



# Brain computational primitives

L. Andrew Coward

*Australian National University, Canberra, Australia*  
*andrew.coward@anu.edu.au*

---

## Abstract

The brain uses computational primitives that are analogous with but qualitatively different from the computational primitives used in electronic computer systems. The primary computational primitives of the brain are described, and their implementation in anatomy and physiology discussed. Combinations and sequences of these primitives implement cognitive tasks. Many of the primitives have also been implemented electronically. The brain is a very effective general learning system, and although an artificial general intelligence system will be required to learn a different range of behaviours from the brain, the computational primitives used by the brain are the best available guide to appropriate primitives for such an AGI system.

---

## 1 Introduction

Many computer systems exist that independently control complex combinations of physical equipment in real time. One example is the flight control system on a modern commercial aircraft, that in many situations can fly the airplane for long periods without pilot intervention. There are extensive computer systems that provide ongoing internet services with little human intervention. A complex real time control system must detect conditions in the constantly changing information available to it and associate the detections of different combinations of conditions with the implementations of different behaviours. For example, a flight control system receives information indicating the state of the aircraft and its environment, and detects conditions in this information that indicate the appropriateness of behaviours such as changing the angles of flaps, rudders etc. or the engine power levels.

The hardware that implements such control has the ubiquitous memory/processing architecture. There is a primary separation between hardware that performs instructions (for example, the CPU) and hardware that performs data read/writes (for example, various memories). The two types of information process form the basis for designing the features of the system in a way that can be implemented on the hardware.

The computational primitives of an electronic system are thus instructions and data read/writes on various levels of complexity. For example, the instruction set of a general purpose CPU includes instructions like *add*, *multiply*, and *branch*. Other instruction sets may be used to control screen displays, such as *plot\_point* or *plot\_line*. Memory operations are supported by primitives like *fetch\_and\_store*, *compare\_and\_swap* etc. All these types of primitives are implemented by different combinations of transistors and other components on CPU, memory, and graphics interface integrated circuits. The software that defines the system features accesses these primitives via the compiler. The set of primitives can vary between different computer systems, and the same group of features could be implemented by different sets, although some sets may implement a given set of features more effectively in terms of factors like execution speed.

The human brain also controls a complex combination of “equipment” in real time. This “equipment” includes the body but also includes the brain itself. However, there is a major difference between a computing system and the brain. In a computing system the conditions, behaviours and associations between them are specified by an external designer, while in the brain they are largely specified heuristically from experience. This difference results in a qualitatively different “hardware” architecture. The two types of information process ubiquitous in the human brain are condition definition/detection and behavioural recommendation [Coward 1990]. There is a primary separation between cortex-like physical structures that perform condition definition/detection processes and subcortical structures that perform behavioural recommendation processes [Coward and Gedeon 2009]. In computing systems the memory/processing architecture is created by design. For brains, natural selection results in a strong tendency towards the cortex/subcortex architecture in all species in which a complex range of behaviours must be learned by experience [Coward 2001; Coward and Gedeon 2009; Coward 2013]. The pressures toward this architecture include the natural selection advantages of a species that can learn a given set of behaviours with fewer resources (like neurons) and of a species that can learn new behaviours without damaging the performance of previously learned behaviours [Coward 2001].

There is a range of “computational” primitives in the brain that implement different information processes of the condition definition/detection and behavioural recommendation types. Although there could be other primitives that could support the learning of a complex combination of behaviours, these brain primitives are a good starting point for the design of artificial general learning systems

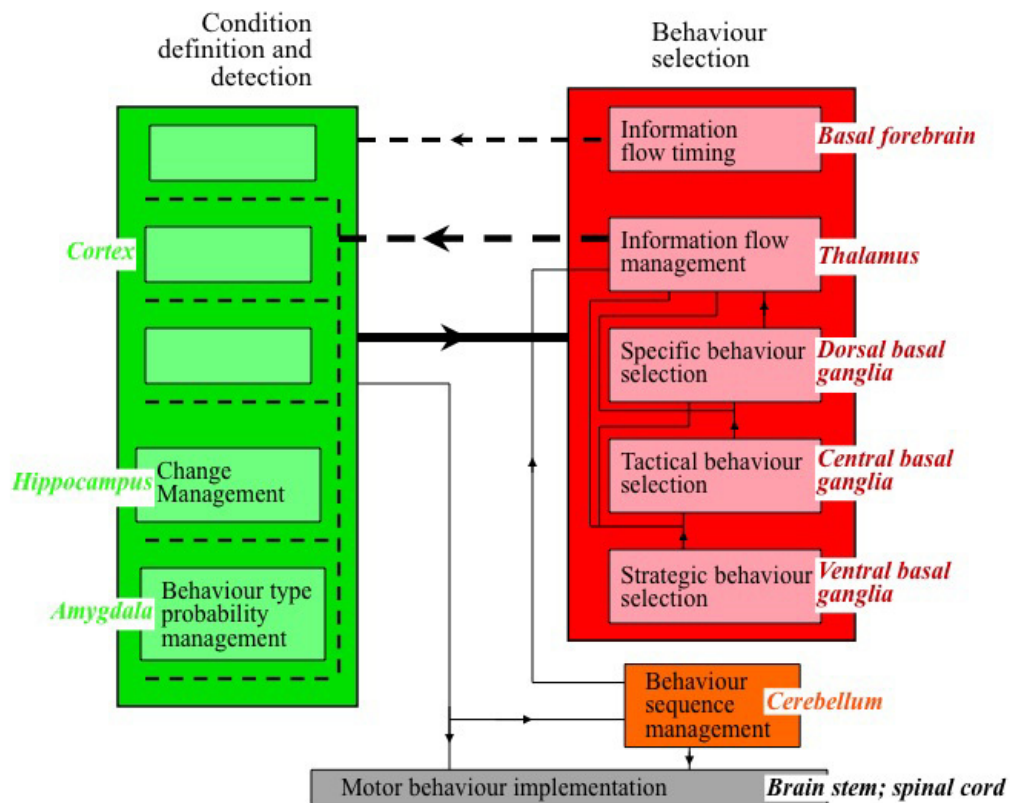
## 2 The Information Architecture of the Brain

