Role of the Cerebellum in Time-Critical Goal-Oriented Behaviour: Anatomical Basis and Control Principle.

Guido Bugmann

Centre for Neural and Adaptive Systems
School of Computing, University of Plymouth, Plymouth PL4 8AA, UK
`http://www.tech.plym.ac.uk/soc/Staff/GuidBugm/Bugmann.htm`

Abstract. The Brain is a slow computer yet humans can skillfully play games such as tennis where very fast reactions are required. Of particular interest is the evidence for strategic thinking despite planning time being denied by the speed of the game. A review of data on motor and cognitive effects of cerebellar lesions leads to propose that the brain minimizes reaction time during skilled behaviour by eliminating on-line planning. Planning of the next action is concurrent with the execution of the current action. The cerebellum plays a role in preparing fast visuo-motor pathways to produce goal-specific responses to sensory stimuli.. Anatomically, the cerebellum projects to all extra-striate components of the fast sensory-motor route: Posterior parietal cortex (PPC), Premotor cortex (PM) and Motor Cortex (M1). Indirect evidences suggest that the cerebellum sets up stimulus-response (S-R) sets at the level of the PPC. Among unresolved issues is the question of how S-R mappings are activated in PPC, how planning is performed and how the cerebellum is informed of plans. Computationally, the proposed principle of off-line planning of S-R associations poses interesting problems: i) planning must now define both the stimulus S and the action R that it will trigger. ii) There is uncertainty on the stimulus that will appear at the time of execution. Hence the planning process needs to produce not a single optimal solution but a field of solutions. It is proposed here that problem i) can be solved if only learned S-R associations are involved. Problem ii) can be solved if the neural network for S-R mapping has appropriate generalization properties. This is demonstrated with an artificial neural network example using normalized radial basis functions (NRBF). Planning a single optimal trajectory enables to generate appropriate motor command even for initial states outside of the optimal trajectory. Current implementations include a simulated robot arm and the control of a real autonomous wheelchair. In terms of control theory, the principles proposed in this paper unify purely behaviour-based approaches and approaches based on planning using internal representations. On one hand sensory-motor associations enable fast reactions and on the other hand, being products of planning, these associations enable flexible goal adaptation.

1. Introduction.

In the game of tennis, the time for the ball to cross the court is almost exactly equal to the reaction time of the player added to its displacement time[1]. There does not seem to be time for planning and it is unclear how players manage to produce strategic shots under these conditions. The cerebellum is known to be involved in the co-ordination of action and its lesion results in slower reactions [1,2]. Can we learn something from studying the cerebellum that may shed some light on the computational strategies used by tennis players? Can we learn something that may help design faster robots despite limitations in computational resources? These are the questions underlying this paper.

How can the cerebellum accelerate reactions? The answer is not straightforward, because the cerebellum does not initiate actions, its inputs arriving usually to the motor cortex around the time when the action starts [3]. Several experiments will be described in section 2 that suggest that the cerebellum helps selecting actions to be executed in response to sensory stimuli. In section 3, a possible biological substrate is suggested. In section 4, a conceptual model based on these observations is proposed that combines planning and reactive behaviour. In this model a planner uses contextual and goal information to calculate a number of goal-specific Stimulus-Reaction (S-R) pairs. These S-R pairs are activated in a S-R map that will trigger an appropriate actions when one of the expected stimuli appears. In this context, a "plan" is represented by a set of S-R pairs. In section 5, a neural network implementation is described for the S-R map sub-component of the model. The generalization properties of this network help reduce the number of S-R pairs that need to be pre-calculated. The conclusion follows in section 6.

2. Role of the Cerebellum in Planning.

Several experiments show that the cerebellum is involved in planning. A more precise view on its role in that respect emerges from an analysis of the following experiments.

