Chapter 8
The Perception-Conceptualisation-Knowledge Representation-Reasoning Representation-Action Cycle: The View from the Brain

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Abstract We consider new and important aspects of brain processing in which it is shown how perception, attention, reward, working memory, long-term memory, spatial and object recognition, conceptualisation and action can be melded together in a coherent manner. The approach is based mainly on work done in the EU GNOSYS project to create a reasoning robot using brain guidance, starting with the learning of object representations and associated concepts (as long-term memory), with the inclusion of attention. Additional material on actions and internal simulation is taken from the EU MATHESIS project. The framework is thereby extended to the affordances of objects, so that effective action can be taken on the objects. The knowledge gained and the related rewards associated with the representations of the objects involved are used to guide reasoning, through the co-operation of internal models, to attain one or other of the objects. This approach is based on attention as a control system to be exploited to allow high level processing (in conscious thought) or lower level processing (in creative but unconscious thought); creativity is also considered as part of the abilities of the overall system.

8.1 Introduction

The list of faculties to be considered according to the title of this chapter is long, covering as it does most powers of the human brain. So it is natural to consider if it would be possible to shorten the list somewhat. After more detailed consideration, one realises that most of these components are needed for each other. Thus, perception is a crucial entry to the creation of object representations, leading to the formation of concepts, laid down in long-term memory and basic to reasoning. Attention is a mechanism allowing the development, through the basic process of

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attention filtering, of representations in the brain of single objects. Without such simplified representations, it would be very difficult to reason to solve important tasks, such as acquiring a highly rewarding object, such as a grape, by a monkey. Knowledge of objects is acquired by actions on them, such as grasping and eating the grape, so completing the list of faculties in the title of this chapter.

That there is need for inclusion of most of the brain's capacities in a reasoning system is to be expected. Reasoning is one of the highest faculties of the human mind and so would be expected to depend on the majority of the brain's components, even if only minimally. Thus we have to explore the manner in which the human brain is able to generate the amazing reasoning powers it does possess. There are other approaches to such high-level cognitive processes that do not depend on the architecture of the human brain. However, we consider it of value to attempt to use cues from the brain even if we may then discover more efficient ways of achieving some powers based on such an approach; the initial guidance from the brain involves a system that has evolved over a million or so years, so is to be expected to provide a reasonably optimised solution to many of the cognitive tasks under consideration.

It is thereby clear that the faculties used in reasoning have been assembled in an efficient manner in the human brain, as part of general evolutionary competition. We can extend from the human to some lower animal brains, especially to the primate brain. A range of primates are now well known to possess reasoning powers, as are various corvids, especially birds like Betty, the New Caledonian Crow. However, there is still not enough knowledge about the bird brain to be able to build suitably detailed neural architectures based on such knowledge, so we will limit ourselves here solely to primates and their brains.

Not only brains but bodies are also important to consider as part of cognitive processing. Without a body to control and use for a variety of responses, we do not expect much of a cognitive repertoire to be accessible. But it is well known that robotics presently has engineering difficulties over developing a truly all singing, all dancing, all games-playing robot. So in GNOSYS, there was simplification of the actions able to be taken to those enabling movement around an environment (so a wheeled robot) and possessing manipulative skills (grasping, putting down) by a gripper; for that was taken a simple two-fingered gripper.

It is arguable that knowledge and reasoning are the two activities at the highest cognitive level in the brain, so their careful discussion and analysis is of utmost importance. There is much progress in both of these areas, with considerable interaction between them. In this chapter, we will consider in what manner our understanding of the brain is adding to these two intertwined topics. The developments will be considered from both a broad experimental as well as a modelling/theoretical aspect, as well as considering the lower-level components needed to sustain such high-level processing.

Knowledge learning by neural networks is already a vast subject: there are 7.6M items to search on Google under that heading. There are at least 60 specific journals on the subject as well as at least 25 scientific organisations whose annual meetings are dedicated to studying the subject. It would thus be effectively impossible to try to cover the area in complete depth. However, the two approaches mentioned above – the experimental and the modelling/theoretical sides – in which new angles and advances are being recognised as important to move the subject forward and create ever better systems to learn and utilise knowledge. This plethora also holds for reasoning, in which, however, some specific advances have also been made.

In spite of the enormous amount of material available in the research community on these two topics and their neural "infrastructures", by restricting ourselves to brain-based approaches for both topics, we make them both more limited and more specific. Thus, knowledge is to be taken to consist of brain-based codes for the classification of objects and actions to be taken on them, and possible extensions to symbolic descriptors of such codes, as by means of language. However, this latter will not be of primary concern in this chapter (although it will be briefly described), since it requires at least a separate chapter (if not several books) to treat properly. Thus, knowledge is effectively non-linguistically defined, as it would be for most animals below humans and humans in early infancy, unless otherwise stated.

Such a restriction to working at a non-linguistic level might be thought of as a severe limitation on the generality of the resulting discussion. As seen from a cognitive science point of view, only a linguistic approach is appropriate for considering higher cognition. Yet, in the brain, the development and adult use of language rests on an underpinning of processing, which involves a large amount of non-linguistic processing. Direct speech input addresses most directly the speech centres, but even then, there are control components and non-linguistic codes that have to be accessed to give meaning and grounding to the language symbols – be they words, phrases or whole stories.

Seen from a different point of view, the most crucial architectural components of the brain to attain higher cognitive powers – those involving attention control systems, reward and valuation systems and coupled internal models – can be discussed for a range of processes that may or may not involve linguistic codes. This will be clear when we consider thinking as mental simulation, creativity as unattended mental simulation and reasoning as rewarded mental simulation.

We will also consider briefly how knowledge is acquired, especially through adaptive processes of neural network modular systems. Here, there is a large amount of data and modelling on the nature of codes for object and action representations, obtained by suitably causal learning laws going beyond the simple Hebbian law into spike-timing-dependent laws for communication between spiking neurons. Yet again, we will not pursue this very rich area of research in any detail but concentrate more on a global picture of how attention control is involved in learning and how the knowledge at a lower level can be combined into internal models that allow for higher cognitive processing. For without such possibilities, especially of fusing in attention control processes, and the brain-based architectures that may achieve such processing, we cannot attempt to explain higher cognition observable in animals as controlled by the brain. A similar approach will be taken to reasoning (although linguistic aspects will be discussed there more fully in association with logical reasoning).

So what is the basis we will use to attack the problems of higher order cognition in the brain? From the experimental side, there have been advances on the codes used in storing various forms of knowledge in the brain, both those involved with objects and those with actions. However, there is still considerable controversy over detailed neural aspects of such coding. This understanding is important in probing the manner in which attention is built as part of object codes. Such intertwining of simple object/action codes with attention has not been considered as an important part of the development of cognitive processing in the past, but in order to take account of the ability of attention to be focussed efficiently on any distributed object representation, the question as to how this facility arises is clearly crucial. Indeed the need for a system to be able to attend at will to a stimulus in its sensory field must be both fast and accurately employed in any attentive scanning of the environment for enemies or other stimuli warranting crucial fast response to enable survival.

At the same time, it is to be assumed that the attended object representations can be further manipulated in "interior planning". Such takes place in the system's brain, without any necessary action being made exteriorly. In this manner, the system can determine the effects of future actions without exposing itself to possible danger in its environment. This leads to the manner in which possible internal models (forward and inverse model controllers) can be trained so as to suitably use the object and action representation learnt as part of the knowledge basis of the brain.

The manner in which such internal models can be coupled and used for mental simulation must be a natural part of this discussion. Again the manner in which attention enters will be important, where it is to be used in a variety of ways: to prevent distracters from derailing any train of thought being followed, to enhance ongoing thinking and so to speed it up, to enhance the use of suitable rules of reasoning, and so on.

Simultaneously, there is the need to consider how attention can be switched off in following any train of thought. This could then allow creativity to enter through the use of lateral spreading of activity across the regions coding for object and action representations. Attention to relevant stimuli will be relaxed during this process of extended searching through semantic maps for suitable stimuli that may be of interest. Otherwise attention would constrain the search space; without it, the expansion of the space allows analogical reasoning to flourish. Such a process, involving reasoning by analogy, needs a careful discussion so as to develop a suitable architecture to achieve such a mixed level of processing (Table 8.1).

Finally, we need to consider reasoning, a process involving the creation of subgoals and their being followed. We discuss some simple non-linguistic examples of reasoning, especially the two-stick paradigm and how this could be simulated by means of a suitable neural architecture. Extension of this both to a general class of reasoning paradigms as well as to reasoning involving language will considered, although more briefly.