As illustrated in figure 1, cortex-like and subcortical structures are both separated into substructures that perform different types of processes of the primary types [Coward 2013]. At the highest level, cortex-like structures define and detect conditions. It is important to note that definition and detection are entangled, there is no detection without definition, and no definition without detection. Behaviourally relevant groups of conditions are called receptive fields, where a receptive field is detected if a significant proportion of the group is detected. The definition of “significant” may involve a complex integration process. To a degree, the behaviours available to the brain are specified in advance. There are muscle movement behaviours that at a detailed level are largely specified by the available muscles. However, the specific combinations and sequences of muscle movements required, for example, by walking or speaking must be defined heuristically.

In a computing system, conditions are unambiguously associated with behavioural commands (i.e. instructions) by the designer. In a complex learning system like the brain, conditions and receptive fields are defined heuristically. Receptive fields therefore change over time. If one receptive field was associated with an unambiguous behavioural command, subsequent changes to the field could mean that when detected later the associated behaviour was inappropriate. For this reason, receptive field detections can only be associated with behavioural recommendations, and to ensure

high integrity an accepted behaviour must be recommended by many different receptive field detections. Furthermore, to economize on condition detection resources, any one receptive field will need to recommend many different behaviours, although the recommendation weight may be different for each behaviour.

Hence within the subcortical structures the basal ganglia receives cortical receptive field detections and associates each field with a set of recommendation strengths in favour of many different behaviours. At each point in time the basal ganglia determines and implements the most strongly recommended behaviour. Within the basal ganglia, different physical components correspond with different specific behaviours. The recommendation strength of a cortical receptive field detection in favour of a behaviour is the weight of its input to the component corresponding with that behavior. There is a competition between different recommended behaviours to make a selection. The actual implementation of a behaviour is generally a release of information into the cortex (in the case of an attention behaviour), out of the cortex (in the case of a motor behaviour) or between different cortical areas during cognitive processing. The detailed management of these releases is performed by the thalamus.



**Fig. 1.** The information architecture of the human brain

Different cortical areas detect fields of different types, where any one type is effective for recommending different kinds of behaviour. Some important kinds of behaviour are strategic, tactical and specific. For example, a musician may select the strategic behaviour of performing at a particular time and place. He may select the tactical behaviour of performing a particular piece of music with

particular instruments. Finally, he may select specific behaviours that include manipulations of the instrument. The selection of a strategic behaviour limits the range of appropriate tactical behaviours and so on. However, one receptive field does not correspond with one behaviour on any level. Rather, receptive fields divide up experience into “similarity circumstances” in such a way that the different sets of fields detected in response to a situation in which one behaviour is appropriate are sufficiently similar to each other and sufficiently different from the sets detected in response to situations in which other behaviours are appropriate that it is possible to assign recommendation strengths that result in high integrity behaviour selections.

Consequence feedback following a behaviour can change the weights that recently recommended the behaviour. Such weight changes have a major impact on performance, and are therefore themselves behaviours which must be recommended by appropriate cortical receptive field detections and accepted or rejected by the basal ganglia. Unlike most behaviours, such reward behaviours are implemented back into the basal ganglia to change recommendation weights. Reward behaviours must themselves be rewarded in appropriate circumstances. Such changes to the recommendation weights in favour of reward behaviours can have a very large impact on brain behaviour, for example leading to addiction. Hence the management of such behaviours is carefully regulated. For example, an appropriate reward for a strategic behaviour may not be appropriate for rewarding tactical or specific behaviours, but may be appropriate for rewarding the behaviour of rewarding such tactical or specific behaviours. In the earlier musician example, applause at the end of a concert may be appropriate for rewarding the strategic behaviour of selecting the time and place of the performance, but will generally not be appropriate for rewarding the selections of every individual piece of music or every individual finger movement while playing. However, applause at the end of the concert may be appropriate for rewarding the behaviour of rewarding the tactical behaviours of selecting pieces of music. Applause at the end of one piece may be appropriate for rewarding the selection of the piece and also for rewarding the behaviours of rewarding individual finger movements.