- In one experiment, human subjects were asked to walk a path of irregularly placed stepping stones as fast as possible [4]. Subjects usually fixate the next stone just before starting to lift the foot to be placed on that stone. To assess the role of visual sampling, tests were also performed in the dark, with stone positions indicated by LED's turned off at different times. Visual deprivation had no effect when the goal was not illuminated during fixation time and swing phase of the movement. However, deprivation towards the end of the swing sometimes affected the accuracy of the next

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[1] The length of the court is approximately 24 m and its width 8m. A ball flying at 100 km/h takes 860ms to travel 24m. Choice reaction time is approximately 270ms and the displacement time, to reach a corner of the court starting from the middle (at half the speed of a 100m world record, i.e. 5m/sec, and moving only 3m due to arm-length of 1m), is estimated at 600ms. Planning normally takes several seconds [5]. The problem is that the approach run is dependent on the intended type of hit. Therefore, the decision must be made almost a the start of the run.

step. This indicates that subjects were planning the move to the next stepping stone, while fixating the current stone an executing the current stepping action. Interestingly, shift of fixation from the current to the next stone took also place in the dark, indicating that the fixation was more a reflection of a pre-existing plan than a source of information needed for its execution. The intermittent effect of visual deprivation could be due to compensation by spatial memory of the layout, which, in another experiment, has been shown to persist for several seconds in the dark [6]. The stepping-stone experiment done in the light with cerebellar patients showed a reduced accuracy and intermittent delays (prolonged stance) correlated with inaccurate fixation saccades to the next stone [7]. The lesion results denote either a problem in using visual information to produce an appropriate action plan, or a problem in accurately executing a plan once set up[2].

- In another experiment, a monkey was trained to touch in the correct order two elements lit simultaneously in a succession of array-like displays [9]. In such experiments, a trained animal shows anticipatory saccades to the next element, indicating knowledge of the sequence, and as suggested above, the existence of a plan as for which element to touch next. Lesions in the dorsolateral dentate nucleus, that relays cerebellar outputs to the cortex, reduced the number of anticipatory saccades and caused more errors. This indicates either a loss of sequence memory, or errors in translating sequence knowledge into a correct action. The next experiment shows that the latter is more likely.

- A patient with cerebellar lesions showed spatial dysgraphia characterised by a large number of stroke omissions or stroke repetitions when writing in upper case, even when copying a word [10]. Errors occurred despite a memory of the sequence of strokes not being required. The authors suggested that this was a case of neglected visual feedback (e.g. informing that all strokes of a letter have been produced), but as the performance worsened in darkness, visual feedback was being used. Somehow, cerebellar lesions prevented available knowledge (visible example or memory of sequence) to be correctly converted into a robust motor plan, e.g. a sequence of S-R sets where one stroke is produced after the other.

- Patients with cerebellar lesions tend to do more illegal moves in a Tower of Hanoi task that is used for testing planning capabilities [11]. This effect is neither due to not understanding the instructions nor to some error in motor control. It is most likely due to rules not being represented internally in a robust way, allowing illegal moves to be selected during planning.

- In a target detection task, a target was presented either to the left or to the right of a central fixation point. A small frame appeared first on the screen at one of the two possible locations of the target. If this preparatory signal was compatible, i.e. the target actually appeared within the frame, the reaction time (RT) was shortened. In the incompatible case, the RT was increased. In normal subjects this effect of the preparatory signal was noticeable for targets appearing as early as 50 ms after the preparatory signal. In patients with cerebellar lesions it took approximately 800ms

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[2] There could also be a problem in keeping an action plan long enough in working memory, but there is no documented involvement of the cerebellum in working memory.

before evidence for increased readiness to respond was seen [2]. Cerebellar lesions seem to cause difficulties in setting up rapidly a response program.

In summary, healthy subjects or animals plan ahead while acting, which is revealed by anticipatory saccades and short reaction times. The symptoms of cerebellar patients can be described as resulting from an inappropriate and late setup of a response rule. The role of the cerebellum in fast responses is seen here as one of preparing the sensory-motor system for producing a task-specific response to a subsequent sensory stimulus.

