

Cognitive flexibility and decision-making in a model of conditional visuomotor associations

Marco Loh¹ and Gustavo Deco^{1,2}

¹Universitat Pompeu Fabra, Passeig de Circumval·lació, 8, 08003 Barcelona, Spain

²Institució Catalana de Recerca i Estudis Avançats (ICREA), Passeig Lluís Companys, 23, 08010 Barcelona, Spain

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Abstract

Arbitrary visuomotor associations map a stimulus onto a particular response upon reinforcing rewards. Changes in the associations between stimuli and responses require the neural networks to discard the already learned mappings and build new ones. This is a key aspect of cognitive flexibility. In addition, learning within this experimental paradigm requires a trial-and-error exploration strategy of the available stimulus–response associations. A system performing this task must be able to both build up mappings for stimulus–response associations and at the same time perform non-deterministically to explore the behavioural space until it reaches certainty. We hypothesize an integrate-and-fire network model that accounts for the neurophysiological data of a conditional visuomotor association task and is able to show non-deterministic behaviour. We aim at identifying multistable attractor regimes in the network dynamics, which intrinsically enable the system to make errors and thereby to perform trial-and-error exploration. Our model combines cognitive flexibility with multistable attractors in neurodynamical systems, believed to be the basis of decision-making. If multistable attractors support the exploration of the behavioural space, then our model predicts that the brain should respond stochastically with correct or incorrect activity to visuomotor associations until it has reached certainty. This should be visible not only in the corresponding activity in the premotor area, but also in activity corresponding to other associations or even other stimuli in the prefrontal cortex.

Introduction

Arbitrary stimulus–response associations build the basis for many complex behaviours of animals and humans. Due to the basic nature of this paradigm, it has been studied intensively in neuropsychology, brain imaging and neurophysiology (for reviews, see Murray *et al.*, 2000; Passingham *et al.*, 2000; Hadj-Bouziane *et al.*, 2003), and it incorporates a wide variety of subtasks: identification of the stimuli; retrieval of associations; decision-making; motor response; and it processing of the rewards. Several imaging studies have identified a network that carries out this task and spans both cortical and subcortical areas (Passingham *et al.*, 2000; Boettiger & D'Esposito, 2005). Electrophysiological recordings specify the characteristics of these brain areas further, namely the premotor cortex (Mitz *et al.*, 1991; Brasted & Wise, 2004), the supplementary eye field (Chen & Wise, 1995a,b), prefrontal areas (Asaad *et al.*, 1998, 2000; Pasupathy & Miller, 2005), the hippocampus (Cahusac *et al.*, 1993; Wirth *et al.*, 2003) and the basal ganglia (Tremblay *et al.*, 1998; Inase *et al.*, 2001; Brasted & Wise, 2004; Pasupathy & Miller, 2005). Clinical studies in humans also show that excisions in prefrontal or premotor areas severely impair the learning of visuomotor mapping tasks (Petrides, 1985, 1997). We investigate a neurodynamical model that addresses this type of task.

The neurodynamical model for the conditional visuomotor learning task (Deco & Rolls, 2003) covers both the basic behaviour of neurons in the prefrontal cortex as measured experimentally (Asaad *et al.*, 1998) and a mechanism that keeps track of contextual contingencies

upon the responses of the reward system (Deco & Rolls, 2005). Decision-making is a crucial part of forming and executing conditional visuomotor associations. At the behavioural level, it is a well-studied topic in psychology. The so-called diffusion models explain a wide range of experimental results (Ratcliff *et al.*, 1999). It has also been suggested that the prefrontal cortex is involved in decision-making (Passingham, 1993; Passingham & Toni, 2001). The synaptic, cellular and network mechanisms of decision-making can be understood in the context of neural networks exhibiting multistability (Wang, 2002). It is not clear if the neurodynamical model hypothesized by Deco & Rolls (2003) supports multistability. We aim here at providing this link.

Furthermore, the organization of the system performing conditional visuomotor tasks is an open question, especially in terms of which brain regions contribute to specific functions. The visuomotor association model (Deco & Rolls, 2003) assumes a processing pathway from stimuli to motor circuits mediated by biasing signals that are thought to originate from the prefrontal cortex (Miller & Cohen, 2001). In this sense, one can view the levels of the conditional visuomotor association model as brain regions along the processing path. We discuss the connectivity between these abstract brain regions and thereby show the dependencies required for decision-making characteristics.

Materials and methods

Conditional visuomotor task: experimental paradigm

We model the experimental paradigm of the conditional visuomotor task used by Asaad *et al.* (1998), Asaad *et al.* (2000) and Pasupathy &

Correspondence: M. Loh, as above.

E-mail: marco.loh@upf.edu

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Miller (2005). In this task, monkeys were presented stimuli foveally and had to make an oculomotor response after a subsequent delay period. The response, a left- or rightward eye movement, was learned on a trial-and-error basis by giving the monkey a liquid reward for performing the correct response. The contingencies were reversed frequently after the monkey performed at a high level. For example, after having learned the pairings 'object A, saccade right' and 'object B, saccade left' (direct rule), the associations were reversed such that 'object A, saccade left' and 'object B, saccade right' were rewarded (reverse rule).

Three types of neurons were reported by Asaad *et al.* (1998) in the dorsal prefrontal cortex. The neurons were either object, direction or object-and-direction selective. First, object-selective neurons showed selectively higher activity to one of the objects but no effect with regard to the saccade direction. Second, direction-selective neurons showed a significant effect of the saccade direction but not of the presented object. Third, cells were selective to combinations of object and direction, i.e. the corresponding associations. Particularly interesting for the decision-making process is that the direction-selective activity in the prefrontal cortex reflected the forthcoming saccade, irrespectively of whether the response was correct or not. Asaad *et al.* (1998) argue that this activity could be due to a premotor signal or a shift in visual attention preceding the eye movement. We focus on whether the proposed neurodynamical model can reflect activity of direction-selective neurons, not only in terms of a correctly computed association, but also in terms of a dynamic decision-making behaviour. That is, the system should respond stochastically to explore the response space and thereby enable the identification of the correct associations.

The integrate-and-fire network

We use a neural network model based on integrate-and-fire neurons and complement it with the necessary concepts and techniques to study higher cognitive tasks. In this section, we describe the single neuron level of the network model. The neural network basis is adapted from Brunel & Wang (2001), and thus we refer to their work for a more detailed description of the basic neurodynamical properties. The detailed mathematical description is provided in the Supplementary material.