Table 8.1 Comparison between the GNOSYS cognitive architecture and that of other proposed such architectures

Name of cognitive architecture	Perception/ concept creation	Sensory attention	Goal creation	Motor attention	Reward learning	Internal models	Reasoning & "thinking"
GNOSYS	√	√	√	√	√	√	√
Global Workspace	X	X	√	X	√	√	X
Self-directed anticipated learning (SDAL)	X	X	√	X	X	√	X
Self-affecting self-aware (SASE)	X	X	√	X	X	√	X
Darwin Robots (Brain-based devices)	√	√	X	√	√	X	X
Humanoid Robot	X	X	√	X	X	X	X

A tick denotes the presence of the relevant cognitive component; a cross denotes its absence

8.2 The GNOSYS Model

8.2.1 The Basic GNOSYS Robot Platform and Environment

The robot used in GNOSYS was a Pioneer P3AT robot, with a Katana arm, a laser with resolution of 05° and a scan rate of at least 10 Hz. The stimuli in the environment consisted of sets of cylinders and sticks as well as a ball and a cube. Perceptual representations of the various objects was learnt by the software and then used in various active tasks, such as stacking the cylinders on top of each other, and of solving various reasoning tasks with the objects; these task solutions will be described later.

8.2.2 Information Flow and GNOSYS Sub-systems

The physically embodied robot was controlled by a remote software system that was running in a network of PCs. The software was the realisation of the GNOSYS cognitive architecture. The main modules that were present and the high level interactions are shown in Fig. 8.1.

The above modules can be partitioned into four major sub-systems:

- Perception (coarse or fine visual systems, attributes, threats)
- Memory (brain, place map, concepts)

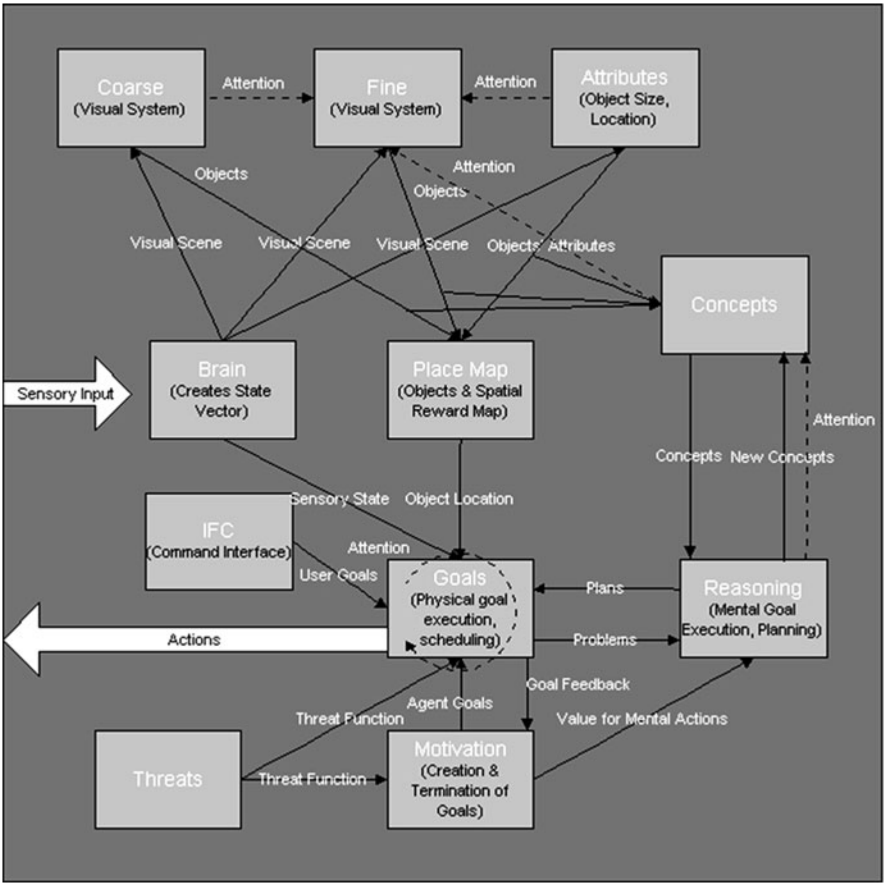

Fig. 8.1 Main components of the GNOSYS brain. The components shown in the figure are described more fully in the text

- Action execution (reasoning, goals, motivation)
- Interface (IFC)

The interface concerns the interaction of the agent with the users and it will not be discussed further here. Instead we will provide brief explanations of the modules of all other sub-systems.

8.2.2.1 Perception

The perception system analyses visual scenes and extracts coloured blobs (defined as a connected region of local intensity and colour different from its surroundings). The system pre-processes the image so as to remove visual noise; the subsequently discovered blobs are sent to the coarse and fine visual scene analysis systems. These provide additional information about the objects, based on the corresponding colour blob.

The coarse visual scene analysis provides object descriptors by using a sparse sampling approach. It sends its output (i.e., the blob descriptors) to the fine visual system for further processing and elimination of false descriptors (which are those interpreted by the software as arising from an object not present in the visual image). The descriptors for each camera are combined for the left and right cameras to produce a single object descriptor before they are exported.

The fine visual scene analysis provides object descriptors using a dense sampling approach, employing the input image for processing and the coarse visual system descriptors for directing attention to the possible objects present. Through attention, false descriptors (those incorrectly implying the presence of a given object) are eliminated. A reduced descriptor set per camera is thereby created. These are then combined across the left and right camera to produce the final fused descriptor set. The threat module uses laser input to track people or other moving agents in space, tracking a set of moving agents over time and providing a simple (linear) prediction of their paths. Its output is a threat map used to determine the threat level of given locations in space.

8.2.2.2 Memory

Brain

This keeps a global state vector for a number of time instances (typically five time-delayed instances of the state vector are kept). The length of each time slot is about 250 ms in real time, which is equivalent to the sampling rate of the laser sensor over a wireless connection. The state vector contains the information produced inside the agent (sensory signals, object descriptors after scene analysis, the set of goals being executed and their status, attention and other low-level hardware/software error events, user goal requests and other necessary information). Such a vector thereby gives a global view of any state in the current or previous time instances.

Place Map

This system keeps two maps internally. The first map is an occupancy map, where found objects are recorded and associated with a specific location. The second is a spatial reward map, enabling the transfer of rewards from specific objects to their spatial location, so as to return a set of probable locations to look for an object when the robot is physically searching for an object. This latter map is needed for when a recorded object is missing from its registered position in the occupancy map. The map also provides memory of rewards associated to places and not just to objects. The contents of the Place Map are updated every time there is visual processing.

Concepts

This stores representations of objects and goals at conceptual level. This information is more concerned with the characteristic properties and general knowledge of the objects. Its contents are used by the reasoning and goal execution processes. The contents are updated after (a) visual processing, (b) reasoning (which can discover and register new "virtual" or imagined objects during reasoning steps), and finally (c) after attempted motor actions on objects in the real world (during goal execution) to establish affordances. These latter affordances are features of objects of importance, allowing them to be manipulated by the system to solve tasks involving the objects (Gibson 1979; Heft 1989; Natsoulas 2004; Young 2006). Virtual objects correspond to either known object classes, but which are not physically present, (i.e., exist only in imagination) or to new concepts of an object (e.g., creating a new longer stick from previous shorter ones; the longer stick is assumed to be a new concept appearing for first time with its own parameters of length, etc).

8.2.2.3 Action Execution

Reasoning

This provides the mechanism, which discovers solution paths from an initial state to a desired state. It takes as input a goal (and its parameters), and the initial state, and then calculates a solution path (if this exists and it can be found). It provides a mental level execution of a goal without taking into account the dynamics of the real world (except that incorporated into the reasoning mechanism, such as the internal models employed in reasoning). It assumes simply a snapshot of the world in the moment of the problem; it then calculates a path using forward model predictions as to the consequences of any potential action (i.e., as in mental simulation). It returns a plan to the Goals module for execution in the real world. When a goal terminates successfully the Goals module provides feedback information in order to update the reward structures of the module.

Goals

This module provides an implementation of the Computational Model for Multiple Goals. These multiple goals are needed in a complex scene since some of them may have to be chosen as subgoals that are attained first, with only the overall goal achieved at the end of the reasoning. This thereby provides a real world execution of the actions of a Plan. The multiple goal manipulation system has been developed as an essential part of the reasoning system (Taylor and Hartley 2007; Mohan and Morasso 2007).

