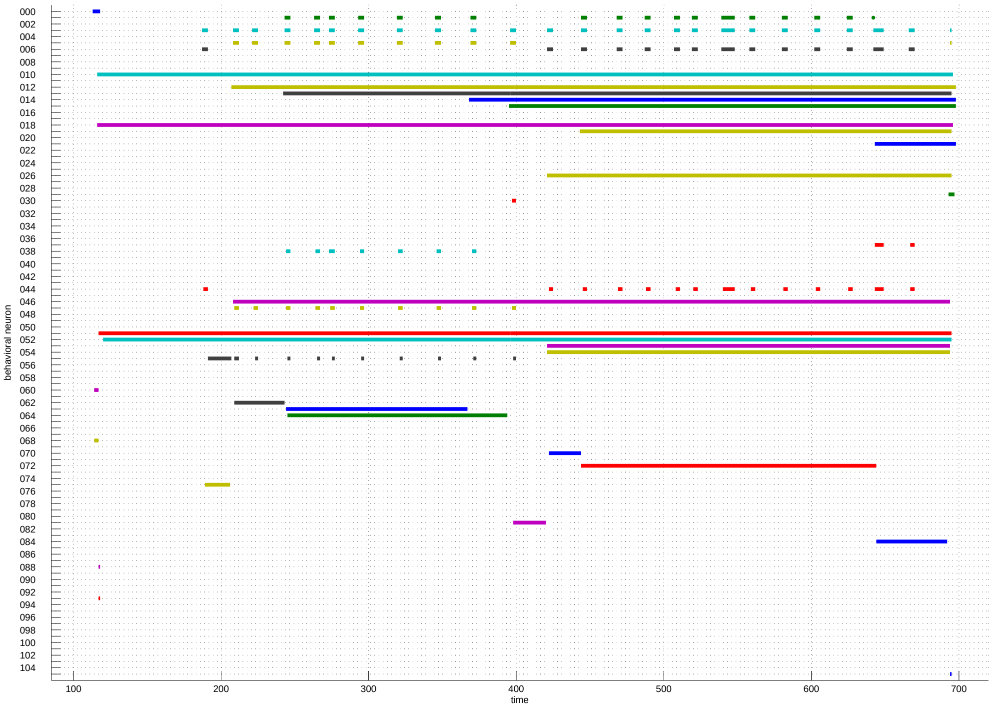

Figure 11: Behavioral neural excitation in task 2A.

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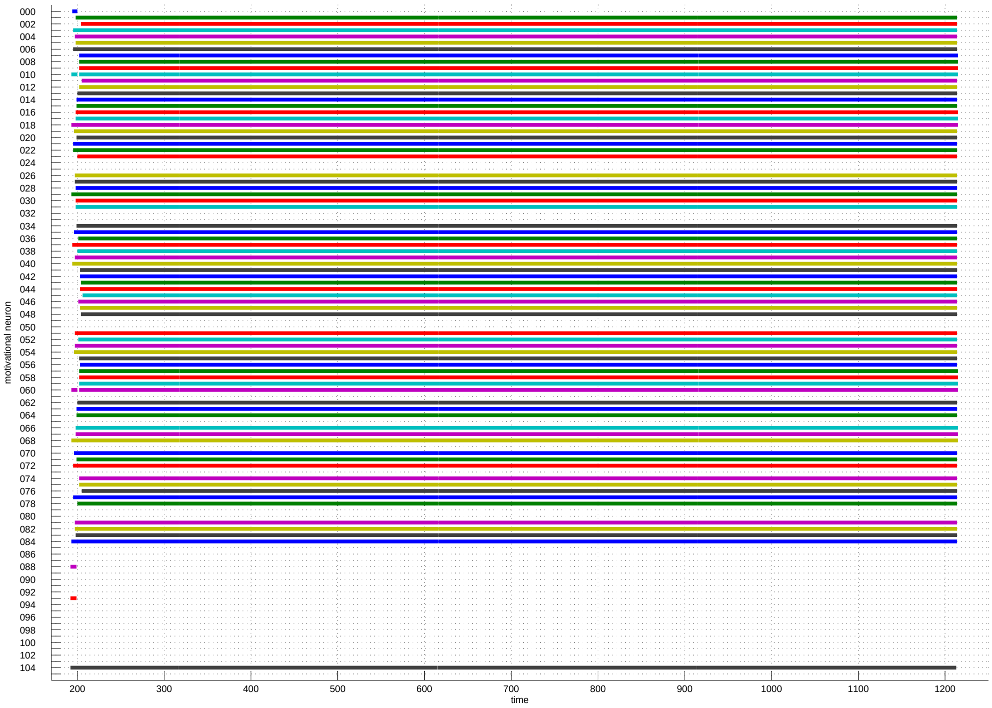

Figure 12: Motivational neural excitation in task 2B.

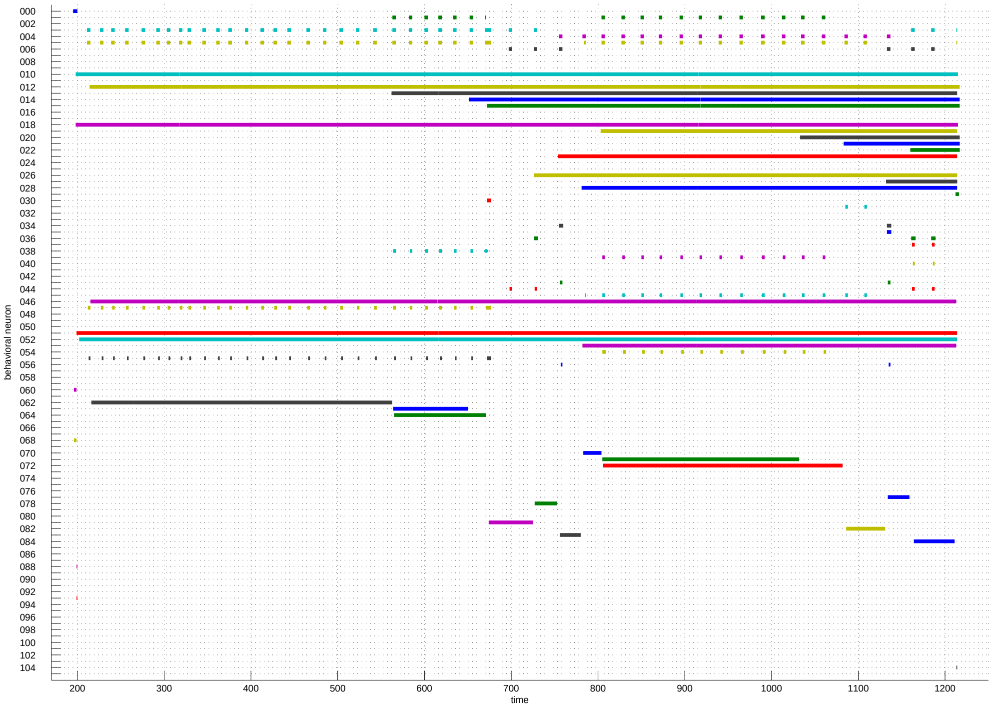

Figure 13: Behavioral neural excitation in task 2B.