We use non-linear leaky integrate-and-fire neurons to model both excitatory and inhibitory neurons. The basic behaviour of a single neuron is reflected in the membrane potential, which is modelled by an electrical circuit consisting of a capacitor C_m connected in parallel with a resistor R_m . This circuit describes the progression of the membrane potential $V(t)$ in time depending on external currents entering from other neurons. When the threshold membrane potential V_{thr} is reached, the neuron is set to the reset potential V_{reset} at which it is kept for a refractory period τ_{ref} , and the action potential is propagated to the other neurons. Both excitatory and inhibitory neurons have a resting potential $V_L = -70$ mV, a firing threshold $V_{thr} = -50$ mV, and a reset potential $V_{reset} = -55$ mV. The membrane parameters are different for both types of neurons: excitatory neurons are modelled with a membrane capacitance $C_m = 0.5$ nF, a leak conductance $g_m = 25$ nS, a membrane time constant $\tau_m = 20$ ms, and a refractory period $t_{ref} = 2$ ms; whereas the inhibitory neurons share $C_m = 0.2$ nF, $g_m = 20$ nS, $\tau_m = 10$ ms and $t_{ref} = 1$ ms. Values are taken from McCormick *et al.* (1985).

The incoming synaptic influences are both excitatory and inhibitory. The excitatory neurons transmit their action potentials via the glutamatergic receptors α -amino-3-hydroxy-5-methyl-4-isoxazole-

propionic acid (AMPA) and *N*-methyl-D-aspartate (NMDA), which are both modelled with exponential terms. The rise time of the current mediated by the AMPA channel is neglected, because it is typically very short ($\ll 1$ ms), and just model the decay period with $\tau_{AMPA} = 2$ ms (Hestrin *et al.*, 1990; Spruston *et al.*, 1995). The NMDA channel is modelled with a rise term ($\tau_{NMDA, rise} = 2$ ms), a decay term ($\tau_{NMDA, decay} = 100$ ms) (Hestrin *et al.*, 1990; Spruston *et al.*, 1995), and an extra voltage dependence controlled by the extracellular magnesium concentration ($C_{Mg^{2+}} = 1$ mM) (Jahr & Stevens, 1990). The inhibitory postsynaptic potential is mediated by the γ -aminobutyric acid (GABA)_A receptor, and is described by a decay term ($\tau_{GABA} = 10$ ms) (Salin & Prince, 1996; Xiang *et al.*, 1998).

The network is fully connected with $N_E = 1600$ excitatory neurons and $N_I = 400$ inhibitory neurons, which is consistent with the observed proportions of the pyramidal neurons and interneurons in the cerebral cortex (Abeles, 1991; Braitenberg & Schütz, 1991). The connection strengths are adjusted using meanfield analysis (Brunel & Wang, 2001), so that the excitatory and inhibitory neurons exhibit a spontaneous activity of 3 Hz and 9 Hz, respectively (Koch & Fuster, 1989; Wilson *et al.*, 1994). The recurrent excitation mediated by the AMPA and NMDA receptors is dominated by the NMDA current to avoid instabilities during the delay periods (Wang, 2002).

This recurrent connectivity represents the baseline for the structuring of the network. We assume that the structuring of the network connections arises due to Hebbian learning (Hebb, 1949). The coupling strength between two neurons is stronger if they have correlated activity, and weaker otherwise. As a consequence of this, neurons that share the same selective response properties are coupled via strong excitatory connections and are clustered into pools. All inhibitory neurons are in a common pool so that there is global inhibition throughout the network.

In addition, the network is exposed to external Poisson input spikes mediated by AMPA receptors of $N_{ext} = 800$ external neurons at an average rate of 3 Hz per neuron, consistently with the spontaneous activity observed in the cerebral cortex (Wilson *et al.*, 1994; Rolls & Treves, 1998).

The stimulus-response architecture

The network architecture is based on the neurophysiological data of Asaad *et al.* (1998), and the processing concepts of cognitive control and biased competition (Miller & Cohen, 2001; Rolls & Deco, 2002). As discussed below, it has certain features in common with the models of Deco & Rolls (2003) and Deco & Rolls (2005). However, there are fundamental differences not only in the model but also in its analysis.

We assume three different types of selective neural populations (pools) as identified by Asaad *et al.* (1998) (Fig. 1). The first type shows object-selective responses to the presented stimuli (A, B). The second type responds to a combination of a particular object followed by a particular response. Specifically, a neuron of this type would, for example, respond selectively to object A followed by a rightward saccade R (AR), but not to other combinations of stimuli and responses (AL, BL, BR). The third type shows direction-selective responses of the forthcoming saccade (L, R). Each of these eight pools contains 80 neurons, the rest of the excitatory neurons comprise a non-specific pool. Neurons in the latter show spontaneous firing rates and introduce noise in the system, which aids in generating Poisson-like firing patterns throughout the system.

Figure 1 gives a conceptual view of the architecture. The selective pools are arranged along a processing pathway from object- to

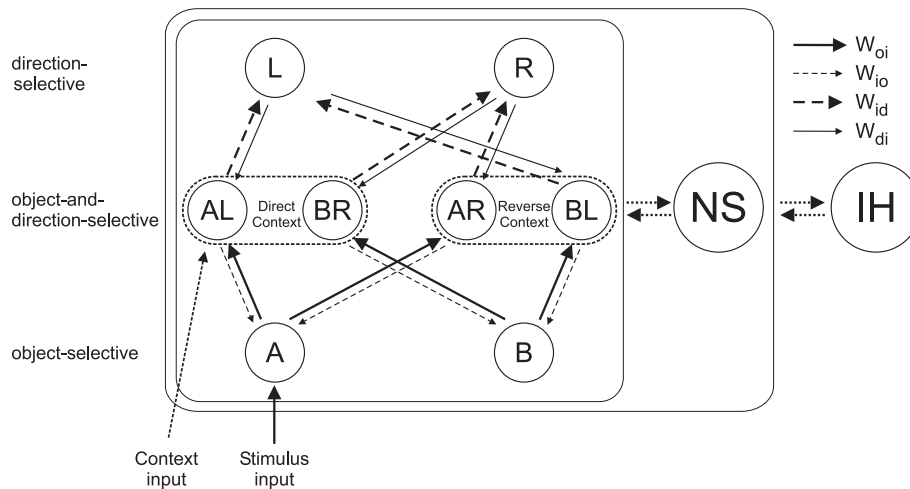


FIG. 1. The cortical network model. The network is fully connected and the figure highlights the discussed interpool connection strengths. The excitatory neurons are divided into selective ones, which build the neural substrate of the experimental findings, and non-selective ones (NS). The inhibitory neurons are clustered in the pool IH. The network receives external input from 800 neurons, which is specifically increased for stimulus and context (direct or reverse). The Supplementary material contains the full connection matrices.