Every action is composed of a set of primitives and sub-plans. Primitive examples consist of requesting a new visual input and scene analysis, moving the robotic arm or the agent's body, etc. Sensory attention, termination conditions and unexpected events are handled at this level. When a plan is executed, typically the corresponding reasoning process is suspended in real time while it waits for the results of an action. When any feedback information is available, such as when an action terminates, fails, or cannot continue execution due to changed environmental conditions, the reasoning process is re-activated and is fed with the current state. A re-plan request is made in an effort to satisfy the original goal before reporting failure of the goal satisfaction. The Goals module takes input from the Motivation System regarding variables that control the lifetime of a goal. It also provides as output the actual implementation of an action plan. As a side effect of the latter, new information may be registered in the system, such as new concepts, location of new objects, new affordances to be established for known objects, detection of novel objects, etc.

Motivation

This module performs a dual function. First, it provides a mechanism that generates new goals, in the absence of any user goal (by activation of newly salient concepts), and second, it evaluates every goal's progress in order to determine its usefulness for the maximisation of the highest-level motivation variable determining the well-being of the agent. The system uses a hierarchical model of drives, which, through their collective dynamics, produce *internal* reward vectors for characterising the progress of a goal and for goal generation. For executing a goal, it outputs variables, which dynamically affect the lifetime of the goal. The system thereby eliminates goals that are not attainable or are not being executed successfully due to loss of any global goal competition.

8.3 The GNOSYS Model Processing Details

8.3.1 The GNOSYS Perception System

The brain basis of visual perception is by means of a hierarchical set of modules modelled on that of human visual perception. In the human brain, information to higher brain sites is carried along the two main visual streams flowing from the thalamus: the dorsal stream, coding for where objects are situated, and the ventral one for what the objects are that are detected at the various sites by the dorsal stream (Milner and Goodale 1995).

Beside the feed-forward flow of visual information in the brain, there is also a feedback of visual attention from higher sites in parietal lobes and the prefrontal cortex to the earlier sites in occipital cortex (Mehta et al. 2000). In this manner, attention control is exerted from the activity stored (for endogenous attention) or it rapidly attains (for exogenous attention) parietal and prefrontal areas. That there is

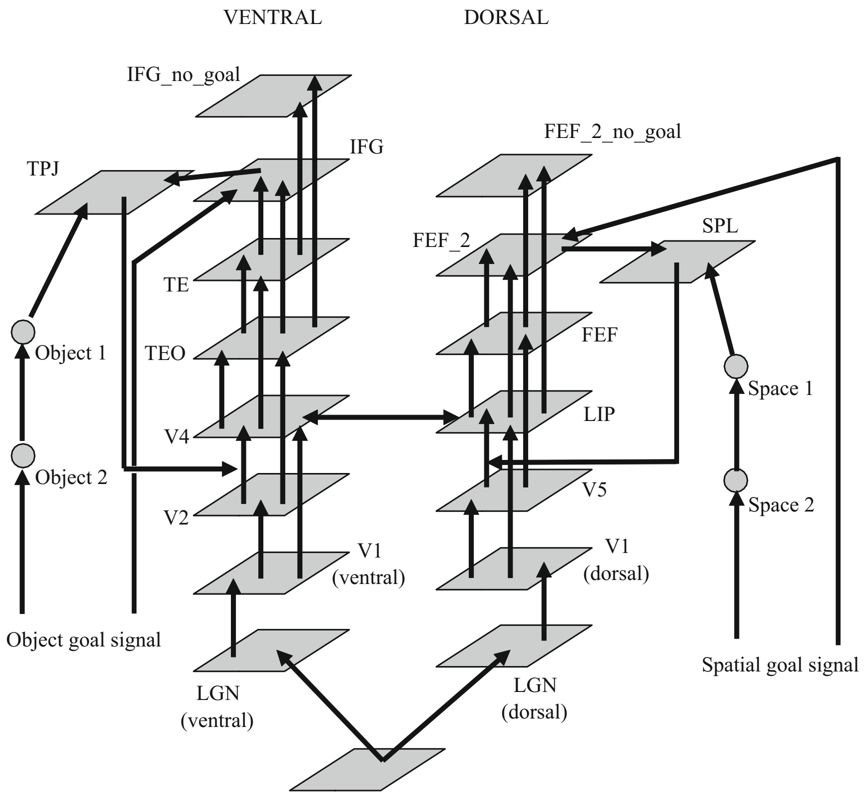

Fig. 8.2 The architecture of the hierarchical neural network

such a division of attention into the control networks in frontal and parietal regions and those regions undergoing attention feedback has also been decisively shown by numerous brain imaging experiments (Corbetta and Shulman 2002; Corbetta et al. 2005; Kanwisher and Wojciulik 2000).

The overall circuitry of the GNOSYS "fine" visual system is shown in Fig. 8.2. The modules have good basis in the brain as arises from many brain imaging and single cell studies, as well as by neuro-architectonic methods (based on different densities of the six cortical cell layers and other features) (Kandel et al. 2000). The GNOSYS software uses a simplified model of this hierarchical architecture, with far fewer neurons and associated trainable synapses.

A schematic of the architecture of visual modules, as used in the GNOSYS system, to generate the hierarchy of feature maps of object representations, is that shown in Fig. 8.2. Input enters at the bottom of the hierarchy and is sent to both the dorsal and ventral components of the geniculate nucleus (LGN), and then to the ventral and dorsal visual streams. It then enters temporal lobe processing in the ventral route (and then to the ventral frontal cortex) and parietal and frontal eye field processing in the dorsal route. Feedback attention signals are generated to these two routes by the TPJ (for the ventral route) and the TPJ (for the dorsal route). An added colour route parallel to the dorsal route, was included in the final processing. Note the reciprocal V4 $\leftrightarrow$ TPJ connection between the two routes, used in moving rewards from the ventral route (so object-based) to the dorsal route. More details of the architecture and its functionality are given in the text.

The above neural network architecture was used in the visual perception/concept simulation in the GNOSYS brain. There is a hierarchy of modules simulating the known hierarchy of the ventral route of V1 $\rightarrow$ V2 $\rightarrow$ V4 $\rightarrow$ TEO $\rightarrow$ TE $\rightarrow$ PFC(IFG) in the human brain. The dorsal route is represented by V1 $\rightarrow$ V5 $\rightarrow$ LIP $\rightarrow$ FEF, with a lateral connectivity from LIP to V4 to allow for linking the spatial position of an object with its identity (as known in the human brain). There are two sets of sigma–pi weights, one from TPJ in the ventral stream, which acts by multiplication on the inputs from V2 to V4, and the other from SPL, which acts similarly on the V5 to LIP inputs. These feedback signals thereby allow for the multiplicative control of attention.

8.3.2 Learning Attended Object Representations

As an infant develops its powers of attending, the period during which it actually does attend to its surroundings grows successively over the weeks and months from its birth. This growth of the time it can attend to the external world is no doubt supported by the growth of joint attention with its carer. This common attention guidance by the carer is expected to allow both the singling out of objects worthy of attention and the subsequent learning of their names. At the same time, the process of joint attention will lead to the infant learning both the object representation and its ability to attend to it.

It is unclear from present analyses of the joint attention process that attention is developed for sensory representations that have already been learnt at an unattended level or if these representations are learnt at the same time as the attention control feedback signals. However, the process of joint learning (by carer and infant) takes place from an early stage of infant development, even before the infant seems to be able to take much notice of its surroundings during its long periods of inattention (these being mainly sleep, especially in the infant's earliest stages). Thus it would be expected that the infant only learns the unattended sensory representations in its environment while it is attending to its surroundings. That it is through these joint attended/unattended sensory representations that are still the main manner of learning is unclear from the present data but will be assumed here. As noted in the recent paper of (Toda 2009), "These findings suggest that joint attention may be the basis for an infant's social and cognitive development".

Certainly, we all know from our adult experience that we learn about new objects while attending to them in our surroundings, both as sources of sensory stimuli as well as providing affordances for present or future manipulations. Thus we take as basic to the learning processes to expand a subject's knowledge base that such an expansion takes place in an attended manner.

We add that automatic responses to objects can be developed as an extension of the learnt processes under attention, so by over-learning (as is well known). Such automatic responses thereby allow sensory attention to be focussed on other areas of experience. An example of this is when gaining one's sea-legs on a ship, or on correcting such automatic processing itself, as in the case of coming back off the ship and having to attend to the non-movement of the surface of the quay.

