

# Flexible sequence learning in a SOM model of the mirror system

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## Abstract

We present initial work on a biologically and cognitively inspired model that may allow embodied agents to autonomously learn sequences of action primitives (forming an overall behaviour). Specifically, we combine a flexible model of sequence generation with a model of parietal mirror neuron activity. The main purpose is to illustrate that the approach is viable. Although further work is needed to improve the results sketched out here, the concept is sound and relevant both to efforts in modelling mirror neuron activity and enabling artificial embodied agents to autonomously learn sequences of action primitives.

**Keywords:** Behavioural sequence learning; Ordinal node model; Self-organising maps; Mirror neurons

## Introduction

We are concerned with the problem of generating sequences of action primitives which are flexible with respect to the precise time it takes to execute the different components (primitives) of the same sequence at different times. A thorough discussion of the issue is given, for instance, by Sandamirskaya & Schöner (2010). In a nutshell, part of the problem is that one cannot simply chain together the different primitives through, for example, simple Hebbian learning. Rather, mechanisms must exist for keeping track of the current location in the sequence, including ways of verifying that the current action has successfully completed or failed to complete. Sandamirskaya & Schöner (2010) describe a general framework which can address these issues and we briefly sketch the main points in the next section.

Overall, the aim of the work in the present paper is to combine said framework with a model of parietal mirror neuron activity (Thill et al., 2011) and to illustrate that such an approach is, in principle, viable. Importantly, since the mirror neuron model used here autonomously organises itself, the work proposed here may be relevant and helpful in designing artificial embodied agents that should autonomously learn sequences of actions and use them to predict actions of others.

## Sequencing via ordinal nodes and conditions of satisfaction

The gist of the framework by Sandamirskaya & Schöner (2010) is the existence of *ordinal nodes* which essentially count through the sequence. These nodes are implemented via coupled dynamical systems (see *Methods*), designed so that only one node can be active at a time. Upon completion of the element of the sequence represented by the active node, activation is passed onto the next node in the sequence. In their work (e.g. Sandamirskaya & Schöner, 2010; Sandamirskaya et al., 2011), the action primitives forming the sequence exist in the sensorimotor representation of an embodied agent, implemented using techniques from Dynamic Field Theory (Schöner, 2009; Spencer et al., 2009). This has the advantage that the sensorimotor representations of these primitives are stable (since they are essentially stable fixed-point attractors), which makes it particularly simple to link specific locations in the dynamic fields representing the sensorimotor space of the agent to specific ordinal nodes. Part of the challenge of the work presented in the present paper is to illustrate that the ordinal node system could also be attached to a representation with more noise and less stability than dynamic fields.

The decision that a given action primitive has completed is implemented a separate system (also exploiting dynamic fields) that checks for a *Condition of Satisfaction* (CoS). One of the open challenges here is the question of how to best learn the CoS for specific primitives (including identifying that the primitive has, for whatever reason, failed). It is not the purpose of the present work to address the open issues regarding the CoS - rather, we focus on combining the ordinal node model with a model of mirror neuron activity discussed in the next section.

## Mirror system sequences

One example of sequencing in biology is given by the hypothesised functioning of the mirror system. Without entering the debate on what higher-level cognitive abilities mirror

neurons may or may not be useful/essential for (see for instance Hickok, 2008; Rizzolatti & Sinigaglia, 2010, for such a debate), it appears that parietal mirror neurons in macaque monkeys organise into pools of neurons responding to specific motion primitives (*e.g.* a *reach* or a *grasp* but not both; Fogassi et al., 2005). It has then been hypothesised (*e.g.* Chersi et al., 2006) that these pools of neurons can be chained together to form sequences of simple, often-encountered actions (such as *reach-grasp-bring\_to\_mouth* for eating). Models on the basis of this hypothesis have proven useful, for instance, in putting forward theories unifying apparently conflicting results on interference and facilitation in action language processing (Chersi et al., 2010).

A particular model that specifically addresses the development of parietal mirror neurons has been previously presented by some of us (Thill et al., 2011). This model uses a self-organising map (SOM) to illustrate how a “blank” structure, through the organisational principles of SOMs can autonomously form an organisation whose activity resembles that of parietal mirror neurons.