Reward feedback cannot be used directly to change receptive field definitions. Consequences are specific to recent behaviours, but receptive fields recommend wide ranges of behaviours. Hence using consequence feedback to guide receptive field changes will generally do more harm than good: the receptive field definition may be improved for the recent behaviour, but will generally be made worse for all the other behaviours it recommends. There is one exception to this limitation on the use of consequence feedback that is discussed below.

Furthermore, although receptive fields are defined heuristically and must therefore change over time, such changes may reduce the integrity of all the recommendation strengths acquired prior to the changes. Hence receptive field changes are also behaviours which must be recommended by receptive field detections and accepted or rejected. However, receptive field change recommendations are accepted or rejected by the hippocampal formation, based on recommendations provided by receptive field detections in some cortical areas closely connected with the hippocampus. Such changes must only occur if really necessary, and the changes must be as small as possible to limit undesirable side effects. Hence receptive field changes only occur if too few fields are being detected to support a high integrity behaviour selection, and changes are made to fields that are not being detected but that could be detected with a very slight change. Changes are implemented by addition of currently present conditions to the existing group that defines a field. Changes are temporary unless additional receptive fields are detected that recommend prolongation of the change. Such prolongations can be for intermediate periods of time or long term. This change algorithm, called receptive field expansion, has the advantage that the receptive field will tend to be detected in any exact future repetition of past circumstances in which it was detected. One exception to expansion is that if the receptive field is detected too often, its value for discriminating between circumstances in which different behaviours are appropriate is reduced. In this situation the overall threshold is increased to reduce detection frequency while leaving the relative contributions of individual conditions unchanged.

It is possible for consequence feedback to be used indirectly to influence receptive field changes. Suppose that a specific group of receptive fields is often detected at the same time, the detections result in the same behaviour, but the consequence feedback is sometimes positive and sometimes negative. The implication is that the receptive fields are not discriminating between circumstances with significantly different behavioural implications. Receptive fields detecting such contradictory consequence feedback could recommend that when the group is next detected, receptive field changes take place even if enough fields are already being detected. Eventually, the changes should result in discrimination between the circumstances being confused.

The basal ganglia must select a behaviour most of the time, but must not select multiple incompatible behaviours such as moving the same limb in two different directions at the same time. However, it may be appropriate to select an attention behaviour, a motor behaviour, a thinking behaviour and a reward behaviour all at the same time. Hence there can be weaker competition between behaviours that are compatible with each other. Receptive field expansion behaviours occur independently of any other behaviour types and competition with other behaviours is not required.

The relative probability of different general types of behaviour can also be regulated. For example, some receptive fields may recommend selection of aggressive, fearful, or food seeking behaviours. The implementation of such recommendations is by increasing the probability of detection of receptive fields with recommendation strengths in favour of specific behaviours of the type, and by targetting the basal ganglia components corresponding with behaviours of the type. Various structures including the amygdala detect receptive fields with this recommendation capability.

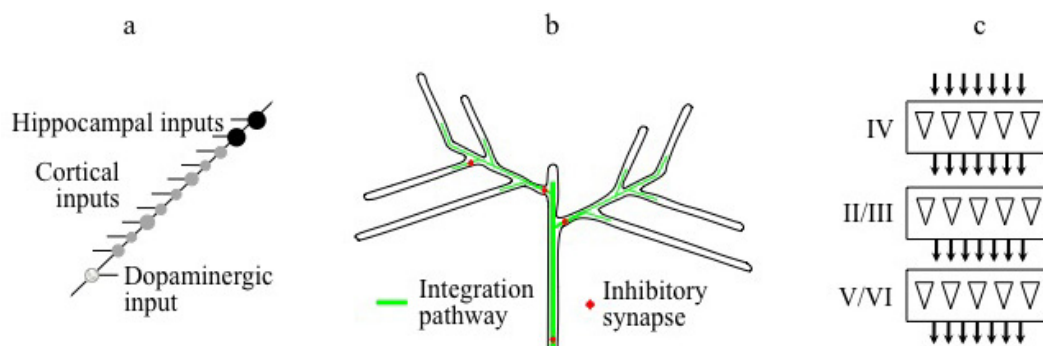
In some cases the relative timing of internal information releases in the brain is critical, and the basal forebrain manages such timing. For example, the hippocampus takes a certain amount of time to determine the most appropriate cortical locations for receptive field changes. During this time, the hippocampus will be active, but its output activity cannot be allowed to actually drive changes. Once the determination process is complete, the basal forebrain provides outputs that trigger release of outputs that change receptive fields in the appropriate locations.

