Cerebellum Model for Movement Coordination

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Abstract

The role of the cerebellum in coordinating motion has been well established but recent findings suggest additional roles in sensory prediction and cognition. We start by reviewing the works of Marr and Albus, some of the most influential theories about the cerebellum. We also look at a less known theory by Mechsner, which proposes that the cerebellar cortex performs a coupling operation, grouping elementary movements executed frequently together. We implemented a simple model capable of guiding an agent in a two-dimensional environment from a starting position to a goal using simple elementary movements. One of its features is a strategy that is capable of making simple combinations of elementary movements, creating new movements. The model also has a method to refine the learned associations in order to make small adjustments to the agent's trajectory. Other strategies were also implemented and we did experiments to compare the performance of the different possible configurations. The final version of the model, however, is still far from our proposed solution.

***Keywords* —** Cerebellum, Motor Control, Sensorimotor Control, Internal Models, Computational Neuroscience

1 Introduction

The cerebellum has been the object of study for researchers for many years. One of its most fascinating features is that, although it only constitutes a small portion of the human brain's volume, it contains the majority of its neurons [1]. From many studies, its role on motor coordination has been well established [2–5]. Many theoretical models have been proposed to explain how this brain structure contributes to coordinate movements. Some of the most influential were the works of Albus and Marr [6, 7]. However, these will not be the only models reviewed in this dissertation.

The work of authors such as Blakemore et al. [8], Nixon et al. [9] and Bell et al. [10, 11] bring forth evidence that this brain structure has the capacity to predict the sensory responses resulting from performing an action. This ability complements its role in motor coordination as it allows it to perform corrections to a movement by comparing its prediction to the actual resulting sensory input.

We developed a simple model, which is designed to guide an agent from a start position to a goal in a two-dimensional environment using simple movements. As the model evolved, we implemented multiple strategies to be used in deciding which movement the agent should perform. Strategies were developed to determine how associations are learned and updated.

The resulting model is capable of guiding an agent to a goal position using simple movement patterns learned by the model cerebellum. We made some experiments to test how the model performed in the proposed task and how the different strategies compare to each other.

2 Related Work

2.1 David Marr (1969)

Much of the appeal of Marr's theory of the cerebellar cortex [7], published in 1969, comes from the fact that it provides an explanation to how its function can be achieved by its neuron organization.

Marr proposes that a complex motion is composed of simpler movements, called elemental movements. Each Purkinje cell affects the execution of a single elemental movement.

According to this theory, the cerebellum learns to execute complex movements by associating patterns of context information with elemental movement patterns. The two types of patterns are proposed to be associated by the Purkinje cells, which provide the only output of the cerebellar cortex. Once an association is made, the simple occurrence of the context should trigger the appropriate movement pattern without the need of conscious intervention by the cerebrum. Once the Purkinje cells respond to a context, the resulting action would form the context for the next part of the movement, triggering the appropriate cells and continuing the movement automatically.

Context input is provided by mossy fibers and it describes the current state of the body with proprioceptive information. This is the sensory information about the position of the different body parts or about resistance to their movement. The information about the movement pattern to be associated is provided by climbing fibers. Their excitatory influence on Purkinje cells is so strong that when they are active the cells fire immediately.

2.2 James Albus (1971)

Albus' proposed theory expands on Marr's work but contrasts it in certain points. In his paper from 1971, he also brings the theory of cerebellar function closer to a computational model for pattern-recognition by relating it with the concept of the Perceptron, developed by Rosenblatt [12].

The Perceptron was designed to work similarly to neuronal cells. The cells receive excitatory and inhibitory inputs of variable strength. If the sum of the inputs delivered to a cell exceed a threshold, the cell fires. The standard Perceptron possesses association cells, which preprocess the initial input, and response cells, which receive the output of the first type of cell. Each association cell will have a different weight on a response cell and it is the proper adjustment of these weights that allows the Perceptron to classify input patterns.