The inputs to the model represent an arbitrary encoding of observed (or executed) motion primitives (*e.g.* based on changes in position per time step) and contextual information (including, for instance, affordances in the perceived scenery). These two components are sampled from two distinct spaces (of arbitrary dimensionality) and concatenated into a single input vector as required by standard SOM implementations (Kohonen, 1997). The model is trained on repeated presentations of all combination of motion primitives and contexts. After training, the model can be run on-line by continuously feeding it input vectors and some plasticity (allowing, for instance, the learning of new primitives) can be retained by not reducing the learning rate to 0 (albeit keeping it at a low level, see Thill & Ziemke, 2010).

The trained maps organise in a fashion remarkably similar to that of parietal mirror neurons (Fogassi et al., 2005): Within the map, different areas encode different action primitives (which could represent motions such as *reaching*, *grasping* or *bring-to-mouth*, similar to *e.g.* Chersi et al., 2006). Within the area encoding one such primitive, some nodes are active whenever the model input encodes that primitive. Others are active only if the action input additionally encodes a specific context in which the primitive is observed (usually sufficient to specify the most likely goal of the action, see Thill et al., 2011). The proportion of context-independent nodes is a direct consequence of the way inputs are represented (specifically, of the ratio between the maximal variability in encoding the primitives and contextual information respectively, called  $\beta$  in the model). Exploring how  $\beta$  (for which values between 1 and 5 cover most aspects of interest) affects the organisation of the maps revealed that, for  $\beta \approx 3.5$ , the proportion of context-independent nodes is similar to the corresponding neurophysiological data observed in the parietal mirror area of macaques (Fogassi et al., 2005).

## Combining models

Previous models of parietal mirror neuron activation tend not to address the timing aspect of the chains in much detail, focussing instead on merely linking the different pools forming a chain through hard-coding (Chersi et al., 2006, 2010) or, for instance, Hebbian learning (Erlhagen et al., 2007). With the exception of Chersi et al. (2010), these models do not take into account that the pools encoding the same primitive under different goals are not entirely distinct (Fogassi et al., 2005). Thill et al. (2011), whose main focus is the exact nature of this overlap between populations, do not specifically address chain formation at all.

The present paper therefore presents an augmented version of the model from Thill et al. (2011). Specifically, we now implement the learning of chains of primitives, using the approach of Sandamirskaya & Schöner (2010). This new model then allows us to address a number of open issues: to what extent is the ability to activate the correct (and only the correct) sequence of events (given the first element) affected by the overlap between neural populations? When observing an action primitive in an unknown context, is it possible to predict all possible chains this action could be part of?

These issues are relevant, both for our understanding of (in particular) sequences in mirror neuron activity and for the ability to endow artificial agents with similar abilities. If one subscribes to the hypothesis that mirror neuron activity helps us understand the actions of others (see Rizzolatti & Sinigaglia, 2010, for a thorough review and discussion), then the ability to predict the likely outcome of an action given the initial movement based on the resulting mirror neuron activity is a desirable ability. This includes the ability to autonomously learn sequences of actions as well as the ability to both correctly identify a sequence if the context is clear and predict all possible sequences if the context is ambiguous (for instance, a familiar gesture observed in a completely new context).

## Methods

### Overall model design

The model (Fig. 1) is composed of a self-organising map which is meant to represent parietal mirror neuron activation (Thill et al., 2011) and an ordinal node model for sequence learning (Sandamirskaya & Schöner, 2010). The activity over time in the SOM is used (1) to train the sequence learning model, (2) to activate learned sequences and (3) to provide the input necessary to move from one sequence element to the next. It therefore combines the idea of chaining pools of neurons (*e.g.* Chersi et al., 2006) with the flexible execution of sequences provided by the ordinal nodes model of Sandamirskaya & Schöner (2010).