Receptive field detections generate the recommendations required to drive behaviour. Such receptive field detections can be made within current sensory inputs. However, such detections may not always contain the necessary recommendation strengths. For example, when planning for a future situation, the sensory inputs that would be present in that situation are not present in the current sensory environment. However, the required recommendation strengths can be accessed by various mechanisms that indirectly activate the appropriate receptive fields. For example, if a receptive field is not being detected within current sensory inputs, but has often been detected in the past when a number of currently detected receptive fields were also being detected, then that undetected receptive field may have some relevant recommendation strengths. Such a receptive field can be indirectly activated to make its recommendation strengths available. Similarly, if an inactive receptive field changed in the past at the same time as a number of active receptive fields, it may also have currently relevant recommendation strengths. Indirectly activated receptive fields could in turn lead to indirect activation of other receptive fields.

These indirect activations could lead to a chaotic pattern of receptive field activation. Indirect activations must therefore also be behaviours that are recommended by receptive field activations, accepted or rejected by the basal ganglia, and rewarded as appropriate as a result of other receptive field activations. Furthermore, detections of directly activated receptive fields must be separated from indirectly detected receptive fields. For example, a field must not be detected on the basis of a proportion of direct conditions and a proportion of indirect conditions that separately would not reach the threshold for field detection.

Sometimes a sequence of behaviours in a specific order may be appropriate. For example, there are sequences of muscle movements required for walking. Such sequences could be managed by detecting receptive fields in the cortex and determining predominant recommendation strengths in the basal ganglia prior to each behaviour in the sequence. However, once a sequence has been learned,

greater speed and accuracy can be achieved by recording the sequence in the cerebellum. The sequence is then selected as a whole by the basal ganglia, but executed without the need for reference to the basal ganglia between each behaviour.



**Fig. 2.** Condition definition/detection by pyramidal neurons. (a). Groups of cortical inputs on a terminal dendritic branch define a condition. Hippocampal inputs encourage expansions to the condition. Dopaminergic and other inputs manage the length of time a change will persist. (b). Condition detections by different terminal branches are integrated by a complex algorithm by the dendritic tree. (c). Cortical columns with three major layers of pyramidal neurons and a predominantly vertical direction of information flow generate the information needed to manage receptive field changes.

### 3 Processing Primitives and their Implementation in the Brain

There are a number of processing primitives implemented in the brain to support the architectural processes described in the previous section. Some of these primitives are physically located within one anatomical structure, others are implemented across multiple structures. The major primitives will be described in turn.

*P1. Condition definition/detection primitive:* A condition is defined by a terminal branch of a pyramidal neuron dendrite. As shown in figure 2a, a branch has three types of input synapses. One type is from other cortical pyramidal neurons. This type defines and detects the branch condition. The synapses have different weights, and the condition detected by the branch includes the range of circumstances in which the total weights of synapses currently receiving inputs is greater than the branch threshold. If a branch detects a condition and that detection results in detection of the neuron receptive field, the synaptic weights of the synapses that contributed to the condition detection are slightly increased. In other words, the range of circumstances in which the condition will be detected in the future is slightly expanded. This expansion decays back to the original state unless other signals are received. The second type of input comes from a range of brain structures including the midbrain dopamine neurons. If these synapses receive inputs soon after an expansion, the time period over which the expansion persists is prolonged, in some cases indefinitely. The third type of input comes from the hippocampus via cortical areas associated with the hippocampus. If the hippocampus determines that receptive field expansion is appropriate for the neuron, these synapses are active. If the total weight of the regular cortical inputs is less than the threshold for the branch, the support of active hippocampal inputs may result in the threshold being exceeded. If the neuron then detects its receptive field, the weights of the cortical synapses is increased, expanding the branch condition even though it could not have been detected without the hippocampal inputs.

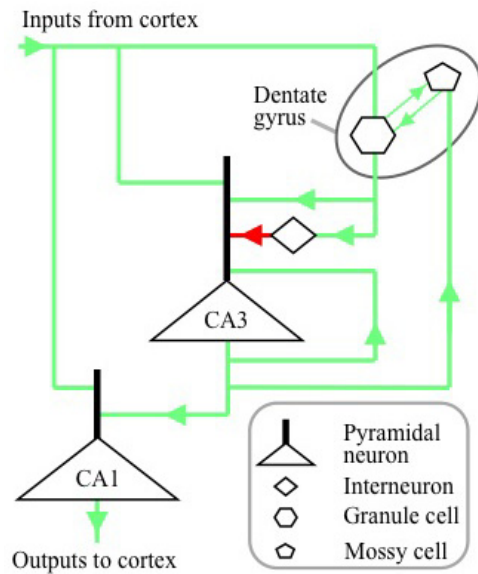
*P2. Receptive field definition/detection primitive:* A receptive field is defined/detected by a cortical pyramidal neuron. Each branch condition is detected separately, and indicates detection by injection of