A similar hypothesis was formulated in more general terms in [12] to explain the participation of the cerebellum in attention orienting. The view put forward here differs from earlier suggestions that the cerebellum may be directly involved in action generation via learned stimulus-response (S-R) mappings, or so-called "context-response linkage" [13,14,15]. In a later extension to these ideas, it was suggested [16] that the cerebellum may also learn context-plan linkages, i.e. inform areas of the cortex involved in planning of a plan - that may or may not be executed - evoked by a context. Specification of an action plan, as proposed in [16], or enabling given S-R sets as proposed here are probably similar concepts (see section 4).

Applying these ideas to the problem of fast yet strategic responses by a tennis player, it can be assumed that the tennis player plans his or her next shot during the flight of the ball towards the other side of the court and during his own shot. The notion of concurrent planning is supported by the stepping stone experiment described above in which planification and action took place in parallel. The cerebellum then sets up the plan in the form of a S-R set that triggers a response as soon as the ball is returned. The stimulus S could be defined as a given view of the court when the ball is fixated.

One problem with that approach is that the response of the opponent is unpredictable. Therefore a series of responses needs actually preparing. We refer to that as a "response field". In the next section, we will examine briefly the network connecting the cerebellum to other brain areas that may support the preparatory role of the cerebellum. The question of response field will be addressed in section 5.

3. Anatomical Basis for the Role of the Cerebellum in Response Pre-selection.

In this section the neural network supporting the preparatory role of the cerebellum is analysed. First, the fastest paths from primary visual areas to the motor output are identified. Then the most likely target areas for cerebellar action are discussed.

Several paths with very short latencies link visual input to motor output (figure 1A, B). A series of paths devoted to the control of eye movements comprise areas V1, PO, LIP, FEF and SC [17]. Another group of paths is devoted to reaching movements and comprises V1, PO, MIP, PM and M1 [18,19,20, 21].

Average visual response latencies in FEF are only 75ms [19] and are close to 100ms in PM [22]. Total eye saccade reaction time (from stimulus onset to movement onset) is approximately 120 ms [23]. Simple arm reaching reaction time is 250ms for

a single fixed visual target, and 270 ms for a target that can appear in one of two positions [24]. This includes a 50-100 ms delay between the issue of the motor command in M1 and the initiation of movement [25,20]. When action selection depends on stimulus properties evaluated in the ventral visual path, reaction times are close to 360 ms [26].
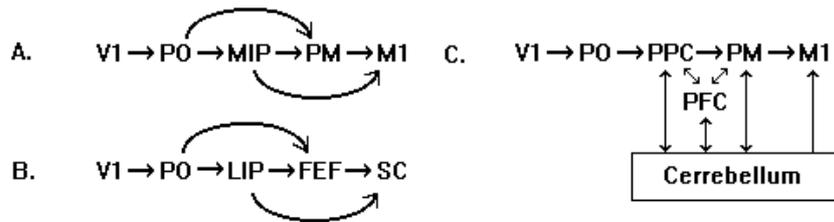

Fig. 1. A. Fastest path from visual input to motor output for arm movements. B. Fast paths for eye movements. C. Cerebello-cortical connections. V1: Primary visual area, PO : Parieto Occipital Cortex, MIP and LIP are the medial and lateral intraparietal areas, parts of Posterior Parietal Cortex (PPC). The frontal eye field (FEF) is a pre-motor area for eye movements, M1: Primary motor cortex. SC: Superior Colliculus, PFC: Prefrontal cortex.

The main outputs[3] of the cerebellum target areas M1, PM and PPC in the fast paths [27,28,29,30]. There is also a projection to the prefrontal cortex (figure 1C). These connections are reciprocal. Other inputs to the cerebellum include higher visual areas devoted to the peripheral visual field, SC, and the cingulate gyrus [31,32].