Albus considers the standard Perceptron inadequate for the complexity of patterns likely occurring in the nervous system. The more complex the input patterns become the likelihood of them being recognized decreases rapidly. An alternative would be the binary decoder Perceptron. In this model, there is one association cell for each possible input pattern. This, however, means that the number of association cells increases exponentially.

Finally, Albus proposes something in-between the two aforementioned types, which it calls the expansion recoder Perceptron. In this case, there are 100 association cells per input. If input was treated was a binary pattern, there would 100 cells per bit. This adds enough redundancy to apply restrictions to association cells. The author suggests that only 1% or fewer cells should be active for any input pattern.

The combination of both of these influential theories came be to known as the Marr-Albus theory of cerebellar function. Although the theory led to many studies that confirmed some of its predictions [5, 13, 14], there is still disagreement as to the actual functioning of cerebellum [15, 16].

2.3 Franz Mechsner (1996)

Franz Mechsner proposed in 1996 a new theory in which the cerebellum performs a coupling operation that creates associations between simple movements that are often performed together. This coupling operation would thus allow accurate and smooth execution of complex movements.

The essential concept of the theory is the elementary movement (EM). Just like in Marr's work, EMs are the simplest forms of movement or muscle activation, such as bending a finger or activating the abdominal muscles. By executing multiple EMs together complex motions can be performed. However, in this theory EMs are variable, as the brain can vary their intensity, speed and duration of execution.

One of the main ideas of the theory is that the cerebrum has limited control capacity and, therefore, there is a limit to the number of EMs that can be combined into a single motion. Not only that but also the speed and accuracy of a complex movement will be affected by the limited attention span of the cognitive apparatus.

This is where the cerebellum comes in. The coupling operation performed by the cerebellum groups EMs frequently executed together into EM clusters. The cerebrum can then control these EM clusters as if they were simple EMs. Consequently, this means that by combining EM clusters with EMs or other EM clusters, the cerebrum can control a larger number of EMs simultaneously and, therefore, execute movements that are even more complex. On the other hand, it can also use the control capacity freed up by the creation of EM clusters to increase the speed of a complex motion or increase its accuracy.

Research has found that the cerebellar cortex is divided into many small compartments whose cells exhibit common properties, denominated microzones [17–19]. The present theory is constructed all around this concept. Purkinje cells from the same microzone inhibit to the same group of cells in the deep cerebellar nuclei. Additionally, climbing fibers seem to synapse with cells within the same microzone.

Mechsner proposes that each microzone controls the execution of a single elementary movement. However, each EM has multiple microzones controlling it. This property allows for refined control of movement, as it is suggested that participation of multiple microzones is necessary to elicit movement.

2.4 Internal Models

It is often suggested that the cerebellum might use internal models for motor control [20–23]. An internal model treats the execution of an action with the system (in this case, the central nervous system) as the controller that commands a plant, the part that performs the action (e.g. an arm). Francis and Wonham first suggested the idea in 1976 [24].

There are two types of internal models: forward models and inverse models. Forward models take a copy of the motor command, which is called the efference copy, and uses it to predict the sensory information that will result from that command. Differences between the expected and the actual sensory input (called reafference) indicate an error that can then be used to adjust the subsequent motor commands [13, 25]. The inverse model receives the desired final position for the plant and outputs the motor commands to be performed in order to achieve it. Forward models and inverse models can be combined in order to design solutions that are more complex.

3 The Computational Model

To implement our basic model of the cerebellum we first needed to choose a problem to solve. We chose to move a cursor between two points in a bidimensional space using a set of simple elementary movements. The function of the model cerebellum would be to learn the trajectory to follow when confronted with different scenarios and execute it automatically with little or no assistance.

The main components of the model are the agent, the environment, the cerebrum and the cerebellum. Both the cerebrum and the cerebellum are capable of moving the agent. The model was implemented using the Python programming language[1].

The model executes two types of runs. During the training runs, the model cerebrum is in control of the agent and the model cerebellum simply observes its choices. During the test runs, the model cerebellum is in control and requests help from the model cerebrum whenever it is unsure of which elementary movement to perform. The model is designed to run a series of training runs followed by a series of test runs.