potential deeper into the dendrite. This potential propagates across the dendrite as shown in figure 2b. This propagation signal decays unless reinforced by combination with potentials from other branches, and can be blocked at different points by signals arriving at inhibitive synapses. If an adequate propagation signal reaches the axon hillock where the axon leaves the neuron, the detection of the neuron receptive field is indicated to target neurons by an action potential along the axon. The integration algorithm defined by the strength of the propagation paths and the location of inhibitive signals can therefore be complex. The algorithm is defined by the branch conditions and the integration process. A very simple version would be that the receptive field is detected if more than a given proportion of the conditions is detected. A more complex version would be if the potential injected by a branch was larger if the total synaptic inputs to the branch were significantly above the threshold, and this larger injection contributed more strongly to receptive field detection. A yet more complex algorithm would be if some combinations of branches contributed more strongly to receptive field detection than others.

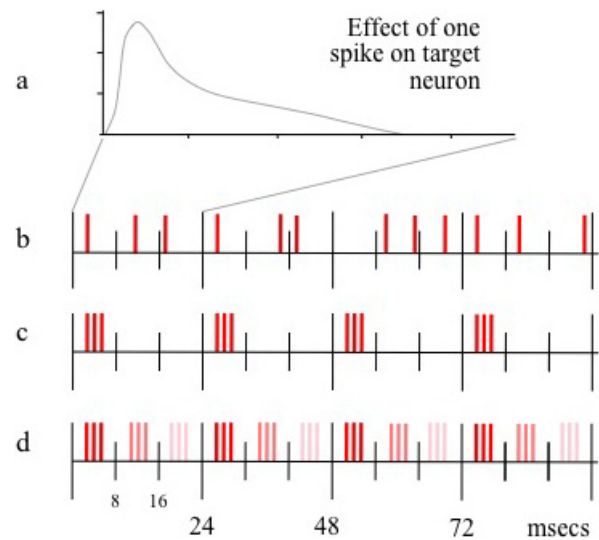
*P3. Receptive field change recommendation primitive:* In order to manage receptive field recommendations, groups of pyramidal neurons with similar receptive fields are collected into columns with several layers as illustrated in figure 2c. The predominant pattern of connectivity in a column is that inputs arrive in layer IV, neurons in layers II/III receive inputs from layer IV, and layers V/VI receive inputs from layers II/III and produce column outputs. These column outputs are the receptive field detections that generate most types of behavioural recommendations. If the column is not producing any output detections, but there are quite a lot of detections in layers II/III, the implication is that relatively small receptive field expansions in layers V/VI would result in column outputs. Layer II/III outputs can therefore recommend receptive field expansions in the column.

*P4. Receptive field change for enhanced discrimination primitive:* Reward feedback cannot be used directly to guide receptive field changes. However, receptive field detections in an area that recommends behaviours can be combined with receptive field detections in an area that receives sensory input from the body following behaviours. These combined receptive fields will correspond with groups of receptive fields often active at the same time that were followed by similar behaviours. These receptive fields can be given recommendation strengths in favour of increased receptive field expansions in the area that recommends behaviours. The expansion recommendation strengths are increased by negative rewards following detections. The overall effect is that if detection of the same group of columns is often followed by the same behaviour and then followed by negative rewards, there will be a greater tendency for receptive field expansion in that group in the future. The implication is that if reduction in recommendation weights in favour of the behaviour is not succeeding in eliminating the negative rewards, the weights must also be increasing as a result of positive rewards. In other words, the same behaviour following detection of the same receptive fields must sometimes be rewarded positively, sometimes negatively. The receptive fields must therefore have inadequate discrimination between circumstances with different behavioural implications. Additional expansions when these receptive fields are detected in the future increases the probability that new receptive field detections will occur that can discriminate between the circumstances.

*P5. Receptive field change behaviour selection primitive:* The selection of the appropriate columns for receptive field expansion involves three factors. Firstly, there must be no expansion unless the degree of current detections is below some minimum level. Secondly, the receptive field of a column can only expand if it is already close to being detected. Thirdly, if within the group of columns close to detecting their receptive fields, there is a subset that expanded their receptive fields in the past at the same time as a number of columns that are currently already detecting their fields, that subset should be favoured for expansion. Receptive fields corresponding with internal activity of groups of cortical columns that expanded their receptive fields at the same time are defined/detected in the three cortical areas associated with the hippocampus. The hippocampus proper receives inputs from these areas and selects the appropriate columns within which receptive field expansions will occur [Coward 2010].