### Self-organising maps as a mirror system

The self-organising maps used in this paper are in essence identical to those used by Thill et al. (2011) and are trained in the same manner. The only difference is that the previous maps explicitly dedicated part of their space to the theoretical

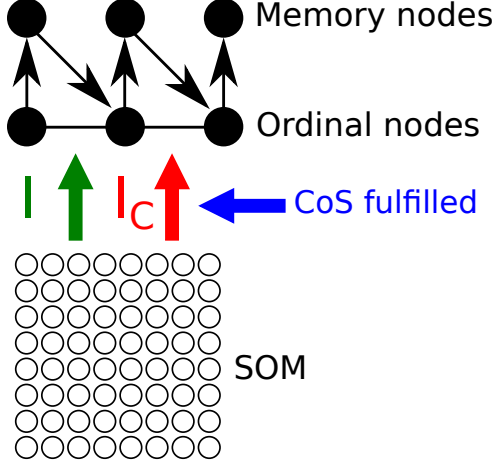


Figure 1: **Overall model architecture.** Activation in the SOM feeds into the ordinal nodes, both to activate the sequence (green) and to move between sequence elements (red) if the CoS is fulfilled (blue). Connections between the SOM and the nodes are bidirectional; node activity can thus also be used to activate regions in the SOM (omitted in the figure for clarity).

possibility of learning motion primitives from a second limb (see Thill & Ziemke, 2010, for details). Since that is irrelevant here, the present maps are trained assuming the need to represent just one limb. The trained maps therefore represent, as before, five motion primitives observed under two different contexts. They behave as described in the introduction: input vectors consisting of a concatenation of observed/executed motion encoding and contextual information are continuously fed to the map. Depending on the previously discussed ratio  $\beta$ , some nodes of the map will be active regardless of the contextual information whereas others will be sensitive to the latter (see Thill et al., 2011, for a complete discussion of the definition of activity).

### Ordinal node model

The ordinal node model used here largely follows Sandamirskaya & Schöner (2010) and is described by the following equations:

$$\begin{aligned} \tau \dot{d}_i(t) = & -d_i(t) + h_d + c_0 f(d_i(t)) & (1) \\ & -c_1 \sum_{i' \neq i} f(d_{i'}(t)) + c_2 f(d_{i-1}^m(t)) \\ & -c_3 f(d_i^m(t)) - c_{CoS} I_C(t) + c_{in} I \end{aligned}$$

$$\begin{aligned} \tau \dot{d}_i^m(t) = & -d_i^m(t) + h_m + c_4 f(d_i^m(t)) & (2) \\ & -c_5 \sum_{i' \neq i} f(d_{i'}(t)) + c_6 f(d_i(t)) \end{aligned}$$

where  $d_i$  refers to the activation of the  $i$ th ordinal node (and  $d_i^m$  is the associated memory node needed for proper

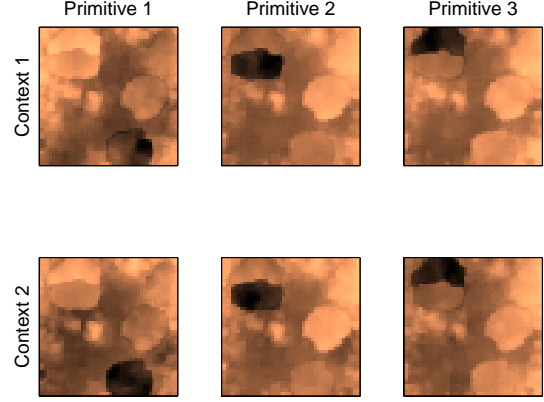


Figure 2: **Sequences in the SOM.** Shown are the activation of three primitives (columns) seen under two different contexts (rows) for a map with  $\beta = 3$ . Dark regions indicate most activity and are clearly in different locations for different primitives. For the same primitives in different contexts, similar regions are activated but the overlap between the most active neurons in each context is limited (see Thill et al., 2011, for a thorough discussion).