Both of these processes can be modelled by a suitable neural architecture. The first process, which is that of developing automatic processing, can be modelled by a simple recurrent neural architecture, which can be implemented in the brain by means of the recurrent circuitry of

$$\text{Pre-frontal CX} \rightarrow \text{basal ganglia} \rightarrow \text{thalamus} \rightarrow \text{Pre-frontal CX.}$$

This can be defined by ever more complex structures involving increasingly complex neurons and neuro-chemicals, especially dopamine (Taylor and Taylor 2000a, b; Gurney et al. 2004). The architecture can thereby be used to model more complex processes involving knowledge representations, such as the process of rapid learning in pre-frontal cortex and the rapid learning of novel but rewarding stimuli (Taylor and Taylor 2007).

For GNOSYS, the development of attention was as follows. Input was created from visual input by suitable photo-detectors whose current was then passed into a spatially topographic array of models of neural cells sensitive to such current input and representing the lateral LGN of the thalamus (one cell layer up from the retina). This input then activated the most sensitive cells to that input, which subsequently sent activity sequentially up various routes in the hierarchy (dorsal, ventral, colour in the GNOSYS case) shown in Fig. 8.2. Attention feedback then occurred from the highest level activity (from FEF or IFG, in Fig. 8.2). There is a similar feedback process in neural models of attention (Mozer and Sitton 1998; Deco and Rolls 2005; Hamker and Zirnsak 2006), with similar amplificatory (of target activations) and inhibitory (of distracter activations) effects.

One of the novelties of our work was the employment of attention, which was crucial in object recognition and other processes involving the components of GNOSYS towards solving the reasoning tasks. The relevant control structure also allows the attention system to be extended to the more general CODAM model (Taylor 2000a, b, 2005, 2007) thereby allowing the introduction of a modicum of what is arguably awareness into the GNOSYS system.

In an earlier visual model of the ventral and dorsal streams, which did not include the recognition of colour and was smaller in size, we investigated the abilities of such a model with attention to help solve the problem of occlusion (Taylor et al. 2006, 2007a, b). This model was trained to recognise three simple shapes (square, triangle and circle) by overlapping two shapes (a square and a triangle) to differing degrees. We investigated how attention applied to either the ventral or dorsal stream could aid in recognising that a square and a triangle were present in such input stimuli. In the case of ventral stream processing, attention was directed to a specific object, which in our case was either the square or triangle. We found that for all the different levels of occlusion that were investigated, the firing rates of neurons in V4, TEO, TE and IFG, which had a preference towards the attended object, increased as against the case where no attention was present. At the object recognition level, in the IFG-no-goal site (in Fig. 8.4), the attended object was the most active. In general, a reduced activation was seen for those neurons, which preferentially respond to the non-attended object within the ventral stream from V4 upwards. This increased activity at V4 level for the attended object was transferred to the dorsal stream via the lateral connections between V4 excitatory layer and the LIP excitatory layer. Via the hierarchical dorsal model, this activity was then expressed as higher firing rates at the location of the attended object in all the FEF modules.

Attention could also be applied within the dorsal stream. In this case, attention was directed towards a small group of FEF2 nodes (3×3) (Fig. 8.2), which then, via the sigma–pi weights acting on the V5 to LIP inputs, led to increased activation at the attended location at the FEF2-no-goal site. Again using the lateral connections between the two streams at LIP and V4 level, this increased dorsal stream activity due to attention at a specific location was able to be transferred to the ventral route. Since V4 is not spatially invariant, this led to increased activation of those active nodes near the attended location. This resulted in correctly identifying in the IFG-no-goal region the object present at the attended location. So for both forms of attention, the model could correctly identify objects present within an occluded composite object (see Taylor et al. 2006, 2007a, b for a more complete investigation).

The various codes learnt by the synapses of the feed-forward connections of the modules of Fig. 8.2, on repeated stimulus presentations, were found to be close to those observed experimentally. Thus for V2, it was discovered that neurons were created, which were sensitive to particular angles between two input slits with their point of intersection at the centre of the receptive field of the cell. In V4, we discovered neurons sensitive to components of the boundary of input stimuli, as shown in Fig. 8.3 and in agreement with experimental results (Pasupathy and Connor 2001).

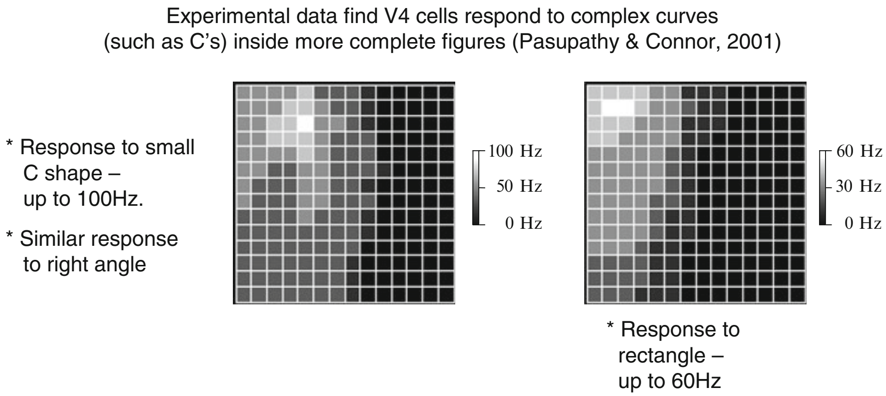

Fig. 8.3 The sensitivity of V4 neurons to partial boundaries of shapes

The response of V4 neurons to the small C-shape in the left figure is up to 100 Hz for some of the neurons; that for a complete rectangle, shown in the right figure, is only up to 70 Hz (from Taylor et al. 2006, 2007a, b).

Finally, we used a fast adaptive method to train the attention feedback (only from TPJ to V4 for the ventral route and from SPL to LIP for the dorsal route). The method used was to insert sigma–pi feedback connections from a given active neuron in TPJ, for a given stimulus, to V4 onto an active neuron there so as to amplify the relevant input from V2 to that neuron in V4 to magnify the stimulus effect (so fitting data on the nature of attended responses of single cells in monkey V4, Reynolds et al. 1999). A similar method was used for introducing attention feedback from SPL to LIP with respect to its input from V5/MT.

In conclusion, we have presented a visual system composed of a hierarchy of neural modules similar to those observed in the brain (but much simpler). Further, we showed that after suitable training on sets of objects, the system has single cell activity similar to that observed in monkeys (specifically described for V2 and V4 neurons). Moreover, the resulting codes at the highest level of the hierarchy (TE and IFG) produced localised codes for the object used in training, which were roughly independent of the spatial position of the object for the ventral route and sensitive to the spatial position of the object for the dorsal route. Moreover, the attention feedback learnt as part of the high-level coding allowed for more efficient object recognition in a complex environment, as was shown by tests in which the coarse visual system was used to feed rough co-ordinates to the fine system (which possessed attention). This allowed attention to be directed to the appropriate position to obtain a more detailed set of stimulus activations, determining the presence and possible nature of the object. Thus, the coarse system acted as a saliency map to bring visual attention to bear, through the fine system.

8.3.3 Learning Expectation of Reward

An important component of a knowledge representation is that associated with the expected reward provided or coupled to the stimulus. This is now considered as being learnt by dopamine in the nucleus accumbens and orbito-frontal cortex (OFC). The basis of the learning process is considered to be the TD learning algorithm (Sutton 1988; Sutton and Barto 1998; Schultz et al. 1997; Schultz 1998, 2004), which can be formulated as an error-based learning process to enable prediction of future reward by an initial stimulus. It is the prediction of reward carried by such a stimulus that gives that stimulus intrinsic value. The overall predicted reward assignment to a stimulus is achieved by adding the value activity by which the stimulus is coded in the OFC to its ongoing activity representation in prefrontal CX. A possible architecture to achieve was given in Taylor et al. (2009).