The cerebellum is thus in position to influence information processing along fast sensori-motor routes. The more likely targets for an action on stimulus-response mapping are areas PPC and PM. Area M1 is activated by the cerebellum after motor commands have been issued [3]. Therefore the projections to M1 are more likely to be involved in controlling ongoing movements [33] than initiating or preparing them. Areas PO and V1 have no documented cerebellar inputs.

The posterior parietal cortex (PPC) contains maps of intended movements relative to objects in the field of view. When given hand, arm or eye movements are intended, specific subgroups of neurones become active [34]. It has been proposed that area PPC rather represents "potential motor responses" that are communicated to the PM where the "intended response" would be selected in a task dependent way [35]. Finally the PM would activate neurons in M1 which initiate the "actual response" [36].

Electrophysiological data give a more complex image of these three processing stages [37,38]. Neurons coding for "potential responses" have been observed in PM [39] and even in M1 [26]. It has been suggested that visuo-motor transformations are a gradual rather than a clear-cut multistage process [21].

In an experiment by [26], a monkey was presented with two colored LED placed on either side of a fixation point. Its task was to point either in the direction of the lit led, or in the opposite direction, depending on the color of the LED. It was found that the activity in a population of cells in M1 reflects initially the cue location (latency after stimulus onset 80-200 ms), then the S-R rule (LED color) (latency 180-240ms) then

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[3] Different sub-areas in the cerebellum are linked to different cortical areas (see. e.g. [12, 27].

the response direction (latency 236-286 ms). On the one hand, such observations are consistent with a multistage sequential process whereby fast position information from the PPC is combined with slower color information from the ventral visual stream to finally determine the response. On the other hand, the fact that area M1 has access to information from intermediate processing stages indicates a distributed rather than hierarchical network organization.

In this experiment [26], the position of the stimulus does not provide complete information on the action to perform and combination of ventral and dorsal visual information is required. The PFC and PM are the more likely areas where multimodal information is combined. Brain imaging experiments confirm the involvement of the dorsal PM in response selection based on non-spatial visual information [40]. However, these experiments also suggest an involvement of the PPC. Clinical studies show that PPC lesions disable voluntary or memory-guided saccades to the side contralateral to the lesion [23]. There is no clear reason for the involvement of the PPC in these tasks, as there are direct connections between prefrontal memory areas and pre-motor areas. Similarly it is unclear why the PFC and PPC are coactive when a response needs to be memorized in a delayed response task [41]. These data suggest that the PPC is a crucial link to the motor cortex. However, transmagnetic stimulation of the PPC impairs the accuracy of memory guided saccades only if applied in the first 50ms after visual cue offset [42]. This suggests that PPC only provides initial movement specifications that are then memorised and executed in further stages.

In any interpretation of these experiments the PPC stands out as a crucial element of the fast sensori-motor path. It is therefore an ideal target for modulation by the cerebellum. Data in [43] suggest that the cerebellum initiates actions commands in M1 via the PPC relay. Imaging experiments show that the PPC and Cerebellum are more active when the S-R mapping rule is frequently changed (e.g. detect a color or a shape in the stimulus)[44]. The same is observed during learning by trial and error of finger flexion sequences [45]. In this experiment, a new finger has to be selected for execution at each pacing tone. Thus trial-and-error learning may involve frequent setting of new S-R rules.

Other issues also need to be resolved before a complete picture of the preparatory role of the cerebellum can be drawn. For instance, it is not known how planning is performed in the brain. It is known that planning requires PFC, anterior cingulate and caudate areas but also the PM, an area in common with fast sensory-motor paths [46]. This complicates further the question of how planning can occur concurrently with action execution. It is also unclear by which route the cerebellum is informed of which plan to implement in the form of S-R sets. Finally, is unclear how a S-R rule can be projected to the PPC. Projections from the cerebellum to PPC terminate in superficial layers [47] and could be better placed for a modulatory role than for a driving role. It is therefore plausible that the cerebellum operates by pre-selecting previously learnt S-R rules rather than by projecting new rules. This would restrict fast responses to learnt movements, highlighting the importance of training.