3.1 The Relative Grid

We needed to give the model a way to distinguish between different contexts and associate elementary movements to them. For this purpose, we implemented a concept we call the relative grid.

We started by creating a special view of the environment where the agent is always at the center. In this view, all possible combinations of agent and goal positions can be represented. We then divide this view with a 3x3 grid, creating the relative grid. Figure 1 illustrates the concept. Each cell encompasses a different region of the relative environment and the model cerebellum can associate elementary movements to them. It can use these associations to attempt to reproduce movement patterns it observed.

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[1] https://www.python.org/

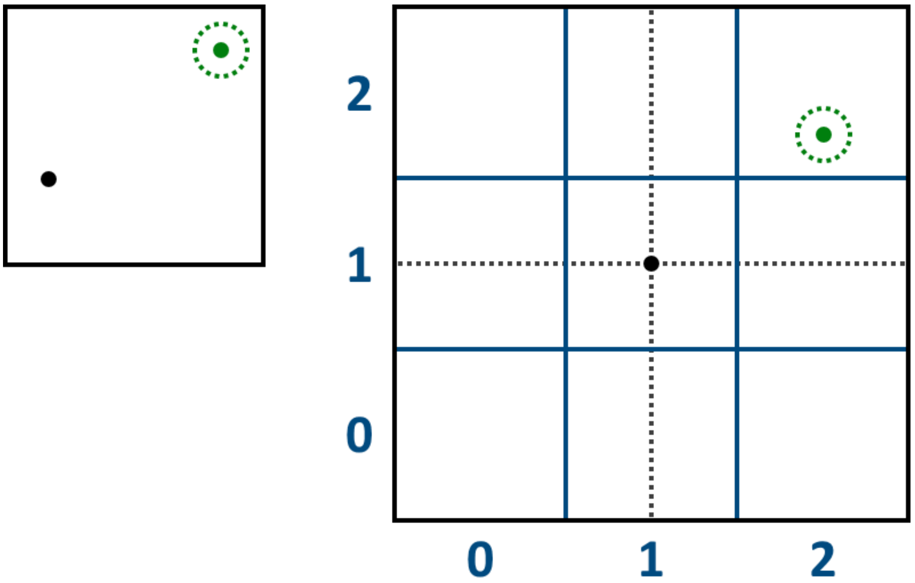

Figure 1: How the relative field and grid are generated. On the left is an illustration of the environment with the agent represented with a black dot and the goal and goal circle represented in green. On the right we have the relative field (in black) obtained from the environment on the left. Then, the relative grid (in blue) is obtained by dividing it into 9 cells. The positions of the agent and the goal are translated so that the agent is in the center. With this setup, the goal is currently in cell (2;2) of the relative grid.

Before each movement, the position of the goal relative to the agent is translated into the corresponding cell of the relative grid. From this perspective, the goal appears to be moving instead of the agent. During training runs, the model cerebellum observes which elementary movement the model cerebrum chooses and associates it with that cell. During test runs, the model cerebellum chooses the appropriate elementary movement to perform according to the observations it made and the associations established.

The model can increase the resolution of the grid in order to allow smaller adjustments to the movement trajectory, which might help the agent move closer to the goal. It does this by dividing each cell into 9 new cells. To conclude the new resolution the knowledge obtained with the previous resolution must be carried over. For this task, we thought of two strategies. We select which strategy to use when we start the model and it is used for all runs.

3.1.1 Zoom Strategy

The zoom strategy copies the observations done in one cell to all the new cells it was divided into.

3.1.2 Tile Strategy

This strategy creates a tiling pattern using the lower resolution and its knowledge as a tile.

3.2 The Agent's Movement

We defined four different elementary movements that can be executed by the agent in order to move towards its current goal. The four movements are: up, down, left and right. The environment is a bidimensional rectangular plane and the agent moves in the direction of its vertical or horizontal axis.