The circuitry of Fig. 8.4 below is an extension of the standard TD architecture, using the spatial position map of rewards from that architecture. The architecture of Fig. 8.4 allows for conditioned place learning as demonstrated in the GNOSYS

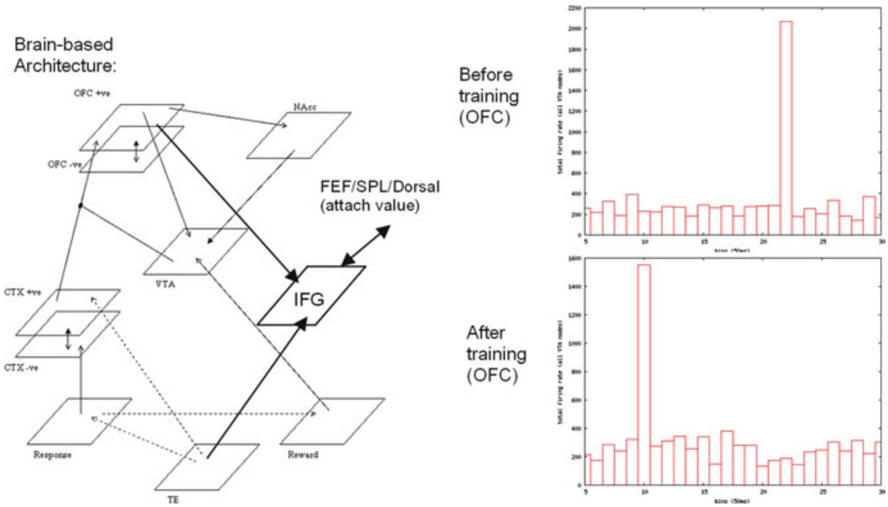

Fig. 8.4 The GNOSYS reward circuit

robot. The reward value for an object can be learnt onto the IFG nodes, via the weights indicated in Fig. 8.4; this value can then be transferred to a global map by locating the local positional information from the FEF dorsal modules in the global environment as indicated in the spatial reward map.

This circuit enables the transfer of the predicted value of an object to the spatial position at which the object is sited. A schematic of the simulation architecture is shown on the left-hand side of the figure. It is composed of a dopamine-based circuit (CTX, VTA, OFC, NAcc) carrying out TD learning of the reward to be attached to a given input stimulus through the CTX modules, having arrived from the object representation module denoted TE. This reward is then transferred by way of the input from OFC to the goal module denoted IFG so as to attach values to goals. On the right-hand side of the figure is shown the learning of the prediction of a reward at bin 22 (each bin is 50 ms long) by a cue at time ten; the top of the two figures shows the initial response pattern of the OFC nodes representing this cue, the bottom figure shows the reward prediction by the response of the cue stimulus representative in OFC when the cue appears. There is then no response to the later reward since it has been correctly predicted (as known to be part of standard TD-learning and noted by observation).

The reward model learns that certain positions within the global environment are more likely to have a specific object present that is also rewarded. The weights from OFC to the global value map are learnt using the value of the dopamine signal and provide for a direct link between the object's reward value and the object's location. The other learnt input weights come from object goal nodes: when the object is present, the object goal node is active and the weights are correspondingly learnt with a simple increment based on the dopamine signal from VTA. Both of these weight groups are normalised. The combination of learning rules means that the weights incorporate such information as frequency of the rewarded object at a specific location as well as how recent was that reward. Normalisation allows for the decay of locations, which may initially contain the rewarded object but, however, after more trials involve an absent object. The global value map can be used in a search mode for the robot, where it is ordered to find a specific object within the environment, so activating the specific object goal node. Since the weights from the goal node to the global value map give a history of the frequency and recency of the object being at certain locations, the map can be used to extract high value locations; an optimal search route can be planned taking in these highly valued positions. If the object is not present at the location, the weight from the goal node to the value map is reduced and weight normalisation follows.

The use of goal nodes as input to the global value map allows for a single global value map for this environment for all objects found within it, rather than multiple copies for each object class. Thus multiple goals can be catered for in this architecture. Nor any other system can transfer reward prediction from the code for a specific object, in a simplified model of OFC, to the spatial map assumed in dorsal part of the prefrontal cortex (such as in FEF).

8.3.4 The GNOSYS Concept System

In this chapter, we take the notion of "concepts" as representations that exist in real biological agents and not those in the statistical/pattern recognition literature, which refers more specifically to clustering. Clustering is one of the operations that is carried out by a real concept system but is not the only one. Some properties, which we ascribe to statistical concepts, do not necessarily hold in all contexts for real concepts. For example, the property of transitive inference does not always hold, such as in the case "all people think chairs are furniture items but most people believe that car seats are not furniture".

The GNOSYS concept system creates concepts out of perceptual representations in an incremental manner (Kasderidis 2007). The system uniformly represents object and goal concepts, calculating the similarity of a new stimulus to a known concept by using spreading activation in a semantic network. Internally, it uses two levels of representation:

- Prototypes (as result of a generalisation process through clustering)
- Exemplars (for boundary cases between concepts of different classes).

It supports the following operations:

- Addition of a new concept
- Incremental change of a concept
- Forgetting rarely used concepts
- Providing default values for missing attribute information
- Activation of concepts with missing perceptual information

- Support for multi-modal percepts
- Activation of multiple concepts due to a given percept, and concept selection by guidance of the reasoning system.

The concept system provides a representation in which objects, goals and relations can be represented. It uses as input the perceptual system (in more detail the descriptors coming out of the fine visual system and the attributes module described earlier) as well as the reasoning system. The latter returns new concepts that have been found/constructed through mental simulation during solution of a goal. Its output is used by the reasoning system primarily in order to use higher-level representation of objects, which are independent of perceptual noise. For example, object affordances are part of object concept representations, thus providing useful information in reasoning processes about possible initial actions to consider taking on an object. A secondary use of concepts in the GNOSYS system is the biassing of perceptual processes for recognition of objects at the perceptual level. In other words, the fine visual system not only takes into account the information coming from the Attributes and coarse visual system modules but also is biassed by the Concept system through the mechanism of attention. The latter is biassed in its turn by the reasoning system when we consider suitable concepts, during the solution of a goal object task, which might be useful in helping advancing our current (partial) solution.

8.4 The Development of Internal Models in the Brain

In order to be able to make predictions as to the effect of future actions, it is necessary for internal control models to be developed in the brain. These may be expected to occur through attention-based learning, with over-learning leading to automatic internal "thinking". The latter process, of becoming automatic through possible sequencing by recurrent internal models (with attention or consciousness), has been recently proposed as basic to creative thinking (Taylor and Hartley 2008); we will consider this later in the section.

We note that internal models in the brain have been heavily researched and developed in association with motor control (Desmurget and Grafton 2000). The existence of forward models (such as predictors of the effects of actions to be taken on the state of the system, or of actions needed to take the system from one state to another) has been detected in the brain in numerous situations and even corollary discharges of motor signals observed in higher order cortex (Sommer and Wurtz 2002; Diamond et al. 2000). This has been extended by the CODAM model to attention control (Taylor et al. 2007b,), where the model has led to the possibility of explaining consciousness as arising from the exploitation of the corollary discharge of the signal to move the focus of attention (Taylor 2009 and references therein).

There are also a number of approaches to understand action models in the brain, such as by means of recurrent networks able to model sequences. However, these models are not as specific as the internal model approach, since they do not specify how actions on state representations lead to new states, only in general how one state will lead to another in a given sequence. But it is the former – of imagining what would happen to X if one did action Y on it – that is needed in reasoning. In other words, the results of actions on given objects, and to what they lead, are crucial to internal reasoning. Stored sequences are clearly of importance to speed up that reasoning if a given state has, many times before, been embedded in a sequence of states or is nearly always the first state in a given sequence of states. But such stored sequences cannot replace the reasoning apparatus proposed here as composed of coupled internal models.

We will start by defining more specifically the internal models to be considered. They will be the simplest possible, but using them, say in parallel, can lead to very powerful control systems such as that of HMOSAIC (Wolpert and Kawato 1998). However, we are considering here not only direct action control in the HMOSAIC manner but also the use of recurrence, with external action output decoupled from the motor response system, in order to achieve internal thinking and mental simulation (which we discuss in the following section), and later (in the next section), the process of reasoning. Such internal recurrence by coupled internal models is, we have suggested, the basis of mental simulation in higher species (Hartley and Taylor 2009) as well as reasoning (Taylor and Hartley 2008; Mohan and Morasso 2007).

To start with, then, let us define the internal models we will consider. The first is the forward model, defined as

$$X' = F(X, u, w) \tag{8.1}$$

where X is the sensory state of the system, and u is the action taken on the sensory state X to produce the sensory state X'. Equation (8.1) has been extended by inclusion of the parameter set w. It is proposed that through suitably adapting this set of parameters, it is possible to modify the forward model so that it gives a good representation of the action of the overall dynamical system of the higher animal whose body the brain inhabits. This uses the fact that neural networks can represent, to within any desired approximation, any given input–output function.