functioning, see Sandamirskaya & Schöner (2010) for details),  $f(\cdot)$  is a sigmoidal nonlinearity and the constants in the present implementation are chosen as:  $c_0 = 7.2$ ,  $c_1 = 3.6$ ,  $c_2 = 4.8$ ,  $c_3 = 0.8$ ,  $c_4 = 4$ ,  $c_5 = 2$ ,  $c_6 = 2.6$ ,  $c_{in} = 0.1$ ,  $c_{CoS} = 0.2$ ,  $h_d = -5$  and  $h_m = -2$ . A detailed discussion of the functioning of the model is given by Sandamirskaya & Schöner (2010). We deviate in two minor aspects: (1) The term  $c_{in}I$  is added and provides an external input (obtained from the activity in the SOM described above). This is only used at the beginning of a sequence to activate the first ordinal node. (2) We simplify the Condition-of-Satisfaction (CoS) aspect. In the original model, this is given by an additional dynamic field which is able to “perceive” that the CoS has been reached. Here, the inhibitory activation is obtained from the same SOM that would provide  $I$  for the activation of the first node, which simplifies the design of the model. Since the model is not actually implemented in an agent, there is also no point in devising a sophisticated “perception” of the CoS here. Rather, the CoS is presumed fulfilled after a randomly chosen number of time-steps and the inhibitory activation released to the ordinal model, thus moving the model onto the next element of the sequence. This is acceptable for the present purposes since the point here is to illustrate the learning of sequences, not the ability to autonomously detect that an element of a sequence has completed (or failed to complete). An implementation of this model in an agent would of course need to address this aspect in more detail.

## Task and learning

For each  $\beta$  value between 1 and 5 (in increments of .5), 100 maps have been generated. Each map is activated manually with a series of input vectors which simulate a sequence of 3 motion primitives being executed first in one context and then in another (see Fig. 2 for an example of two sequences). Two sets of ordinal nodes are used to learn these two sequences. Learning is achieved during manual activation of the map by clamping the relevant ordinal node to an active state and then using simple Hebbian learning to train weights between this node and all neurons in the map (with normalised activation). After training, any weights below a threshold of 0.5 are set to 0 to allow only the SOM nodes with the strongest activation to connect with the relevant ordinal nodes.

Of particular interest are the following questions: Will both sets of ordinal nodes correctly activate if the SOM activity is that of the first element of their respective sequences? Also, will a set of ordinal nodes trained on the first sequence remain *inactive* if the SOM activity represents the first element of the second sequence (and vice versa)? Illustrating these behaviours would confirm good performance of the model given that sequences are correctly activated if and only if the map activity corresponds to their first element. It should be remembered at this point that map activity is noisy and fluctuates over time - the task is therefore not trivial.

An additional interest is the behaviour of the model in case of ambiguous contextual information. As discussed in the introduction, this could correspond to observing a familiar primitive in an unfamiliar context and predicting what the likely outcome of the action could be. It is of course a matter of debate what the exact behaviour of the model should be in this case; one could for instance argue that it should depend on how similar the unfamiliar context is to previously encountered ones. Here, we simply investigate the behaviour if the vector encoding contextual information is truly ambiguous, namely by corresponding to the point in the input space whose coordinates are equidistant from the subspaces encoding all known contexts. In other words, the ambiguous context encoding vector cannot be uniquely assigned to any previously encountered case. We simply postulate that, in the absence of any information that could favour either of the chains, the desirable behaviour of the model is to activate both, essentially predicting that both behaviours are equally likely.

## Results

### Correct activation/non-activation

For each value of  $\beta$ , 100 sets of 2 sequences have been learned. Per set, the sequences differ only in the context in which they have been executed. As  $\beta$  increases, the proportion of neurons active in one but not both of the contexts decreases (Thill et al., 2011). It can therefore be expected that the basic task of correctly activating a sequence if the map activity corresponds to its first element (and not activating said sequence if the contextual information is that of the sec-

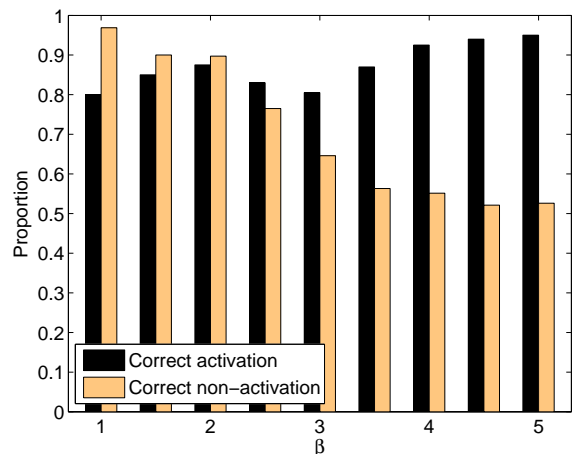


Figure 3: **Correct activation/non-activation.** Dark bars indicate the proportion of cases in which presenting the first element of a sequence correctly triggered the sequence. Light bars indicate the proportion of the cases that correctly trigger which correctly remain silent if the first element presented has the same motion primitive but different contextual information.