The agent's movement is tied to the current grid resolution. The distance travelled with each elementary movement is the distance between the center points of two adjacent cells. As the resolution increases, the distance travelled becomes smaller allowing for finer adjustments to the trajectory.

3.3 The Goal

The goal is a circle with a small radius and its position is generated randomly for every run. If the agent reaches this circle then the model considers the goal was reached.

The center position of the circle is translated into the cell of the relative grid that contains it for the purpose of helping the model establish the current context and select the appropriate elementary movement to perform.

3.4 The Model Cerebrum

The role of the cerebrum in this model is to act as a teacher for the cerebellum during the training runs. The model cerebrum controls the agent, choosing which elementary movements it should perform at a given moment, and the model cerebellum observes its actions, learning how it should behave.

The model cerebrum checks the current position of the agent relative to the goal and chooses an elementary movement that would move it closer to it. When more than one elementary movement is viable it chooses one of them randomly. This means that the resulting trajectory can be very different each time the same start and end positions combination is presented.

A training run ends successfully whenever the agent reaches the goal circle. If both the agent and goal are in the same cell of the relative grid but the agent is not inside the goal circle then the resolution is increased. This allows the model cerebrum to guide the agent closer and closer to the goal.

3.5 The Model Cerebellum

During the training runs, the model cerebellum observes as the model cerebrum moves the agent on the environment and creates associations between the elementary movements and the cells of the relative grid the goal goes through.

During the test runs, every timestep the model cerebellum decides which elementary movement to perform based on what it learned during the training runs using a movement selection strategy. We implemented four strategies. The strategy to use is selected when we start the model and it is used for all runs.

Whenever the model cerebellum is unable to make a choice using its current knowledge, it asks the model cerebrum to intervene. It will then observe what the model cerebrum does and updates its associations in the relative grid. In the following timestep, the model cerebellum regains control of the agent.

A test run ends successfully whenever the agent reaches the goal circle. If both the agent and goal are in the same cell of the relative grid but the agent is not inside the goal circle then the resolution is increased. This allows the model cerebellum to guide the agent closer and closer to the goal.

3.5.1 Weighted Random Strategy

The model cerebellum selects an elementary movement at random but the probability of a movement being chosen depends on how frequently it was observed in the current context. Elementary movements observed more often are more likely to be selected.

3.5.2 Highest Percentage Strategy

In this strategy, the most observed elementary movement for a given context is executed.

3.5.3 Confidence Threshold Strategy

A confidence threshold is set. The model cerebellum executes an elementary movement if its percentage of observations in the current context beats the threshold. All elementary movements that beat threshold are executed and combined into a single movement. A threshold of 35% allows two elementary movements to be combined. For instance, combining the ”up” and ”right” elementary movements allows the agent to move diagonally.

3.5.4 Point Threshold Strategy

The previous strategies have the disadvantage that they will select movements that were only observed once for the given context. This led to the model cerebellum sometimes getting stuck moving back and forth between two positions of the environment. The point threshold strategy stops it from making associations prematurely.

While observing the model cerebrum, the model cerebellum adds points to the elementary movement it observes and removes points from all other movements for the current context.

While the model cerebellum controls the agent, all elementary movements that beat the defined point threshold in the current context will be selected. It is possible for multiple movements to beat the point threshold and to be combined into a single movement.

All elementary movements start with zero points in every context of the relative grid and can only increase their score to a defined maximum value. A score cannot go below zero.

4 Experiments

4.1 Setup

We tested all eight possible combinations of resolution update strategies and movement selection strategies. To evaluate the performance of the model cerebellum we selected three measures. The indecision

Configuration	IR (%)	SR (%)	DDP (%)
Zoom + Weighted Random	0.40	99.92	2.50
Zoom + Highest Percentage	0.41	99.52	13.89
Zoom + Confidence Threshold	0.61	99.58	−9.98
Zoom + Point Threshold	48.42	100.00	−1.23
Tile + Weighted Random	0.55	94.52	60.16
Tile + Highest Percentage	0.46	83.42	177.52
Tile + Confidence Threshold	0.76	79.53	61.61
Tile + Point Threshold	53.64	100.00	−4.46