Such learning as is required can be achieved by use of the simple LMS algorithm

$$\Delta w = (\text{error}).w \tag{8.2}$$

where the error is defined as

$$|X(\text{actual}) - X'| \tag{8.3}$$

with X(actual) defined as the actual value of the sensory state after the action u has been taken in (8.1) and X' is as defined in (8.1).

This process of training looks biologically feasible. Both the actual final sensory state X(actual) and the predicted state X' can be sent to the same area of parietal lobe from early visual cortex (for X(actual)) and from the site of the forward models (for X'). This latter site has been suggested a being in the parietal-frontal network involving premotor cortex (Miall 2003). Thus the two values of X(actual) and X' can be combined (with one being inhibitory) so as to lead to the error as defined in (8.3). Finally, the learning arising in (8.2) can be obtained as a Hebbian learning rule, with the neuron output being proportional to the error (8.3) and the input being proportional to the input weight w (as, say, arising from the output of the neuron for a linear response nerve cell). Overall, this leads to the learning rule of (8.2).

The inverse model IM is rather different. This is defined as:

$$u = \mathrm{IM}(X(\text{initial}), X(\text{final}), v) \tag{8.4}$$

where v are a further set of adaptive parameters so as to allow the output action u in (8.4) to take the sensory state of the system from X(initial) to X(final).

The inverse model would appear to have a similar structure to the forward model, although its training is more complicated. This is because the natural training set for the IM (8.4) only will have input states consisting of pairs of $\{X(\text{initial}), X(\text{final})\}$ and output state the corresponding action u needed to make the transition from $(X(\text{initial}) \to X(\text{final})$. In using this training set, it would be necessary to encode the necessary actions as well as the pair of initial and final sensory state. It is the former of these that will in general be difficult to encode, at least at the high level at which the IM is supposed to be functioning.

An alternative training scenario is by the development of a coupled FM/IM system. In that case, the error of (8.3) can be used directly to train both the parameters w and v, provided that the action u in the FM (8.1) is the same as that used in the IM (8.4).

In GNOSYS, we took from the EU MATHESIS project the architecture developed to model (successfully) some of the brain processes occurring in observational learning. This was based on brain activities observed in monkeys during their observations of the actions of an experimenter (Raos et al. 2004). The observation process employed for the macaque was for it to watch an actor or experimenter execute a learnt reach and grasp movement on a familiar object. The subject then had to match the observed grasp to one of the set of learnt grasps and associate that grasp with the object. The subject's task was then to reproduce that grasp when the object was later presented. It was assumed that grasps are learnt by learning the affordances of stimuli, in other words those features of the to-be-grasped object that allowed for its being accurately grasped. This could occur either by trial and error or by observation. We can construct a neural architecture to model these processes, as shown in Fig. 8.5.

In the figure, blue = observe only; red = execute only; purple = shared circuit. Activity passes from visual input via processing to activate an object module. In the execution case, this object then activates a grip, and the result is passed to motor planning where it can be integrated into a full movement. The inverse model controller (IMC) and forward model (FM) internal model control loop ensures the movement is executed correctly. In the observation case, additional circuitry is used to analyse the grip used and help to match against the internal list of grasps.

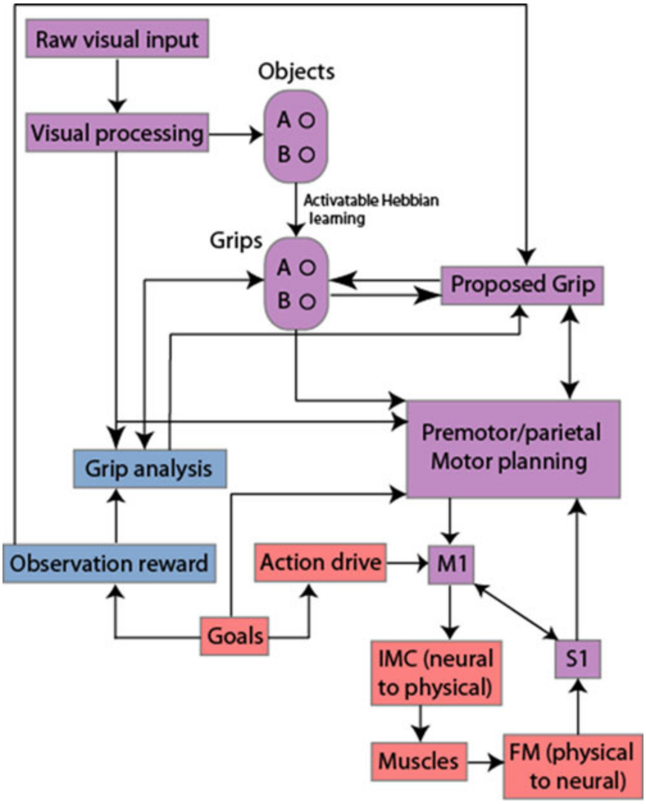

Fig. 8.5 The circuits involved in observation and execution of grasping an object

The architecture of Fig. 8.5 uses two internal motor models: an IMC, which generates a desired action to achieve movements from one state to a desired goal state, and a forward or predictor model (FM), which changes the estimated state of a system given its present state and the given action about to be taken.

We note that in terms of the architecture of Fig. 8.5,

1. Both reach and grasp movements are being modelled, and that the circuit for them has considerable overlap.
2. We have included an internal model FM/IMC pair for high-level motor planning.
3. We may determine the grasp parameters by a number of methods, such as by PCA or by time-dependent exponentials (Santelli et al. 2002). However, we used a very simple dedicated coding of requisite grasps, which only required differentiation between the few grasps assumed to be used by the macaques by the activations of the different dedicated neurons in the various modules of Fig. 8.5; this obviated the need to computing detailed parameters of the grasp trajectories.
4. We have included an action drive module in the architecture. This is expected to be present, turned on by various primary drives such as hunger, thirst, etc in a

macaque and its equivalent drive for energy and safety in a robot. It would also help the robot to distinguish the actions of self from those of others, so as to avoid acting in an externally driven manner (as occurs in humans who have lost certain parts of prefrontal cortex and repeat all actions they observe).

We then simulated simple grasps on objects (using dedicated neurons in M1 and S1 to represent particular actions and proprioceptive feedback). The results agreed well with those of Raos et al. (2004), as seen in Hartley et al. (2008).

Given suitably trained coupled FM/IM pairs, it is now possible to consider higher cognitive processes such as thinking and reasoning. We turn to each of these in the following two sections.

8.5 Thinking as Mental Simulation

Mental simulation is basic to thinking. It is presently of great interest in numerous areas: philosophy, psychology, business, defence/attack military planning, and so on. It involves the processing in the brain of internal images of the outside world and determining how they might be changed if certain actions were made on the contents of these images. In the case of observational learning, it allows for the acquiring of new skills (new strategies, new affordances and new ways of acting on objects) in a manner that leapfrogs trial and error learning. It is known to occur in chimpanzees (careful and well-known studies have been made of the learning by younger chimps of nut cracking by means of "hammer and anvil" set of stones by practiced elders). In infants, similar studies have been done and neural models built of how this could occur in developing infants (Hartley et al. 2008). There it is suggested that this uses the mental simulation loop to learn new strategies by observation, and ultimately new actions and affordances that would otherwise take a long time to learn by trial and error.

We show in Fig. 8.6 a simple neural architecture into which the mental simulation loop is embedded to allow actions on representations of object stimuli to be taken. The other modules have been introduced in other parts of this paper: the vision system including an object recognition module (for feature analysis of input stimulus activation), an object codes module (coding for separate objects by a form of self-clustering in the object feature space) and affordance extraction (by trial and error or observational learning); the executive control system as highest order control module (to guide the attention system to function in visual form for object and affordance coding or in motor form to achieve the processing of motor control), also activation of the goals module (with associated sub-goals as they are discovered by exploration, either actually or mentally through the mental simulation loop); the motor control system (involving action planning processes and action codes at a lower level; in GNOSYS, this was implemented as part of the robot control system outside the GNOSYS brain); and finally the sensorimotor system, not shown in the figure (involving proprioceptive feedback codes), coupled with the hand position vector in the sensorimotor module to bias the motor planning module.