ond sequence) becomes harder as  $\beta$  increases. This is indeed what we find (see Fig. 3). Specifically, it is possible, in most cases, to correctly activate a sequence by presenting its first element in map activation (although it does fail on occasion, likely due to the noisy map activity). Importantly, this is independent of  $\beta$ , which is expected. The light bars in Fig. 3 then show how many (proportionally) of the sequences correctly activated by their own first element also remain silent when the first element of the second possible sequence is presented instead. As expected, this number decreases over time but remains over .5 in all cases.

However, this measure iterates over sequences that are correctly activated (or not); it does not measure the number of maps for which both sequences are correctly activated (or not). The evolution of this proportion is shown in Fig. 4 (black bars) and is decreasing more dramatically as  $\beta$  increases. At the same time, it should be noted that for *e.g.*  $\beta = 4$ ,  $\approx 60\%$  of nodes in the SOM encoding a given primitive are active independent of context (leaving only 20% capable of uniquely identifying each of the contexts).

### Correct behaviour under ambiguous context

The second interesting question was whether both sequences would be activated by the first motion primitive shown in a perfectly ambiguous context. Considered independently of the performance on the previous task, we find that a large number of models indeed activate both sequences given an ambiguous context. In particular, we find that this proportion increases with  $\beta$  (from 0.4 to  $> 0.9$ ), likely due to the increasing number of neurons which are active irrespective of con-

## Discussion

### Insights from the model

Most of the results shown have their main purpose in illustrating that the model works as expected, including the increasing difficulty in obtaining “perfect” models as the  $\beta$  values of the underlying maps increase. The exact extent of this increase in difficulty is hard to judge from the work presented here as several aspects can be improved. First and foremost, the parameters for the ordinal nodes model are set independently of  $\beta$ , even though  $\beta$  has a rather significant effect on the input into the ordinal nodes and therefore the behaviour of the sequences. The fact that it was possible at all to create successful models across the entire range of  $\beta$  values underlines the potential of the approach. In future work, however, the focus would have to be on  $\beta$  values around 3 – 3.5, since these are the values for which the activity in the SOM most resembles that observed by Fogassi et al. (2005) in parietal mirror neurons (Thill et al., 2011).

The self-organising maps themselves are randomly generated; nonetheless it seems that some are more suited for a combination with an ordinal nodes model than others (since some “perfect” models were found even for  $\beta = 5$ , although the number was very low) and more work would be needed to investigate what features of these maps, if any, facilitate the task. Insights into this question could prove very valuable in more general future work combining the ordinal node model with sequences that are generated in systems which do not offer the “nice and clean” activation patterns of dynamic fields.

The connections between the activity in the map and the ordinal nodes are learned with a simple general Hebbian learning approach and the only transformation of the map activity consisted of a simple normalisation. Again, this is about the simplest approach imaginable and it is likely that improvements, including possible non-linear transformations of map activity, can lead to a higher proportion of “perfect” models for larger values of  $\beta$  (in particular of course for  $\beta \in [3, 3.5]$ ).

The most interesting result in the present paper was that the largest difficulty resided in finding models which perform as expected when started with a first element from either learned sequence and not, as one might have expected, in finding such a model that *also* perform correctly on the prediction task. This is encouraging as it illustrates that the concepts of using a combination of our previous SOM models of mirror neurons and the ordinal node model has potential, not just for generating the sequences one wishes to generate but also for predicting what sequences observed actions can be part of; this both in the case where the contextual information strongly favours one of the learned sequences and when the contextual information is perfectly ambiguous.