Table 1: Comparison of the different strategy combinations using 1500 training runs. IR - Indecision Rate; SR - Success Rate; DDP - Distance Deviation Percentage.

rate indicates the percentage of steps made with assistance of the model cerebrum for the steps taken across all test runs. The success rate measures the amount of successful test runs compared to the total test runs. The distance deviation percentage indicates how much the distance travelled by the agent deviates from the expected distance. The expected distance is the Manhattan distance that connects the start and goal positions. The performed movement may deviate from this expectation because the model cerebellum may become lost or due to the execution of diagonal movements. We average this deviation for all test runs. The value indicated for this measure is the percentage added or subtracted to the expected distance.

For each strategy combination, we ran 100 test sets. Each test set was composed of 1500 training runs followed by 100 test runs. The environment was a field of 20 by 20 units. For the confidence threshold strategy, the threshold was set at 35%. A timestep limit of 1000 steps was defined for the test runs. The limit was set because the model cerebellum may get lost or stuck because of conflicting movement patterns, mistakes in the implementation or problems with the strategies themselves.

The point threshold strategy was setup as follows. Whenever the model cerebrum selects an elementary movement, the movement earns 2 points for that context. All the other elementary movements lose 1 point for the same context. The point threshold is 20 points and the maximum amount of points that can be accumulated for a context is 50 points. Our intention when selecting these values was to make it possible for two elementary movements to beat the point threshold and allow the agent to move diagonally.

4.2 Results

Table 1 summarizes the results. All tile strategy configurations had a better indecision rate than the zoom strategy configurations. Despite that, it is important to note that having a better indecision rate does not necessarily mean a better chance of reaching the goal. All zoom strategy configurations had a better success rate than the tile strategy configurations.

The point threshold strategy was able to achieve a 100% success rate in both configurations. However, it has a very high miss rate when compared with the other configurations. This is to be expected because with the point threshold strategy the model cerebellum must build enough confidence with an elementary movement before using it in a specific context. The agent moves through many distinct contexts between the start and goal positions and the model cerebellum has to make enough observations for each of them in order to stop relying on the model cerebrum.

For the distance deviation percentage, the configuration using the confidence threshold strategy and the zoom strategy had the best performance. On average, it was able to achieve distances shorter than the expectation. The confidence threshold strategy is able to combine multiple elementary movements and move the agent diagonally which gives it an advantage in this measure. The trajectories produced by the point threshold strategy were also shorter that the expected distance on average. This means that the strategy was also successful in moving the agent diagonally.

5 Conclusion

We implemented a model that guides an agent between two points in a two-dimensional space. We train a model cerebellum by observing how the model cerebrum guides the agent. Based on the observations, the model cerebellum makes associations that it can use to reproduce movement patterns.

The model went through many versions and we experimented with many concepts. We tried various strategies to select the appropriate elementary movement, which use the associations made by the model cerebellum. The last one we implemented uses a point system to determine the strength of those associations. Using this system, it is capable of combining multiple elementary movements to produce a new movement. It also solved a problem we had with the model cerebellum making associations prematurely, which would sometimes impede it from guiding the agent to the goal.

In order to refine the movements generated by the model we added a way to change the resolution at which the model cerebellum perceives the environment. We did this by creating a view of the environment centered on the position of the agent. This view starts by dividing the surroundings of the agent into a small number of zones and associating elementary movements to them. The number of zones is then increased in order to make smaller adjustments to the trajectory and guide the agent closer and closer to the goal. In other words, the model cerebellum starts with a general view of the environment, which then becomes more and more detailed.

The final version of the model can learn simple movement patterns and reproduce them to guide the agent towards the goal. However, it still needs be improved in order to make it produce a smooth trajectory and make it able to adapt movement patterns to varying conditions. An idea to make the movement smoother would be to keep the momentum created by an elementary movement between timesteps. The elementary movements would change from simply changing the coordinates of the agent to instead applying an acceleration to it.

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