direction-selective pools. Furthermore, we assume selective connections along the pathway in accordance with the Hebbian learning paradigm. These connections could be the results of a learning process and reflect the combinations to which monkeys have been exposed to during learning. We assume selective associations between the object-selective pool A and the object-and-direction-selective pools AL and AR, analogously for B, BL and BR. The same applies between the object-and-direction-selective pools and the direction-selective pools, i.e. L with AL, BL and R with AR, BR. Accordingly, the interpool connections yield four different connection parameters between the layers denoted by w_{oi} , w_{io} , w_{id} and w_{di} (o, object; i, intermediate; d, direction, see Fig. 1). In addition, the network contains a parameter for the intrapool connection strength w_+ of the selective pools. These are the connections between neurons of the same pool. The intrapool connections are like the interpool connections motivated by Hebbian learning, as neurons that show highly correlated activity are assumed to have a strong connection strength. Accordingly, the intrapool connections should be stronger than the interpool connections.

The other connections between the selective pools are calculated by $w_- = (1 - f_s w_+) / (1 - f_s)$, where $f_s = 0.05$ is the fraction of neurons in a selective pool in relation to all excitatory neurons. Neurons in the non-specific pool are connected to themselves with $w_+ = 1$, as they do not share common selective features. The connections from the non-selective pool to the selective pools w_{nj} are calculated so that the average input to each selective pool is 1 after having added all additional connections [$w_{nj} = (1 - \sum_{i \in n} f_i w_{ij}) / f_s$]. These calculations regard both the AMPA and NMDA connections. For all GABA-ergic neurons, w_s for both self-connections and connections to other populations are equal to 1. The complete connection matrices are given in the Supplementary material.

The network receives two inputs: the stimulus and the context input. Both are added to the network by increasing the frequency of the external input of the corresponding pools. This external input originates from 800 external neurons firing at 3 Hz. The stimulus input λ_{stim} is added to one of the two object-selective pools (A, B) by increasing the firing rate of the external neurons from $v_{ext} = 3$ Hz to $v_{stim} = v_{ext} + \lambda_{stim}$. The context input acts analogously with $v_{context} = v_{ext} + \lambda_{context}$ on the two corresponding object-and-direction-selective pools. These are AL and BR for the direct context,

and AR and BL for the reverse context (Fig. 1). This input influences the competition between the processing pathways, and favours the stimulus-response mappings associated with reward. For a detailed discussion of the nature of context input, see Deco & Rolls (2005).

Analysis

To identify and analyse parameter configurations that show multistable behaviour, we used two techniques, namely spiking trial and meanfield simulations. Spiking trial simulations integrate the neural and synaptic dynamics over time. Each simulation started with a pre-period of 500 ms to allow for network stability. According to the experimental paradigm (Asaad *et al.*, 1998), this period was followed by the cue period in which both the cue and context input were added for 500 ms. We used $\lambda_{stim} = 0.1$ Hz (80 Hz for total external input). The strength of the context input was varied. Afterward, the cue input was turned off and the network was run for another 1000 ms, which corresponds to the delay period. The context input was present until the end of the simulation. All simulations were performed with the presentation of stimulus A and the direct context. Note that it is sufficient to test this one combination of stimulus and context, as the network is symmetric and the other combinations yield analogous results.

Spiking simulations are time consuming and they cannot be done for many parameter configurations of the network. Therefore we used a meanfield approach to calculate the attractor states of the network for the delay period (Brunel & Wang, 2001). The attractor states represent the behaviour of the network in terms of neural firing rates to which the system would converge in the absence of fluctuations and external changes. We targeted our analysis to identify regions in which multiple attractors are present and fluctuations could cause the system to switch to one or the other attractor. The initial conditions for numerical simulations of the meanfield model were set to 3 Hz for all excitatory pools and 9 Hz for the inhibitory pool. These values correspond to the approximate values of the spontaneous attractors when the network is not driven by stimulus-specific inputs. In addition, an object-selective pool had a higher initial value (40 Hz) to account for the excitation of these neurons during the preceding cue

period. To get a first approximation for the multistability behaviour, we performed several explorations for the same configuration with different starting values for the intermediate pools. Altogether we performed five explorations: one with all intermediate pools at 3 Hz and four others, each with one intermediate pool at a starting value of 20 Hz.

Multistability is only manifested when a dynamical system is able to explore various stable attractors by virtue of random fluctuations or inputs. Given such fluctuations, the probability of finding the system in either of the attractor states at long times given identical initial conditions can be computed numerically with multiple spiking trial simulations.

Results

On the basis of the meanfield analysis, we identified parameter configurations with three attractors. Subsequently, we performed 2000 spiking trial simulations at such a parameter configuration. Figure 2 shows the histograms of firing rates of the delay period (averaged

between 1500 ms and 2000 ms) of these trials. The averaged firing rates correspond to the outcome of the computation of the network. The corresponding three meanfield attractors are indicated by the tick marks at the bottom of the diagrams. In addition, three peaks can be identified in the histogram, in particular in the subplot for pool A: one peak at 0–3 Hz; a smaller one at about 25 Hz; and another significant peak at about 70 Hz. The same qualitative characteristic is also visible in pool B and weaker in the pools AL, BR and L. In order to capture the three stable attractors present in the system, we cluster the trials according to the data of pool A in three parts, as indicated in Fig. 2A: trials in the histogram of below 10 Hz ($n = 301$); between 10 Hz and 40 Hz ($n = 259$); and above 40 Hz ($n = 1440$). The latter contains the majority of the trials (about 70%).