**Fig. 3.** Receptive field change behaviour selection by the hippocampus.



**Fig. 4.** Frequency modulation mechanism for managing release of cortical activity.

Within the hippocampus proper there are neurons with receptive fields corresponding with internal activity in very large groups of cortical columns that have tended to expand their receptive fields at similar times in the past. Similar fields of this type are possessed by pyramidal neurons CA3 and granule cells in the dentate gyrus. In CA1, the receptive fields correspond with internal activity but no output activity in similar large groups of cortical columns. As illustrated in figure 3, within the dentate gyrus there is a positive feedback loop with mossy cells exciting granule cells and vice versa. Within CA3 there is a positive feedback loop with pyramidals exciting many other pyramidals. There is a positive feedback loop between CA3 pyramidals and granule cells via mossy cells. Finally there is an inhibitory link via interneurons from granule cells to CA3 pyramidals. For low mossy cell activity, the excitatory link is stronger, but as mossy cell activity increases, the inhibitory link overpowers the excitatory link. Outputs of CA3 go to CA1, and from CA1 to the cortex to drive receptive field expansions.

The operation of this primitive is as follows. Inputs from across the cortex arrive at CA3 pyramidals and dentate gyrus mossy cells. If there is little novelty in the current cortical circumstances, there is strong input from the cortex, strong mossy cell activity, strong inhibition of CA3 activity, weak output from CA3 to CA1, and no output from CA1 to the cortex. There are therefore no receptive field expansions. If there is novelty in the inputs to some cortical areas, mossy cell activity is a little weaker. There is some net excitatory input to CA3 neurons corresponding with cortical regions that have less than minimum level of receptive field detections. Activity develops in CA3. The feedback within CA3 means that this activity is concentrated in pyramidals corresponding with groups of cortical columns with strong internal activity. These CA3 pyramidals target CA1 pyramidals with receptive fields made up of similar groups of cortical columns but with internal activity discounted by the degree of column receptive field detections. Outputs from CA1 drive receptive field expansions in columns that feature in many of the groups.

*P6. Receptive field detection limitation primitive:* To prevent an excessive degree of receptive field detections in any given situation, there is inhibitive feedback via interneurons within and between



columns. Interneurons generally target pyramidal neurons in the same column and receive inputs from the same column and sometimes from other columns in the same area.

*P7. Indirect receptive field activation primitive:* To avoid inappropriate receptive field detections, the conditions making up the circumstances in which a receptive field is directly detected within current sensory input must be separated from the conditions making up the circumstances in which a receptive field is indirectly activated on the basis of past temporally correlated activity. On cortical pyramidal neurons, direct receptive field conditions are located on basal dendrites, and indirect field conditions on apical dendrites.

*P8. Long term threshold modulation primitive:* Each time a neuron detects its receptive field (i.e. fires) it releases a neurotransmitter called BDNF. If the neuron fires frequently, BDNF concentration builds to a level that reduces all excitatory synaptic weights on the neuron by the same proportion. Hence the detection threshold for the receptive field is increased while retaining the relative weights of all conditions.

*P9. Provisional connectivity management primitive:* The appropriate cortical connections for defining conditions and basal ganglia connections for defining recommendation weights are not “known” by the brain in advance. Hence provisional connections must be defined and used if required. Such provisional connectivity can only be established randomly, but the cost of connectivity is reduced if a bias is placed on the random selections in favour of connections more likely to be useful. The criterion for “more likely to be useful” is frequent simultaneous activity in the past, with the more distant past having a smaller (but not negligible) relevance than the more recent past. The brain therefore performs a rapid partial rerun of past experience, with a bias in favour of the more recent, and uses the rerun to identify provisional connections more likely to be useful for recording information during future experience. To avoid confusion, the brain is taken off-line during this connectivity process for a period called sleep.

*P10. Short term threshold modulation primitive:* The number of conditions required to detect a receptive field can be modulated by inputs to a cortical pyramidal neuron. Such inputs are generated by various structures including the amygdala, hypothalamus, and the locus coeruleus and Raphe nucleus neurotransmitter distribution systems.

*P11. Information release primitive:* Release of information is managed using primitives that implement a frequency modulation mechanism. This mechanism can be understood by consideration of figure 4. One condition defining input to a pyramidal neuron injects a potential that rises and decays as shown in figure 4a. The majority of the effect is therefore within a period of less than 5 msec. Unless two inputs arrive on a terminal branch within 5 msec of each other, they will not reinforce each other significantly. Hence for the detection of a condition, numerous inputs must arrive within the same 5 millisecond window. Suppose time is divided up into time slots slightly longer than this 5 msec window as illustrated in figure 4b. Regular firing of pyramidal neurons is relatively random in time, and too few inputs to one branch will arrive within the same time slot to result in condition detection. However, if as illustrated in figure 2c, a frequency modulation in the EEG gamma band with a 24 msec (i.e. three time slot) period is imposed on the inputs, the result is concentration of inputs into the same timeslot in each period. The inputs within each such timeslot reinforce each other, making condition detection in response to essentially the same input information much more likely. Hence in general, unmodulated inputs will have little effect, but modulation will result in strong downstream condition and receptive field detection. This primitive is implemented by interneurons that tend to fire at the modulation frequency. Some of these interneurons are located in the thalamic reticular nucleus (TRN) located between the thalamus and cortex. The thalamus implements behaviours by triggering activity in these interneurons, which impose the modulation on thalamic neurons that project to the cortex, and through them on cortical pyramidals, partially through cortical interneurons that also tend to fire at the modulation frequency.