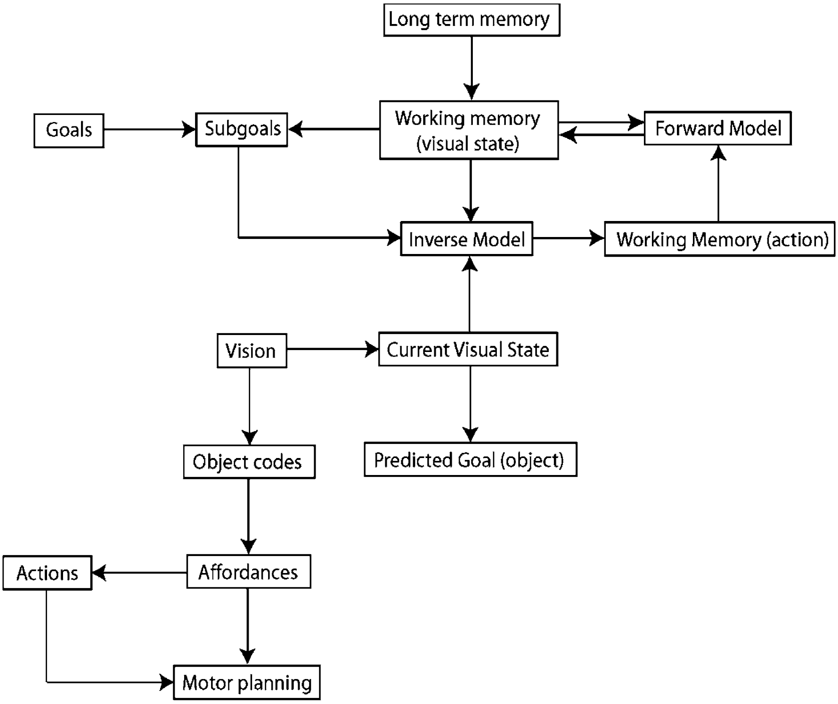

Fig. 8.6 Neural architecture for simple observational learning

The mental simulation loop itself consists of short-term memories (denoted working memory in Fig. 8.6 for visual states and motor acts) coupled to a forward model and an IMC. The inverse model produces the required action to lead from a given initial to a final state; the forward model is a predictor of the next state from a given state and an action on it, as discussed in the previous section.

Two forms of activity of the mental simulation loop are possible. The first, to be further discussed in this section, is that under attention control. As such, the two working memory buffers are used to having consciousness of the relevant states and actions. The second is subliminal, with no attention being applied so that the working memory buffers are inactive. This second form of mental simulation has been conjectured to be that of the creative thinking process, which is often interspersed with the conscious process of thinking in every-day life. We address this simulation process in the next section.

These various modules have been simulated in a very simple manner for infant development of observational learning (Hartley et al. 2008) and its successful duplication of experimental infant development data; we refer the interested reader to that publication.

8.6 Creativity as Unattended Mental Simulation

Let us first consider how we might, in principle, implement the several creative processes in the model of creativity of (Wallas 1926). This has been explored by numerous further researchers, such as (Wertheimer 1945), and in a brain-based neural model in (Vandervert 2003). The first of the processes in this model involves hard work in preparing the ground about the problem at hand. This hard work is expected to be under attention control with the subject conscious of their gathering apposite knowledge. The second process involves the incubation period. During this, attention is directed away from the original task, possibly to another task, or the subject just relaxes in total with no specific focus of attention. In the third process, attention is suddenly switched back on in the "eureka" moment. Finally, the subject has to get back to the hard work of verifying that the illuminating thought could solve the problem after all.

Thus we have the three stages as far as attention is concerned:

1. Attention is applied and the database of the subject's knowledge of particular relevance to the problem is expanded maximally.
2. Attention is relaxed (directed elsewhere) and the creative process occurs.
3. Attention is then switched back on by the illuminating thought appearing valuable, and the hard work in the verification has to be done (if it is needed).

Our model will assume that stage 1, the hard work of developing the relevant database, has been completed. It will allow the thinking process to generate a sequence of thoughts that is finally blocked, so that the solution to the given problem is not reached. Attention must then be switched. How that occurs is not relevant here, except that a switch is triggered by the failure of the model to reach a solution. The process of creativity then takes over to generate further (unconscious) thoughts, one of which finally leads to a mental state recognised as having value (say by being able to roughly extrapolate to a solution of the problem). Attention is then switched on by the reward value thereby given to this illuminating thought, so that the verification process can be started.

We consider the architecture of Fig. 8.7 as supporting the process of thinking at the two levels we have just described and in the introduction: at conscious and at unconscious levels. In order to switch between these levels, it is necessary to consider in more detail than hitherto the visual attention components in the architecture of Fig. 8.7, especially the visual attention IMC and the further attention connections included in the figure. It is through these, in concert with the other modules already present and some additional ones to be mentioned, that it will be possible to see how two levels of processing, conscious and unconscious, will be possible with the architecture.

We described briefly earlier the manner in which visual activity can be used as part of the motor control system. In addition, and as seen from the architecture of Fig. 8.7, it is also possible to see how the position of the working memory (visual state) module as sandwiched between the forward and inverse models allows there to be consciousness of the set of visual states in a mental simulation loop.

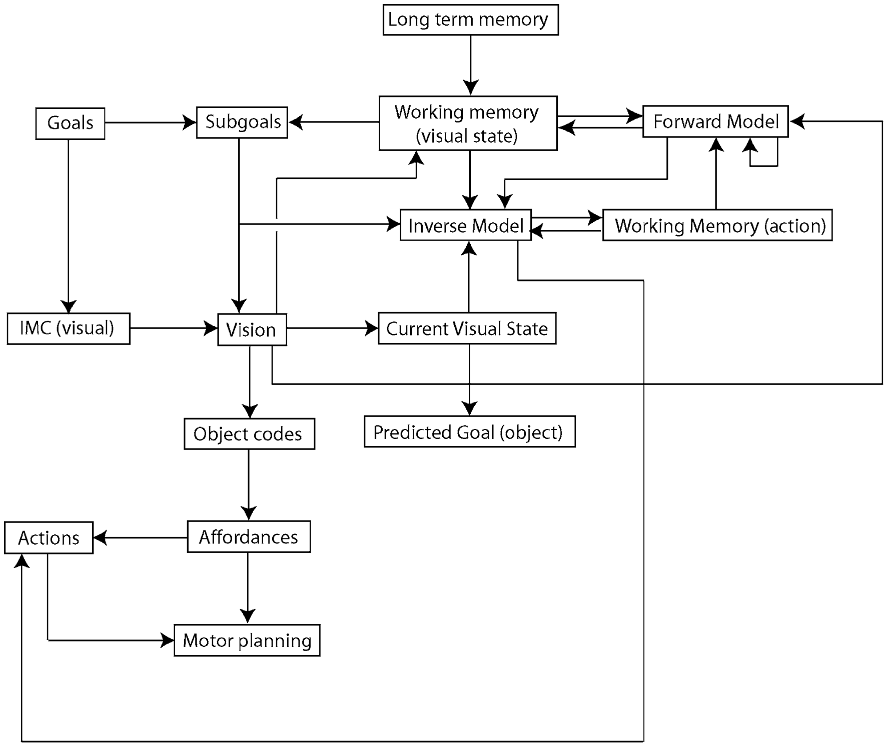

Fig. 8.7 Extension of the architecture of Fig. 8.6 to include attention in an explicit manner. The most important component added to the architecture of Fig. 8.6 is the visual attention signal generator, denoted IMC (visual). This causes attention amplification of specific attended target material in lower visual areas (in the module denoted 'Vision' in Fig. 8.7). This causes attended activity to be amplified sufficiently to attain the Working memory (visual state) in Fig. 8.7, and hence reach awareness. This attended, conscious route of using the mental simulation loop can be sidetracked, as shown in the architecture of Fig. 8.8

We need now to consider how the visual states in a mental simulation loop can be taken out of consciousness but yet be part of the mental simulation loop. This can be achieved by the insertion of a switching device to allow output from the forward model to avoid the working memory (visual state) module, so totally avoid conscious report. This switching device will be based on an error module, as in the CODAM model of attention (Taylor et al. 2007).

The mechanism to achieve mental simulation at a non-conscious level is by means of the connection lines in Fig. 8.7 described in the previous section, which avoid the working memory (visual state) module:

(a) The direct connection from the forward model to the inverse model. This enables the inverse model to produce the next action to achieve the sub-goal.

(b) The direct connection from the visual state module to the forward model. This will allow generation of the next state brought about by the new output of the inverse model and the visual state.
(c) Recurrent connection of the FM to itself if there is a sequence of virtual states to be traversed.