Note that we lost the relationship between the single trials in the histograms due to the binning of the frequencies. By means of the clustering of trials we resolve this relationship. Although the borders of the clustering are merely picked on a visual basis, this is just done for pool A and defines the clusters of the other ones. If the clustering chosen on the basis of pool data A corresponds to the attractor states,

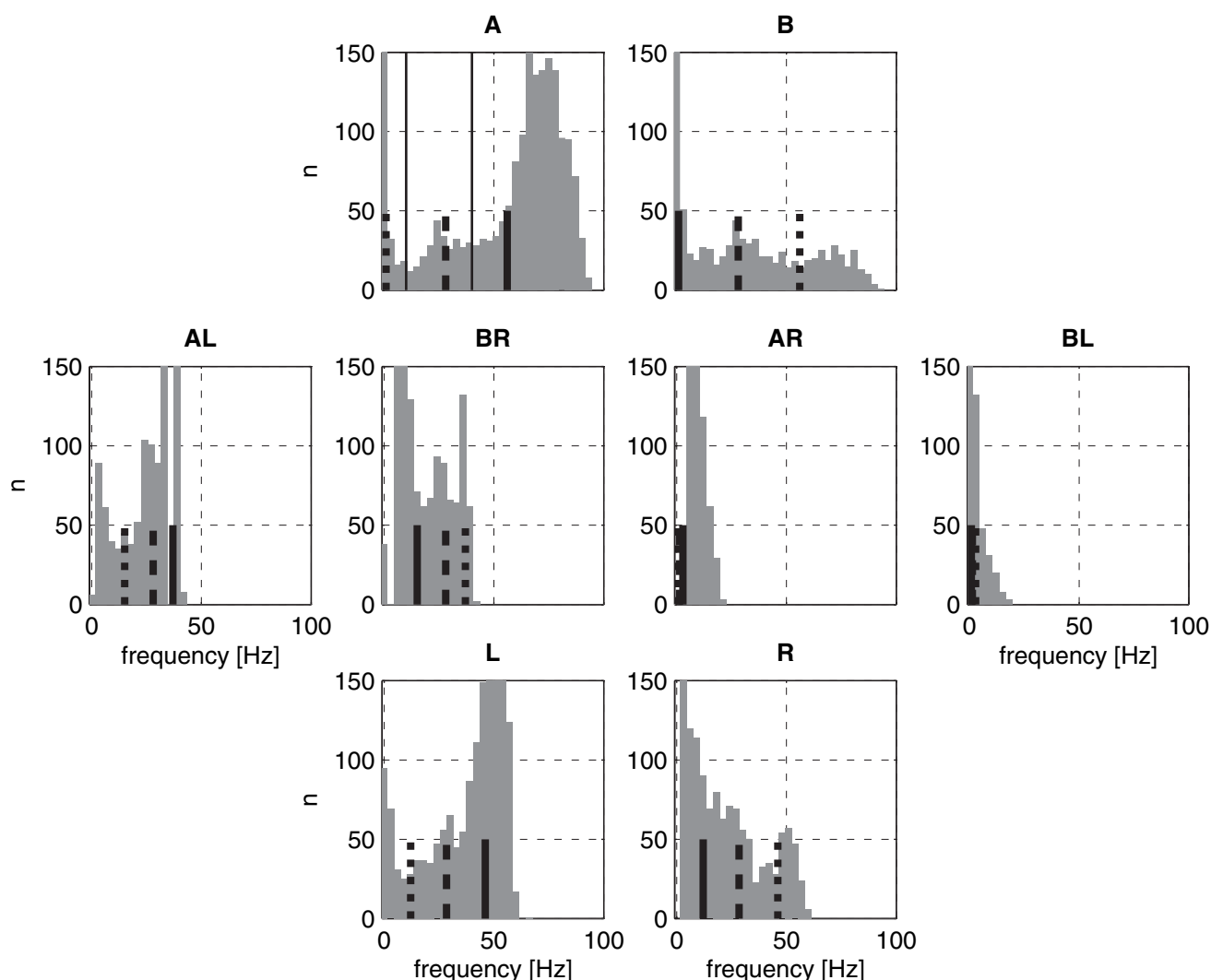


FIG. 2. Histograms of the firing rates averaged over the second half of the delay period (between 1500 ms and 2000 ms) of 2000 spiking trial simulations ($w_+ = 3.0$, $v_{\text{context}} = 3.1$, $w_{oi} = 1.1$, $w_{io} = 2.6$, $w_{id} = 2.6$, $w_{di} = 0.9$). The eight subplots show the result of the selective pools of the model: upper row – object-selective pools; middle row – object-and-direction-selective pools; lower row – direction-selective pools. The delay period averages were counted in 3-Hz bins between 0 and 99 Hz. The symbol n represents the number of trials in a particular bin (peaks are higher than shown). The tickmarks correspond to the attractor states identified by meanfield analysis. The vertical lines in subgraph A show the partitioning used to cluster the trials for the temporal analysis.

then it should also yield a clustering of the data of the other pools, which corresponds to the attractor states.

Figure 3 shows the average firing rates of the clustered trials. As proposed, the three cluster averages show a strong correlation with the identified attractors of the meanfield analysis. The symmetry in frequency between neighbouring pools (e.g. see Fig. 3A and B) is striking, which was not apparent in the trial histograms of Fig. 2 and also not implicitly contained in our clustering technique. Two patterns are distinguishable: the solid and the dotted lines seem to reflect oppositional attractors with one resulting in a correct response (higher activation in L than in R) and the other one in an incorrect one. Thus, these two attractors represent decision-making properties of the network biased by the context input toward the correct response. According to our clustering, 1440 of the 2000 trials belong to the correct mapping, while 301 trials belong to the incorrect one. The remaining 259 trials belong to the second pattern reflected by the dashed line. It shows no directional preference on any stage of the processing pathway and resembles the spontaneous state of the

network under the influence of the context input. In addition, we observe an almost linear ramping activity in the pools AR and BL (Fig. 3). This could be an indicator for a linear integrator, but further investigation is needed to discuss this phenomenon.

Beyond the existence of the multistable behaviour, we aim at identifying its causes using the meanfield technique. First, we discuss the influence of different context inputs on the attractor states and use the parameter configuration of Figs 2 and 3 as a reference. Figure 4 shows the development of the difference of activity between the two object-selective pools of the three attractors, which have been shown in the spiking simulation analysis above. Interestingly, the trace of the attractor states does not look as symmetric as suggested by Fig. 3. Several non-linearities appear when the context input is increased and symmetry is just observed in configurations of low context inputs (below 3.075 Hz) and within a small area between 3.1 Hz and 3.11 Hz. In general, the figure suggests that classical decision-making behaviour, i.e. two oppositional attractors, is effective at lower context inputs. Within the decision-making regime, an increasing input leads