Another question is the coordinate frame in which the stimulus is defined. If the PPC is an intermediate stage in the conversion from retinocentric to, say, shoulder centred coordinates, then it may be essential to control visual fixation to ensure a

unique relation between stimulus and response. This could explain the link between preparation for action and eye fixation, as shown by several experiments (section 2).

In summary, there is still some way to go before we will be able to produce a definitive biological model of the role of the cerebellum in fast responses. Although many details on the biological circuits are unknown, the computational principle may prove useful in the design of artificial control systems.

4. Conceptual Model of the Role of the Cerebellum.

The review of behavioural and neurophysiological data in sections 2 and 3 lead to propose following model of response generation (figure 2).

1. The context C elicits a plan P, via a mapping C-P that could be located in the cerebellum [16] but possibly also elsewhere, e.g. in PFC.
2. The plan P is communicated to the cerebellum that implements a mapping between plan P and stimulus response set S-R.
3. The S-R set corresponding to the plan is pre-selected in the PPC via cerebellar projections.
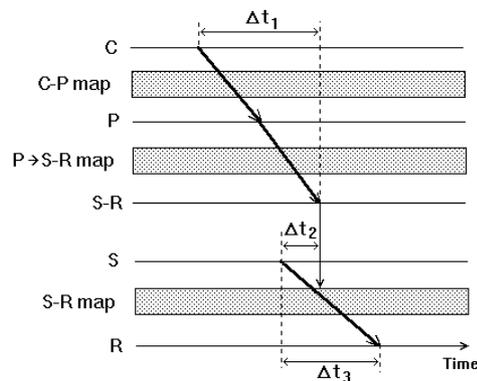4. The stimulus S activates the response R.

Fig. 2. Timing of the processes leading to the pre-selection of a S-R set in PPC and response selection. The delay $\Delta t1$ is the time for information from cortex to reach the cerebellum and from there the PPC (estimated 100-200ms). The delay $\Delta t2$ is the time for visual information to reach the PPC (approx. 70-100ms). The delay $\Delta t3$ is the reaction time (approx. 270ms). C: Contextual information, P: Plan, S: Stimulus, R: Response. The C-P map links context to plan. Possibly located in Cerebellum. The P to S-R map converts a plan into a stimulus-response (S-R) selection. This map is possibly located in the cerebellum. The S-R selection is conveyed to the S-R map that will compute the response upon arrival of the stimulus. This map is probably located in the PPC.

Observing the diagram in figure 2, one may wonder if the mapping from context C to S-R set needs to be a two-stage process. It may be possible that the cerebellum realizes the mapping directly from context C to S-R set. In that case, the cerebellum

would need accessing contextual information which comprise sensory and motivational information. It remains to be verified if the necessary projections exist.

In the proposed system, the S-R set can be adapted dynamically to changes of the context. Hence the response R is appropriate for a context not more than $\Delta t = \Delta t1 - \Delta t2 + \Delta t3$ old. This may be not more than 200-300 ms, depending on the circuits involved and the nature of the relevant contextual information. In the tennis example described above, it would be the game situation 30-130ms before the opponent hits the return that determines the selection of a response strategy. This time window contains the last moments of the opponent's swing.