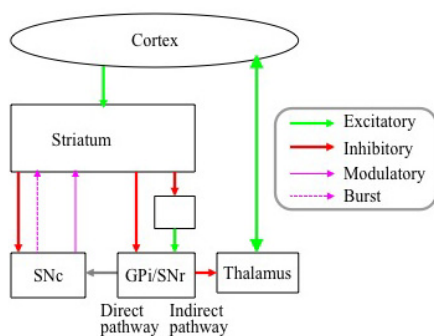
*P12. Information segregation primitive:* The same frequency modulation mechanism can be used to support receptive field detections in several different sources of information. For example, it is

possible to remember several different objects at the same time. Inputs to a neuron from different sources can be segregated into different timeslots as illustrated in figure 4d. Receptive field detections will appear in different output timeslots. This result can be achieved by placing modulations at the same frequency but different phase on the different input source populations.

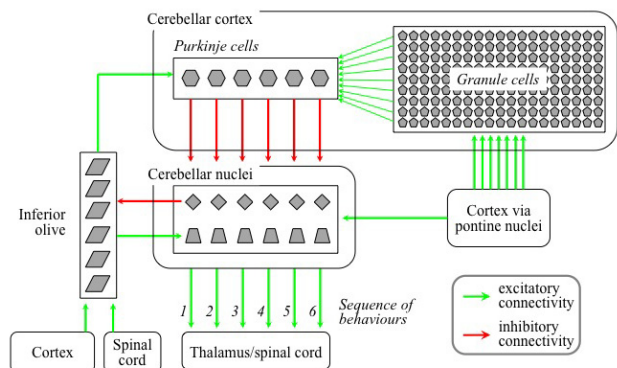
*P13. Information release timing primitive:* When the competition process is under way in the hippocampus, many neurons are active and their outputs will therefore be active. However, these outputs must not be allowed to drive receptive field expansions until the competition process has reached a conclusion. Thresholds are therefore set at a level where outputs from the hippocampal system must be even more concentrated than by the gamma band mechanism. The required concentration is achieved by placing an 8 Hz (theta band) modulation on top of the gamma band once activity in CA3 has stabilized. When the gamma and theta band modulation peaks coincide, there is an even higher concentration of inputs. The thresholds are set so that receptive field expansions will only occur at such higher concentrations.

*P14. Information prolongation primitive:* Some receptive field detections can recommend the prolongation of the activity of other receptive field detections.

*P15. Total recommendation weight determination primitive:* As shown in figure 5, within the basal ganglia, the striatum receives most cortical inputs. Striatal neurons correspond with individual behaviours, and the weight of a cortical input is the recommendation weight of the receptive field in favour of the behaviour. The output of the striatal neuron therefore corresponds with the total recommendation weight in favour of the behaviour.



**Fig. 5.** Primary behaviour selection connectivity



**Fig. 6.** Cerebellar connectivity implementing one frequently used sequence of behaviours.

*P16. Selection of one and only one behaviour primitive:* The competition to determine behaviour selections is also illustrated in figure 5. There is a constant base inhibition of the thalamus by the GPi/SNr in the basal ganglia, so that at base level all behaviours are inhibited. Striatal neurons corresponding with behaviours inhibit the GPi/SNr neurons corresponding with the same behaviours over the direct path, reducing the inhibition on the thalamic neurons corresponding with the behaviours and therefore encouraging the release of cortical outputs corresponding with implementation of the behaviours. Over the indirect path via intermediate structures, other striatal neurons corresponding with behaviours excite GPi/SNr neurons corresponding with all behaviours except their own, thus inhibiting all those other behaviours. Hence within the GPi/SNr there is effectively a competition to determine the behaviour with the largest current recommendation weight.

If the degree of activity in the GPi/SNr indicates that more than one behaviour is being selected, this higher activity results in the SNc sending a signal to the striatum that changes the background

level of dopamine in a way that reduces the direct path activity relative to the indirect. If activity in the GPi/SNr is low, the SNc signal has the opposite effect. This SNc feedback loop therefore ensures that in general one but not more than one behaviour is selected. Where multiple behaviours of different types are possible, there is regulation within a type but less regulation across striatal neurons corresponding with the different types.

*P17. Reward primitive:* When a striatal neuron fires, the weights of recently active synapses increase. These increases decay over a period of minutes. If a reward behaviour is sufficiently recommended by the cortex, striatal neurons corresponding with the behaviour generate burst firing of dopaminergic neurons. This burst firing results in prolongation of the recent weight increases, hence increasing the recommendation weights of recently detected cortical receptive fields in favour of the recently selected behaviour. There is an additional primitive that prevents excessive growth of individual recommendation weights that will not be discussed here.