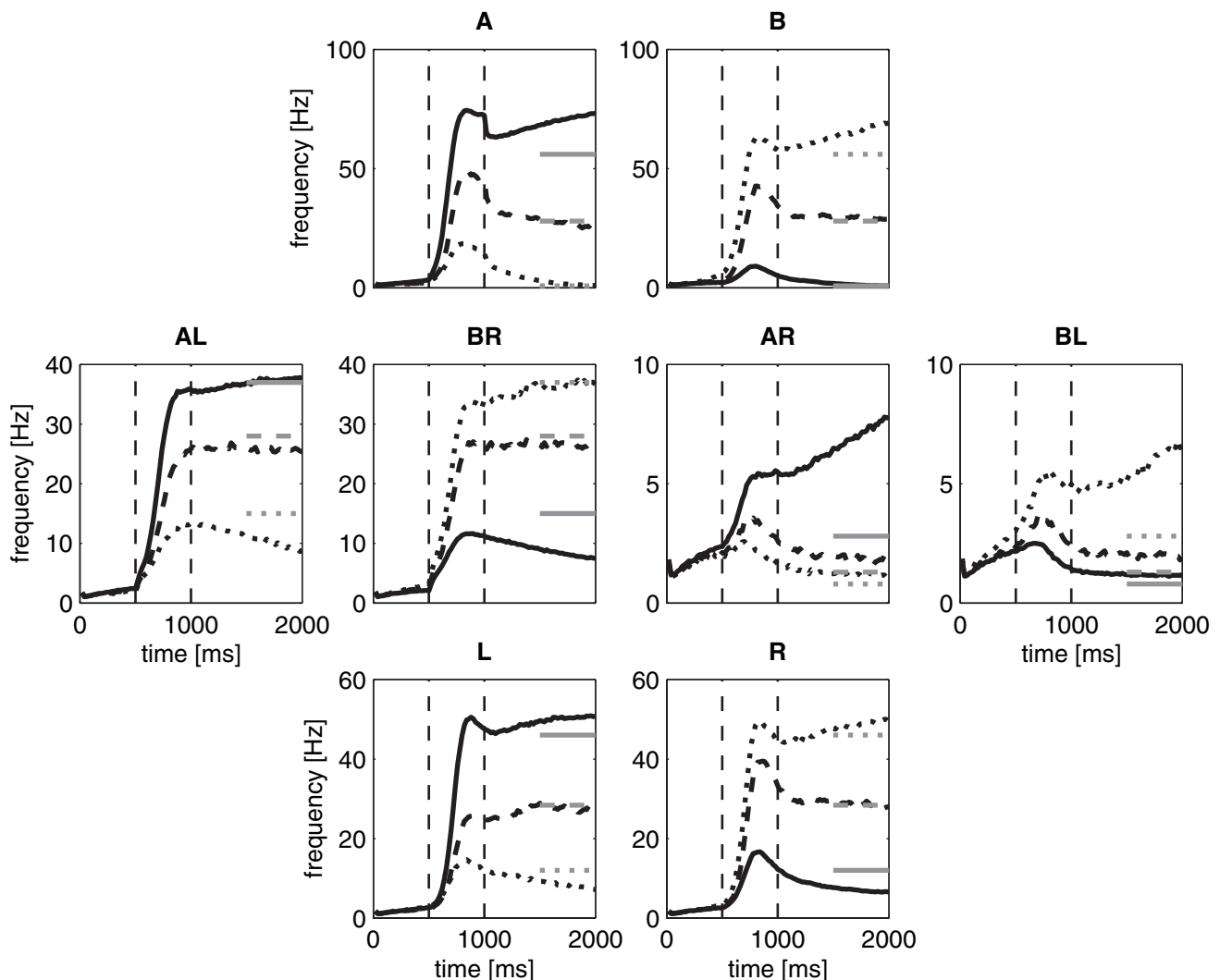


FIG. 3. Mean spiking frequencies for each pool vs. time for parameter configuration ($w_+ = 3.0$, $v_{\text{context}} = 3.1$, $w_{oi} = 1.1$, $w_{io} = 2.6$, $w_{id} = 2.6$, $w_{di} = 0.9$, see Fig. 2). The trials are clustered in three categories (see vertical lines, Fig. 2A): Below 10 Hz dotted line ($n = 301$), between 10 Hz and 40 Hz dashed line ($n = 259$), and above 40 Hz solid line ($n = 1440$). The simulation is conducted consistently with the actual experiment: 500 ms pre-trial period (stabilization of the network), 500 ms stimulus presentation for pool A, followed by a 1000 ms delay period. The stimulus input is present from 0 to 500 ms, the context input from 500 ms until the end of the simulation (direct context: AL, BR). The horizontal lines between 1500 and 2000 ms indicate the meanfield firing rates of the multistable states (see also tickmarks, Fig. 2). Note that the ordinates are not scaled uniformly.