From a control perspective, the key notion in the hypothesis is that actions are *selected*. This suggest that time can be saved if, instead of planning on the basis of current sensory information, pre-calculated sets of sensori-motor responses (a "plan") were available and appropriate responses were selected on the basis of current sensory information.
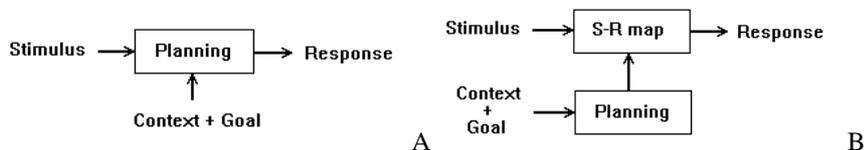

Fig. 3. A. Serial model of action selection: Sensory information is used for planning and the resulting plan is executed. B. Proposed model: Planning precedes the stimulus and sets up a stimulus-response (S-R) map. The stimulus selects the response in the S-R map.

Figure 3 illustrates the difference between the classical serial approach to goal-directed action generation and the proposed pre-planning model. In the serial approach, the response needs to be predictive to compensate for computational delays in planning. In the proposed approach, the stimulus must be predicted. An important characteristic of a controller implementing such a principle is that a plan must be reflected in a variety of response being set up, to account for the variability of ones action execution and the unpredictability of the of the environment. Choosing a plan therefore corresponds to the selection of a large set of possible sensory-motor associations. Another solution would be a representation of the S-R mapping that generalizes over variants of S and produces variants of R that compensate for deviations from expectations. In the next section an artificial neural network with this property is outlined.

5. Neural Network Implementation of the S-R map.

The neural network architecture combining off-line planning with an S-R map controlling actions was initially described in [48]. As a planner, a neuro-resistive grid was used that approximates Laplacian planning [49]. In principle, any other techniques could have been be used, directed graphs, etc. For encoding sensory-motor associations, a network of Normalized Radial Basis Functions (NRBF) was used.

This section describes the operation of the NRBF network and will highlight its generalization properties using the example of a S-R map coding for the trajectory of a 2-jointed robot arm.

5.1 The Robot-Arm Planning Problem.

The task that the planner had to solve was to find a sequence of arm configurations allowing the gripper to reach the object marked by the black circle in figure 4A. The result obtained using a resistive grid planner is a trajectory in configuration space shown in figure 4B [48].
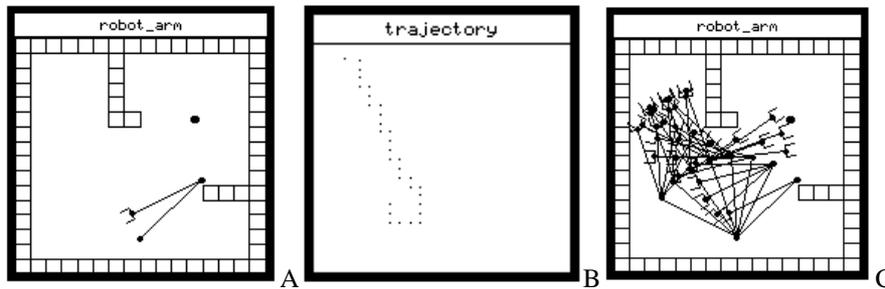

Fig. 4. A. Robot arm in its initial configuration in the workspace. B. Trajectory in configuration space. The x-axis is the shoulder joint angle. The y-axis is the elbow joint angle. The initial configuration is at the top left. C. Sequence of arm positions corresponding to the trajectory in B.

The main advantage of the resistive-grid method is that it guarantees finding a solution to the planning problem, if there is one. However, it has also the limitations of grid-based methods: a limited resolution. For instance, underlying figure 4B is a 25 x 25 grid that represent combinations of the two joint angles in discrete steps of 14.4 degree (360/25). This has two consequences, i) the planned movement is very saccadic (Figure 4C), ii) the goal is not reached (Figure 4C) because its exact location does not necessarily correspond to the centre of a node in the grid. The first problem can be solved using the NRBF net described in the next section (see fig. 6B). A solution to the second problem is described in [48].