*P18. Behaviour sequence recording primitive:* As shown in figure 6, there are groups of neurons in the cerebellar cortex that correspond with sequences of behaviours that are often utilized in the same order. For each such sequence there is also a group of neurons in the cerebellar nuclei and in the inferior olive nucleus. The neurons in the cerebellar cortex are called Purkinje cells. These neurons have extremely specific receptive fields defined by very large numbers of inputs from granule cells, each granule cell having multiple inputs from the cortex via the pontine nucleus. These very specific receptive fields correspond with precisely defined circumstances in which it is appropriate to initiate one behaviour in the sequence. Different neurons in the cerebellar nuclei target either the thalamus or the spinal cord to drive different behaviours in the sequence. Once the sequence is initiated, the Purkinjes fire in sequence to drive the sequence of behaviours. If the timing of one behaviour is slightly inappropriate, an inferior olive neuron fires resulting in a slight change to the Purkinje receptive field which generally improves its correlation with the appropriate moment for its behaviour.

It can be demonstrated that sequences and combinations of these primitives implement the different major types of memory observed in human beings [Coward 2005] and a wide range of other cognitive tasks [Coward 2013]. The effectiveness with which learning can occur is considerably increased by biases placed upon initial resource configurations by genetic information. For example, genetic information specifies the number of cortical areas and the initial connectivity between the areas, thus specifying the information content and range of complexity of the receptive fields in each area. Genetic information also specifies the initial connectivity between cortical areas and regions of the basal ganglia, thus specifying the types of recommendation strengths that will be possessed by different receptive fields. Although the starting points are genetically defined, the actual receptive fields and recommendation weights are defined heuristically. Furthermore, primitive *P9* could add a proportion of connectivity from outside the initial limits.

## 4 Electronic Implementation of the Primitives

Simple versions of many of the primitives have been implemented electronically. These implementations have demonstrated the abilities of the primitives to support heuristic definition of receptive fields that can discriminate between situations with different behavioural implications [Gedeon et al 1999; Coward 2009]; to assign recommendation weights in a way that controls interference between early and later learning [Coward et al 2004]; to manage information releases using the frequency modulation mechanism [Coward 2004]; to reduce connectivity requirements using past experience as a guide [Coward 2001]; and to achieve memory phenomena using indirect receptive field activations [Coward 2001].

## 5 Discussion and Future Directions

There are two important sources of information that can be used to guide the design of systems capable of learning complex combinations of behaviours in response to complex environments. Firstly, there are some general architectural constraints that are imposed on the architectures of such systems by practical considerations such as the need to limit information processing resources and the need to learn without interference with prior learning [Coward and Gedeon 2011]. These architectural constraints include the general types of computational primitives required. Secondly, there are the ways in which the brain has implemented the required primitives as described in this paper. These implementations are to some degree specific to the learning problem the brain is solving, but represent the only example of primitives that work in a successful general learning system.

Future work includes more realistic simulations of the individual brain primitives and the interactions between them. Investigation of brain connectivity has the potential to improve understanding of how the brain implements the primitives. For example, the precise way in which information reaches the hippocampus indicating internal column activity discounted in some way for column output activity needs clarification. More realistic simulations based on better understanding of brain implementations will make it possible to scale up electronic systems to learn complex combinations of behaviours in complex environments.

## References

For reasons of space, references to the primary neuroscience literature have been omitted from the current paper. However, an extensive set of such references can be found in Coward [2013].

Gedeon, T. D., Coward, L. A., and Zhang, B. (1999). Results of Simulations of a System with the Recommendation Architecture, Proceedings of the 6th International Conference on Neural Information Processing, Volume I, pp 78-84.

Coward, L.A. (2001). The Recommendation Architecture: lessons from the design of large scale electronic systems for cognitive science. *Journal of Cognitive Systems Research* 2(2), 111-156.

Coward, L. A. (2004). Simulation of a Proposed Binding Model. *Brain Inspired Cognitive Systems 2004*, L. S. Smith, A. Hussain and I. Aleksander, (editors), University of Stirling: Stirling ISBN 1 85769 199 7.

Coward, L. A., Gedeon, T. D. and Ratanayake, U. (2004). Managing Interference between Prior and Later learning. *ICONIP 2004, Calcutta. Lecture Notes in Computer Science* 3316, 458-464.

Coward, L. A. (2005). Accounting for episodic, semantic and procedural memory in the recommendation architecture cognitive model. Proceedings of the Ninth Neural Computation and Psychology Workshop: Modelling Language, Cognition, and Action.

Coward, L. A. and Gedeon, T. D. (2009). Implications of Resource Limitations for a Conscious Machine. *Neurocomputing* 72, 767 - 788.