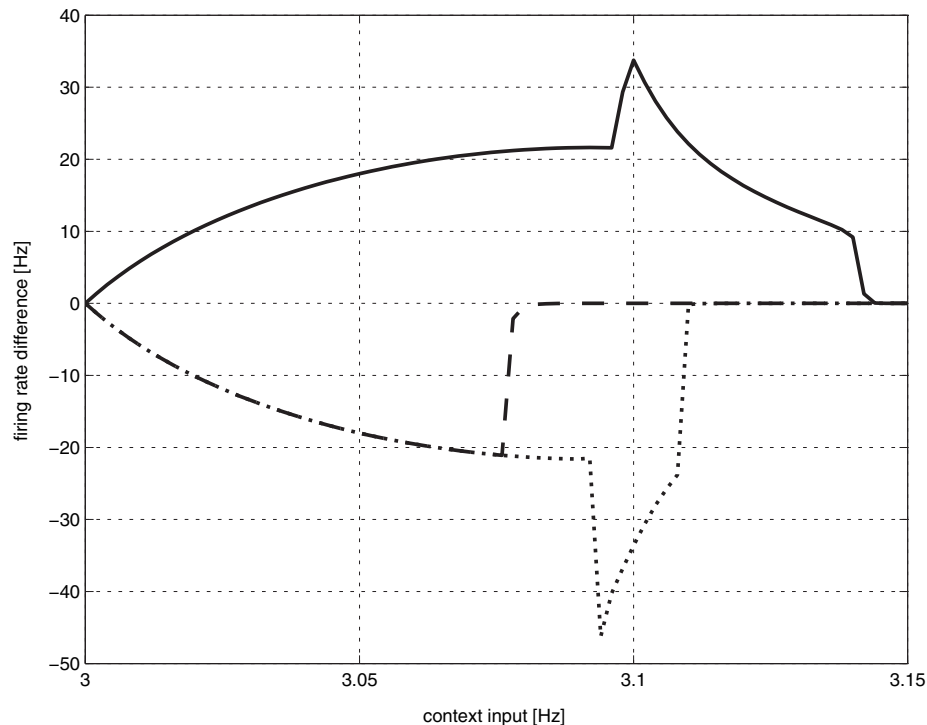


FIG. 4. Evolution of the three attractors with variation of the context input using the meanfield analysis. As before, the remaining values are set to ($w_+ = 3.0$, $w_{oi} = 1.1$, $w_{io} = 2.6$, $w_{id} = 2.6$, $w_{di} = 0.9$). Remember that the parameter configuration of the spiking simulations is at $v_{\text{context}} = 3.1$. The line coding (solid, dashed, dotted) corresponds to the one in Fig. 3. The frequency values show the difference between the two direction-selective pools (L – R). A difference of 0 Hz implies that there is no difference in activation between the two pools and thus no decision between the two directions. This is the case with no context input (0 Hz) for all attractors. With increasing context input, both the correct and the incorrect response emerge, at about 3.08 Hz, complemented by the non-responsive attractor. The attractor values are obtained with the meanfield technique using different starting values as initial conditions (for details, see Materials and methods).

to a higher difference between the two attractors. Too strong of a context input leads to non-linearities and finally to a non-responsive system (here above 3.14 Hz).

Note that the attractor analysis does not reveal to what extent fluctuations can cause the system to run into the corresponding attractors. This is reflected in the percentages to which the system ends up in one or the other attractor, which can just be assessed using multiple spiking trial simulations and a subsequent clustering analysis. Nevertheless, the existence of multiple attractors is essential for decision-making.

Furthermore, we analysed the dependence of the behaviour on the connection strength between the three layers. We asked whether the system could perform the mapping task with all interpool connection strengths being equal ($w_{oi} = w_{io} = w_{id} = w_{di}$). Using this constraint, we were not able to find any parameter configuration with responsive properties. Therefore there must be some kind of structuring in the connection strengths between the layers. For example, biasing the connection strength to stronger in direction toward the direction-selective neurons ($w_{oi} > w_{io}$ and $w_{id} > w_{di}$) allows for parameter configurations that show the correct response upon stimulus presentation such as used by Deco & Rolls (2003, 2005).

However, the parameter configurations used by Deco & Rolls (2003, 2005) do not show evidence of multistability and are not capable of contributing to the response space exploration. Figure 5 shows the response as functions of the connection strengths between the object-selective and the intermediate layer. The response direction is assessed by calculating the relative difference between the two direction-selective pools and using a threshold value of 30%. Other threshold values such as 20% or 40% yield similar results. Several aspects are noteworthy. First, the regions in which the network

responds to the task seem to be well bounded and our data suggest that fine-tuning is needed. Second, multistable regions are present in an area with stronger connectivity from the intermediate to the object-selective layer. This balance seems to be necessary to achieve multistable behaviour and thus response space exploration properties. The parameter configuration used by Deco & Rolls (2003, 2005) is located in the single attractor region of the correct response and does not show multistable behaviour.

Discussion

We have presented a detailed analysis of a generic neurodynamical model for an arbitrary visuomotor task. As shown by Deco & Rolls (2005), this model is not only applicable to stimulus–response associations (Asaad *et al.*, 1998), but also to stimulus–reward associations (Thorpe *et al.*, 1983), and probably to a variety of other experimental paradigms that require a mapping between two aspects upon previously learned rules. Working memory is important to bridge the period between cue presentation and response in delayed response tasks. We extended the working memory model of Brunel & Wang (2001) through a structured architecture that is motivated by the neurophysiological data (Asaad *et al.*, 1998) and processing principles, the latter being cognitive control and biased competition (Miller & Cohen, 2001; Rolls & Deco, 2002). We show that multiple attractor states exist in this extended working memory model and that fluctuations are sufficient to drive the system to these attractors. This is the main characteristic of dynamical systems exhibiting decision-making properties and is essential for trial-and-error learning of stimulus–response tasks.

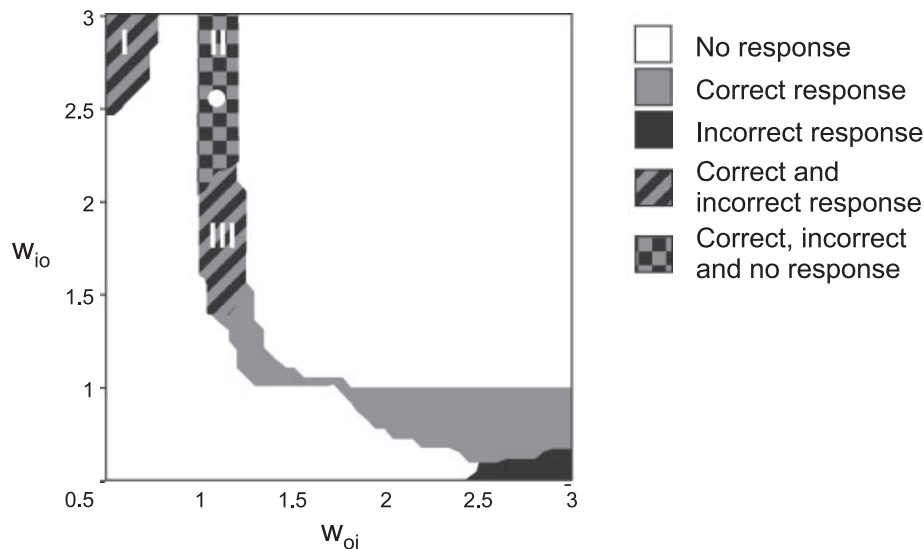


FIG. 5. Categorization for response direction of a parameter scan. The results of the meanfield calculation are categorized using the difference in spiking frequency between the two direction-selective pools. No response corresponds to a difference below 30% between the two direction-selective pools, while correct (incorrect) response corresponds to a 30% higher (lower) frequency in the L pool than in the R pool. The connection strengths between the object-selective and intermediate pools are varied (w_{oi} , w_{io}), while the remaining parameters are fixed at ($w_+ = 3.0$, $v_{\text{context}} = 3.1$, $w_{id} = 2.6$, $w_{di} = 0.9$). Three multistable regions are identified: regions I and III show two different attractors, one of the correct and one of the incorrect response; region II shows additionally a third attractor yielding no responses on occasion. The parameter configuration discussed earlier (Figs 2 and 3) is marked by the white dot. The sampling of the parameter space is $\Delta w_{oi} = 0.05$ and $\Delta w_{io} = 0.05$.