Again, there is a need for future work in this aspect. It seems reasonable (for the purposes of predicting likely sequences an observed primitive could belong to) to expect that a perfectly ambiguous context should activate all candidates but it is less clear - and beyond the scope of what can be

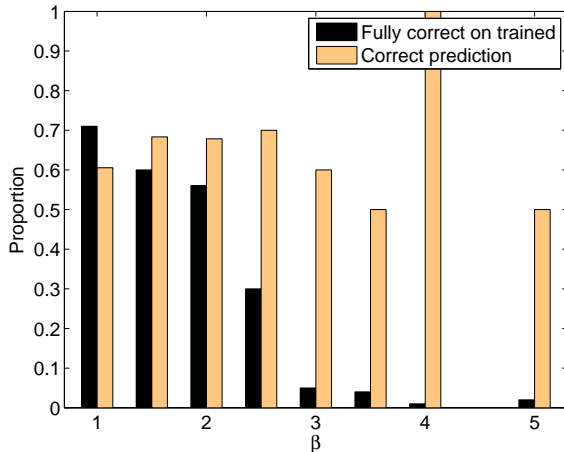


Figure 4: “Perfect” models. Black bars indicate proportion of cases in which the same model activates the correct sequence for each of the two learned sequences if presented with the first element of each sequence and does not activate the wrong sequence. Light bars indicate the proportion of cases fulfilling the first condition which also correctly activate both sequences if the contextual information is ambiguous

text.

This illustrates the expected effect of  $\beta$ : as the distinction between contexts diminishes, activation of both sequences is facilitated. However, this measure can again be seen as being a bit too general since there is not necessarily anything special about activating both sequences if the same model failed to *not* activate a sequence when primed with the first element (including the contextual information) of the second sequence. The more interesting question is therefore simply how many of the models that correctly behave given the learned sequences (black bars in Fig. 4 *also* behave as expected given the first primitive under an ambiguous context (within the context of this work, we can call these models “perfect”, since they fulfil all the expectations set out to them). Surprisingly, this proportion appears to be independent of  $\beta$  (light bars in Fig. 4), although it has to be kept in mind that for  $\beta \geq 3$ , the number of models which fulfill the first condition is rather low.

In other words, if a model is capable of correctly activating the relevant sequence (and only that sequence) given a full first element of that sequence, it is likely to *also* activate both sequences if given the first primitive under an ambiguous context. This is the most significant result in the present paper: although it is increasingly difficult to find a model which will correctly activate its sequences given the first element as  $\beta$  increases, it is then much easier to find a model which can also activate both sequences in the case of perfectly ambiguous contextual information.

achieved in this space - what should happen if the context is merely ambiguous but closer in input space to some known contexts than others. Should the model simply activate the most likely sequence or would one prefer a mechanism that could attach a confidence value - indicated for instance by the time it takes the first ordinal nodes of all candidate sequences to activate - to indicate most and least likely sequences?

### Overall relevance

The work presented here is relevant for at least two areas. First is the modelling of mirror neurons as it is one of the first attempts to explicitly include the idea that executing the same action primitive at different points in time can lead to different durations, thus going beyond simple Hebbian-type associations directly between the primitives forming an overall action sequence (e.g. Chersi et al., 2010). Second, by modelling the specific organisation of parietal mirror neurons (which can develop autonomously, see Thill et al., 2011) and using that as an input to the ordinal node system, the model may provide a way for an artificial agent to learn sequences of primitives online and autonomously, which is still an open challenge (Sandamirskaya & Schöner, 2010).

The practical future applications are thus primarily in the design of future artificial cognitive systems; however all aspects of the model are inspired by biology; any implementation of the model could thus also be relevant to improve our understanding of the analogous biological systems.

### Conclusion

We presented an initial implementation of a mirror system activity model augmented with a framework for generating sequences. The main purpose was that it is in principle feasible to use the ordinal node framework to this effect. Although further work is needed to improve the quality, it was possible to show that the model can learn sequences based on the noisy SOM activity as well as correctly predict the likely sequence an observed initial primitive can belong to (including predicting both if both are equally likely). Since the SOM autonomously organises, the model presented here may be a viable candidate for autonomous sequence learning using the ordinal node framework (Sandamirskaya & Schöner, 2010).

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