5.2 A Normalized RBF Network Representing Sensory-Motor Associations.

A normalized RBF net has the same architecture as a standard RBF net (fig 5). The only difference is the normalized sum done in the output nodes. The input nodes code for the stimulus and the output nodes code for the desired response. Any number of outputs can be used. Each node in the hidden layer (S-R Map) encodes one association between a stimulus and a response.

In this simplified example, sensory inputs are measurements of the joint angles α_1, α_2 and motor outputs are desired joint angles α'_1, α'_2. This input corresponds to

proprioceptive information rather than visual input, but the network could operate in the same way with appropriately encoded visual information[4]. A complete trajectory of the robot arm is encoded here rather than a single response. Inputs and outputs are defined by the trajectory (fig 4B) produced by the planner. Each point in the trajectory is successively used as input (corresponding to the current values α_1, α_2 of joint angles) and the next point is used as desired output (corresponding to the next set of values α'_1, α'_2). One new node in the hidden layer is recruited for each S-R association. When the arm reaches a given point in configuration space, the most active hidden node in the sensory-motor association network will indicate the next configuration to be reached.
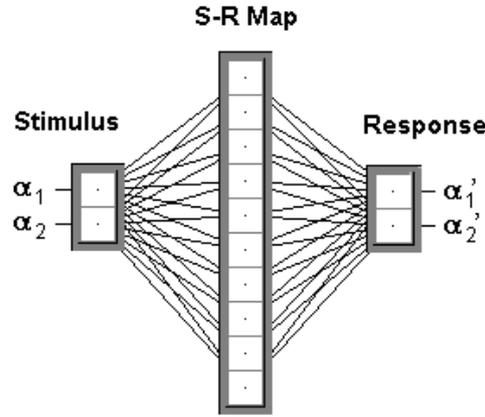

Fig. 5. Neural network for Sensory Motor Association.

The sensory motor association network has two active layers, as depicted in Figure 5. Nodes in the hidden layer have a Gaussian radial basis transfer function. Their output ϕ_j is given by

$$\phi_j = \exp\left(-\frac{1}{2\sigma_j^2} \sum_{i=1}^{2} (\alpha_i - \alpha_{ij})^2 \right) \tag{1}$$

Hidden layer nodes respond maximally when the input angles α_i are equal to the preferred input values α_{1j} and α_{2j} set during learning. These define the centre of the node's "receptive field" in the configuration space. The value of σ_j sets the width of the tuning curve (or size of the receptive field). Hidden layer nodes project to the output "Response" layer with weights W_{j1} and W_{j1}. The output layer comprises here two nodes with outputs α'_1 and α'_2. These outputs are calculated as follows:

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[4] The representation of visual information needs to generalises in such a way that the activity at each input of the net diminishes gradually as the image is transformed. This is satisfied by brain cells, but is difficult to achieve with artificial vision systems.

$$\alpha'_i = \frac{\sum_j W_{ij}\phi_j}{\sum_j \phi_j} \qquad (2)$$

This is a weighted average over the input weights, where the input activities ϕ_j play the role of weights. The weights W_{ji} are actually the desired output angles. This can be checked by assuming that only one hidden node is active (e.g. because the current input falls into its receptive field). In that case the output is equal to W_j. Interestingly, the actual value ϕ_j does not influence the output value. This is the basis of the generalisation property described in the next section.

It may be possible to approximate the normalization function with biological neurones, e.g. assuming feedforward inhibition.

Training the network consists of setting the weights from hidden to output layer to the desired values of the next angles. This is a fast one-shot learning procedure.