The research described here adds in crucial points to the work of Deco & Rolls (2003) and Deco & Rolls (2005). First, on the conceptual level we extended the conditional visuomotor mapping model by studying fluctuations and multistability. Second, we analysed the neurodynamical behaviour in more detail. Beyond the single spiking trial analysis used by Deco & Rolls (2003) and Deco & Rolls (2005), we introduced extensive multiple spiking simulations with subsequent clustering of the trials. This allows for an assessment of the influence of fluctuations and the identification of multiple attractor states. However, these simulations are computationally expensive so that only a limited number of parameter configurations can be assessed in detail. Thus, we complemented the spiking simulation analysis by a meanfield analysis to study the influence of the parameters on the neurodynamical system thoroughly. In particular, we used this approach to identify parameter values for which the system shows fluctuation-dependent multistable behaviour. Hence, we go significantly beyond the proof of principle presented by Deco & Rolls (2003) and Deco & Rolls (2005). In particular, we showed that asymmetries of the interpool connection strengths along the processing pathway are essential for the computation of a response by the network. In future work, further constraints of the parameter space could be derived from additional biological data and theoretical considerations. In addition, improved theoretical techniques could promote the analysis of the networks dynamics.

Earlier models of visuomotor associations addressed learning using different degrees of biological realism. Based on experimental data by Mitz *et al.* (1991), Fagg & Arbib (1992) proposed a model of the premotor cortex consisting of motor selection columns. While the hierarchical structure of these columns is similar to the work presented here, the model of Fagg & Arbib (1992) is less refined at the neural level and more of an algorithmic nature. Dominey *et al.* (1995) presented a multiregional connectionist model using a mean approach on the neural level for learning of visuomotor associations by corticostriatal plasticity. It would be interesting to analyse such a system using spiking neurons. The work presented here is an important step in this direction, as the

decision-making properties discovered in our model are required for the exploration and learning of associations. Chialvo & Bak (1999) and Bak & Chialvo (2001) focus on learning mechanisms themselves and put forward the ideas of extremal dynamics and learning by mistakes. They highlight interesting mechanistic aspects of learning dynamics that should be considered in future work.

A basic feature of our conditional visuomotor association model is the hierarchical processing pathway. We emphasize that our model is of an abstract neurodynamical nature. While our model reflects the data of neurophysiological recordings, we do not make any specific claims about how the structure could be implemented in the brain. However, there are anatomical and physiological reasons, which suggest such an organization from object-selective to response-selective neurons. First, the cortical organization in several interconnected layers suggests such an organization. For example, in the visual system feedforward connections originate mainly from cells in layer III and terminate mainly in layer IV, whereas feedback projection between the stages of processing originate from cells in layer V and VI and terminate in layers I/II and VI (Rockland & Pandya, 1979). Hence, the connectivity between cortical layers could result in a hierarchical organization with asymmetric connections. The model of motor selection columns by Fagg & Arbib (1992) is related to this principle in the sense of computations in the cortex within structurally organized cortical columns.

Second, the neurophysiological properties of different frontal areas can be interpreted in terms of a processing pathway. The ventrolateral prefrontal cortex receives direct inputs from temporal visual areas and might select the information that is relevant for the task, i.e. the stimulus identity (see Rushworth & Owen, 1998; Passingham *et al.*, 2000). Hence, the object-selective layer could model functions of the ventrolateral prefrontal cortex. The dorsolateral prefrontal cortex area contributes to the manipulation of information (Rushworth & Owen, 1998). The stimulus information and the learned rules are combined to the corresponding association. Consistently, the dorsolateral prefrontal area contains neurons, which are not only selective to the stimulus and

the response direction but also to combinations of both (Boussaoud & Kermadi, 1997; Asaad *et al.*, 1998). This object-and-direction-selected activity is shown by the intermediate layer of the model. Finally, the dorsal premotor cortex contains a high proportion of direction-selective neurons (Mitz *et al.*, 1991; Boussaoud & Kermadi, 1997) and is also known to be crucial for arbitrary visuomotor tasks (Halsband & Passingham, 1982; Petrides, 1982). Therefore it might take part in the final stages of processing and is described best by the direction-selective layer in our model. Taken together, a pathway for the processing of visuomotor associations could be implemented in the frontal cortex from the ventrolateral area to the premotor area. Moreover, based on imaging data Koechlin *et al.* (2003) hypothesize a cascade organization of frontal regions reflecting different levels of processing depth, which further supports the assumption of a hierarchical structuring within the frontal cortex.

In contrast to lesions of the ventrolateral prefrontal cortex (Bussey *et al.*, 2001), lesions of the dorsolateral part cause no or only a mild deficit in visuomotor mapping tasks (Petrides, 1982; Gaffan & Harrison, 1989). In addition, imaging studies have indicated no major contribution of this area (Deiber *et al.*, 1997; Toni *et al.*, 2001), at least in simple versions of this task (Boettiger & D'Esposito, 2005). This suggests that the pathway including the dorsolateral prefrontal cortex might play a minor role (Hadj-Bouziane *et al.*, 2003). Correspondingly, as an alternative to the cortical pathway, a pathway involving the corticostriatal system has been proposed by Houk & Wise (1995), Toni & Passingham (1999) and Hadj-Bouziane *et al.* (2003). This corticostriatal pathway involves the following brain regions: (i) the ventrolateral prefrontal cortex might hold the presented stimuli in working memory and select the relevant information; (ii) the striatum integrates sensory, motor and reward information; and (iii) the premotor cortex selects the motor response. The integrative property of the striatum, which is implemented by the intermediate layer of the model, is the key aspect of the context detection (Houk & Wise, 1995; Dominey & Boussaoud, 1997; Djurfeldt *et al.*, 2001; Pasupathy & Miller, 2005). The reward information might originate from the midbrain dopamine system, which sends projections to medium spiny neurons in the striatum (Schultz, 2000). Furthermore, Toni *et al.* (2002) showed by structural equation modelling on imaging data that the effective connectivity in frontostriatal circuits increases during learning. This also supports a processing pathway, which includes the striatum. Like the striatum, the orbitofrontal cortex contains cells, which code reward information (Watanabe, 1996; Rolls, 2004) and might also be important for the processing of arbitrary visuomotor associations. The involvement of the orbitofrontal cortex is addressed by Deco & Rolls (2005).

We emphasize that we do not assign properties to the specific layers in our model explicitly. Their properties emerge due to the various influences that act on the layers. For example, the selectivity of the neurons in the intermediate layer does not arise because of the network structure itself. Rather, the connectivity, the activations in neighbouring layers and the context input must act together. This yields an alternative interpretation of the neural activity in brain regions. The neural activity in a brain region does not arise on its own but by interaction with neighbouring regions. Thus, questions concerning the functions of brain regions might as well be formulated in terms of interactions of that region with its neighbours. This view could shed light on apparently contrary functions of a given brain region that might have a common theme in terms of inter-regional interactions.

The context input represents an abstract rule because it gives input to those two associations connected with the given rule. For example, the direct rule activates the pools AL and BR. This corresponds to the assumption that rules instead of single associations are learned. After a rule switch, the monkeys detect a change by a wrong answer to one

stimulus. Consequently, the next answer to the other stimulus should already be correct or at least have a higher probability of being correct. Optimally the monkey could perform a rule switch after a single error. The stimulus–reward association experiment by Thorpe *et al.* (1983) shows evidence of such behaviour. Because synaptic plasticity would take a few trials to adapt to the new contingencies, neurodynamical mechanisms are assumed to account for this behavioural adaptation (Deco & Rolls, 2005). However, the conditional stimulus–response association experiment (Asaad *et al.*, 1998) does not show evidence for one-trial reversal, although the monkeys detect changes rapidly. Brasted *et al.* (2005) recently targeted this question of one-trial learning in stimulus–response associations. They found that prior error trials impair one-trial learning. This is important for experiments by Asaad *et al.* (1998) and Pasupathy & Miller (2005), because the monkeys could only detect a change in the rule by making errors. Accordingly, this made it more difficult for the monkeys to learn new associations quickly. However, this does not resolve the issue of why the monkeys needed several dozens of trials to reach a plateau in performance. Clearly more research is needed to identify the crucial factors underlying one-trial reversal learning.

The systems responsible for familiar and novel associations have different properties. For familiar associations errors are rare, and therefore the system is not multistable, i.e. it almost always ends up in the attractor state of the correct association. We identified such a single attractor dynamics in the correct response region in Fig. 5. Experimental evidence also supports that familiar association might be executed by different neurodynamical mechanisms, because different brain regions and pathways are involved. Nixon *et al.* (2004) interrupted the connection between the basal ganglia and the central premotor cortex using a cross-lesion method whereby a unilateral lesion of the internal pallidum in one hemisphere was combined with a premotor lesion in the opposite hemisphere. The learning of novel associations appeared relatively unaffected by the disconnection, whereas the monkeys were impaired in re-learning pre-operatively learned associations and made three times as many errors once they succeeded. These results suggest that the connections between the basal ganglia and the premotor cortex are crucial for the execution of familiar visuomotor associations but not for learning of novel associations. Thus, the transition from a novel to a familiar association might go along with a shift to another pathway that shows multi- and uni-stable characteristics, respectively. Moreover, the experiment by Bussey *et al.* (2001) has revealed pathways with different learning rates. After bilateral ablation of the orbital and prefrontal cortex, the learning of novel associations was no longer possible within one session but rather required several daily sessions. Thus, fast learning was impaired, whereas a slow learning was spared. This is compatible with the cascade learning model proposed by Fusi *et al.* (2005) in the sense of learning on different time scales. In our model, we envision fast-changing context inputs (Deco & Rolls, 2005) and slow Hebbian network structuring for novel and familiar stimuli, respectively.

We derive predictions from our model. First, the existence of a system that encodes abstract rules could be indirectly tested. Figure 3 shows the spiking activity during trials in which stimulus A and the direct rule were presented. The activities associated with the active rule (AL and BR) are always higher than the ones of the inactive rule (AR and BL). In particular, note that the pool BR had a higher activation than AR, although the pool AR received direct input from the object-selective pool A. This is possible because not only AL but also BR received an input associated with the active context and thereby establishing an abstract rule. This abstract rule reflects the direct context. Hence, we predict that if the system uses a rule mechanism then the activity of the object-and-direction-selective

neurons belonging to the active rule should be higher than the activity of neurons belonging to the other rule.

Second, error trials represent a valuable source of information, because they allow a different view on the system. If error trials are implemented in a neurodynamical system such as the one proposed here, then the monkey should make exploratory errors. This is best illustrated in Fig. 3. In most trials (70%), the activity is high in the pools A, AL and L (solid lines), correctly responding to stimulus A and the direct rule. However, in some trials (15%), the network responds to the presentation of stimulus A and the direct context with a high activity in the pools B, BR and R (dotted lines, Fig. 3). Thus, the system responds with an incorrect answer although it has been exposed to the correct input. It is already known that the activity of direction-selective neurons in the prefrontal cortex indicates the impending response regardless of whether it is correct (Asaad *et al.*, 1998). We predict on the basis of our model that the error activity should also be reflected in the activity of the object-and-direction-selective neurons and maybe even in the object-selective neurons. Specifically, when stimulus A is presented during the direct context and the monkeys make an error (response R), we predict high activity for neurons selective to the association BR and to the object B, such as the picture in Fig. 3 (dotted lines). This type of error is not due to processing errors in parts of the system but due to properties of the whole stimulus–response system. In addition, our simulations suggest a second cause of errors, namely the indecisive state (dashed lines, Fig. 3). Although the stimulus A and the direct context are influencing the network, the activities of the pools L and R remain at the same level, and analogously the activities of the pools AL, BR and A, B. Consequently, the monkeys have to guess. Both patterns, the exploratory and the guessing errors, could support the response space exploration during the learning phase. However, response space exploration is only one of different possible causes of error trials.

In addition, we emphasize that the response space exploration could also be targeted experimentally. We envision experimental setups in which monkeys are forced to make exploratory errors. For example, monkeys that are well trained on learning and performing a visuomotor association task could be confronted with rapidly changing associations. They should constantly try to identify the associations and explore the behavioural options. The neural activity during the exploration could reveal the mechanisms that underlie the response space exploration and guide the learning process.

Supplementary material

The following supplementary material may be found on www.blackwell-synergy.com

Appendix S1. Detailed mathematical description of the model, including the neural and synaptic dynamics, the meanfield formulation, and the connection matrices for all synaptic channels of the model.

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Abbreviations

AMPA, α -amino-3-hydroxy-5-methyl-4-isoxazolepropionic acid; GABA, γ -aminobutyric acid; NMDA, *N*-methyl-D-aspartate.

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