During replay of the learned sequence, the output of is used to control the arm movement, i.e. modify it towards the desired configuration. The actual values of joint angles are used as input. As soon as one configuration has been reached, the network provides the next values of joint angles. As NRBFs have overlapping receptive fields, a small number of nodes in the hidden layer are simultaneously active which may each point to different future configurations. However, the function (2) of the output nodes allows the most *active* of the inputs to have the largest *weight* in the decision.
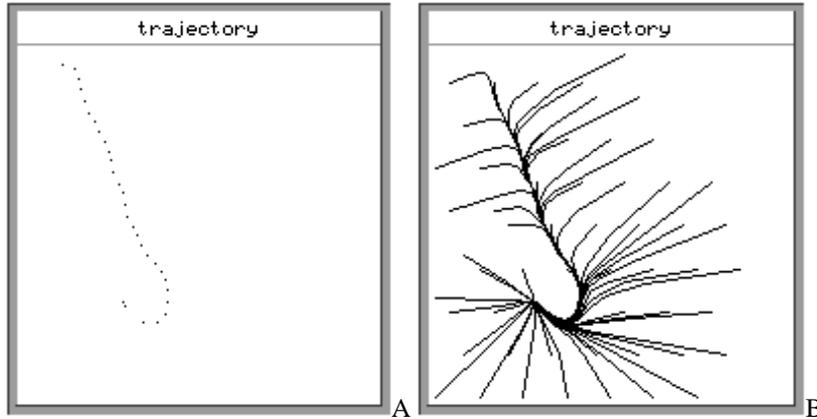

Fig. 6. A. Trajectory in configuration space produced by the Sensory Motor Association network trained on data from figure 4B. B. Example of generalization: Trajectories in configuration space generated by the sensory-motor association network for various initial arm configurations. It should be noted that the network was trained solely with the trajectory data shown in figure 4B.

Figure 6A shows the trajectory in configuration space produced by a movement controlled by the sensori-motor association network. The sequence is not replayed with the same number of steps or speed as the sequence used for the training (Figure

4B). The steps in the replay depend on the size of the receptive fields. If these are large, many hidden nodes respond for any given position, and the next value of the angles is an average over the values set for each of the active hidden nodes. This average can be close to the current angle and only a small displacement occurs. If the receptive fields are too small, the smoothness of the trajectory is lost, but the original sequence of steps is reproduced. For the results shown here $\sigma = 2\pi/25$ was used.

5.3 Generalisation

NRBFs nets behave as nearest neighbor classifier [50]. This has the consequence that inputs far from any input value used during training produce the response ("next position") corresponding to the nearest input in the training set. Figure 6B illustrates the trajectories in configuration space generated by the sensory-motor association network for various initial positions.

The particular type of sensory-motor association network used here needs to be trained only on *one trajectory* produced by the planner, and can lead an arm to the goal from *any* initial configuration. Hence, the need for planning a field of sensory-motor associations that is mentioned in section 4 might not be a practical problem. This property was used for a robust control of the trajectories of an autonomous wheelchair [51]. In that application, an additional contextual input was used to select among several sub-sequences.

6. Conclusions.

Observations of deficits caused by cerebellar lesions have suggested that one of the roles of the cerebellum is to prepare fast sensory-motor paths to express pre-planned or learned S-R associations. Such a model enables fast skilled behaviour by eliminating the planning time from the perception-to-action cycle. Yet, contextual input or off-line planning can dynamically modify the active S-R association and enable strategic thinking to influence fast responses.

As for the underlying circuit, it is proposed that input from the cerebellum to the PPC may pre-select responses that are then triggered by sensory inputs. This is speculative but not inconsistent with available data.

An artificial network has been described that implements the S-R map component of the proposed model. The S-R map design using NRBF networks may solve one of the conceptual problems with the model, i.e. the need to predict a wide range of possible sensory stimuli S and calculate the corresponding responses R. Thus, implementation of the complete model with artificial neural networks may not be of overwhelming complexity.

From a control theory perspective, the proposed model unifies i) behaviour-based control [52] that is fast but with limited flexibility in terms of goals and ii) classical plan-based control which is flexible but slow due to the computational overhead.

Further work is needed to evaluate the relative contributions of Basal Ganglia and Cerebellum in setting up S-R sets and the potential of the model for encoding complex schemas and their management [53].

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