However, more is needed to be considered in the overall creative process. Let us turn to the example of giving unusual uses for an object: we take a cardboard box as an example. We can say "As a hat" as one such unusual use. That could arise from the flow of information in our brains:

Cardboard box (in picture or as words) → input processing → box nodes in object map → hat nodes in object map (by learnt lateral connections) → hat nodes in affordance map (by direct connections from the hat node in the object map and by lateral connections from the box representation of affordances to the hat representation there) → test of viability of putting on the box as a hat.

If the test of viability works, then the "putting on hat" action becomes attended to and there is a report, either by putting on the box as a hat or saying "As a hat". If the box is too large to fit stably on our head, then we put it on our head and keep our hands on it to steady it; if the box is too small, then we may desist from saying it could be used as a hat, or try it on as a little "pillar box" hat.

These various responses indicate that we try out subliminally what happens if we try to put the box on our head, using the simulation loop. If successful and the action is viable, then we attend to it and hence report it. If it is not, we move on to another subliminally analysed use.

To achieve the subliminal processing stage as well as the final report, there must be an attention switch, generated as part of the IMC (visual), so that when there is an attention control signal output, there is normal transmission from the forward and inverse models to their relevant working memory modules shown in Fig. 8.7. When there is no attention, then the mental simulation loop circuit functions without the relevant working memory modules. It thus functions in a subliminal or unconscious manner. There will need to be an extra module for assessing the relevance of states achieved during this unconscious activation of the loop; that will be fed by the forward model in parallel with the self-recurrence (or external running of the FM) and the signal to the inverse model. Given an error-based output from this assessment module, then its output would be used to bring attention to the final state and the sequence of intermediate states (assumedly not many) so as to attain the sub-goal more explicitly.

The reason for the presence of the switch itself is that of allowing the reasoning process to go "underground" when an apparently insuperable obstacle is met by the conscious reasoning system. This may be seen as part of the extended reasoning system discussed, for example, in Clarke (2004). However, such a switching process plays a crucial role in the truly creative cognitive process. When a blockage is met in "simpler" logical reasoning, then the attention control of processing has to lose its iron grip on what is allowed to follow what in the processing, with increased reasoning and recall efficiency by subliminal-level processing. This feature is well known, for example, in answering quiz questions and solving puzzles of a variety of sorts. So the switch into the subliminal mode may be achieved in the case of quizzes or creative processes such as painting or other artistic acts from the start of the search or creation process. In more general reasoning, the creative and subliminal component need only be used at points where logic gives out and more general "extended" and creative reasoning has to step in.

In the case of our example of unusual uses of the cardboard box, the attention switch is assumed to be turned off by the goal "unusual uses", since we know that going logically (and consciously) through a list of all possible uses of anything will not get us there, nor will any other logically based search approach. We have learnt that we need to speak "off the top of our head", in an unattended manner. So we can regard, in a simulation of this task, that we are not using attention at all after the switch has turned it elsewhere or reduced it to a very broad focus.

From this point of view, there may well be access by the internal models during this creative phase to a considerable range of neural modules for memory of both episodic and semantic form right across the cortex. The best approach to model this would thus be to have these connections develop as part of earlier learning processes, but such that they can function initially in an attentive phase and then be useable in a subliminal one. But the presence of the unattended learning of the required lateral connections may also be possible and need to be considered.

8.6.1 Simulation Results for Unusual Uses of a Cardboard Box

To simulate the paradigm involving imagining unusual uses of a cardboard box, we emphasise certain aspects of the model described above. In particular, we need to allow the use of lateral spreading with object and affordance codes and look at the more specific effects of attention. We can see the architecture of the model to be used here in Fig. 8.8 (as an extension of parts of Fig. 8.7 to handle the switch between attended and unattended processing).

Here we detail the function of the specific modules used in Fig. 8.8.

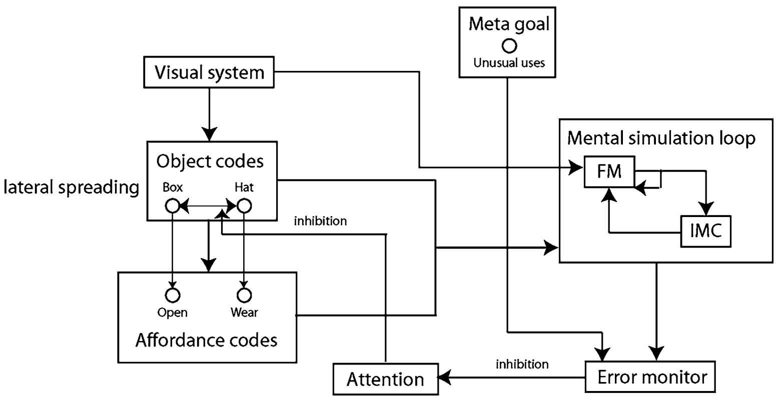

Fig. 8.8 Simplified brain-based architecture for creativity: solving the "Unusual Uses Task". The functions of the modules in Fig. 8.8 are specified in the text

8.6.1.1 Meta Goal

The overall goal of the simulation is to find unusual uses of the cardboard box. As part of this process, simple action/object goal pairs are created, so we need to code both the overall goal of imagining unusual uses and the immediate goals that are tested to see if they are unusual. We have not specified the immediate goals, since we are unclear if these are used in the creative, unattended lateralisation processing. If the processing is automatic from the affordance/action codes module to the action being taken, and then used by the mental simulation loop, then no such immediate goals module is needed; that is what has been used in our architecture and simulation. If needed it can be included between the affordance codes and the mental simulation loop without any expected change in the results we report below. The meta goal is coded as a single dedicated node (with the possibility of adding more nodes for expansion, either as a distributed representation or to include other meta goals).

8.6.1.2 Object Codes

Here objects are represented by single nodes. Lateral connections between the nodes allow similar objects to be activated by this spreading, in addition to visual stimulation. It is these lateral connections that allow the use of analogy. It is assumed that these lateral connections had already been learnt during the earlier "hard-working" attended phase of the (Wallas 1926) model mentioned earlier, with attention control in the lateral spreading as shown in Fig. 8.8 being learnt simultaneously.

8.6.1.3 Affordance Codes

The affordance module contains nodes representing specific affordant actions that can be used on objects (such as the action of opening a box). These are primed by the object code module using pre-selected connections.

8.6.1.4 Mental Simulation Loop

In the full model shown in Fig. 8.7, the mental simulation loop incorporates a forward model (FM), inverse model (IM) and buffer working memories. In unattended mental simulation, we suggest that these working memories are not active, such that activity passes straight between the FM and IM. The forward model generates an expected result of carrying out the action (these are pre-coded in this simplified model) while the inverse model determines the action necessary to achieve a suggested state. The function of the mental simulation loop in this simulation is to test subliminally the pairs of objects and affordances/actions generated by the lateral spreading to see if they are considered "unusual". If the use is considered unusual, then the attention is brought back to the system. We have not included these working memory buffers in Fig. 8.8, for simplicity.

8.6.1.5 Error Monitor

The error monitor is needed to determine whether a given object/action pair tested by the mental simulation loop has fulfiled the goal criterion of being unusual. If this criterion is met, it then activates the attention control module such that attention is restored to the goal of finding an unusual use for the box. In this simulation, the error monitor compares the selected action result (passed on from the mental simulation loop) against an internally maintained list of those considered novel.

8.6.1.6 Attention

Here we use a more specific property of the attention control system than that used so far. In particular, we now require the attention system to control lateral spreading in both object and affordance modules by inhibition of lateral connections. In our model, this occurs by output from the attention module stimulating the inhibitory connections present in the object code module. When attention is focussed, representations will be activated singly in each region, while after the removal of attention, activity can spread to similar representations (we assume that the organisation of the module is such that similar objects are laterally connected). How this attentional attenuation of lateral connection takes place at the neurobiological level is indicated to some extent by studies of visual attention (Fang et al. 2008; Friedman-Hill et al. 2003). We have not included the working memory buffers, present in Fig. 8.7, in Fig. 8.8, so as to keep the architecture as simple as possible, although they should be there; they play no direct role in our simple simulation.

We can see the flow of activations of the simulation areas in the following chart of Fig. 8.9. Activation can be split into two phases, where the first activates the goal of finding an unusual use and tries the action of opening the box, which is found not to be unusual. The second, after attention is relaxed, spreads activity such that the extra object (the hat) and its affordances become involved.

The flow paths in the upper diagram carry attention-controlled processing. That in the lower diagram have no attention focussed on them, so allowing more lateral spreading between concepts, as shown in the first line of that flow.

Recent brain imaging results (Kounios et al. 2008; Christoff et al. 2009; Bhattacharya et al. 2009) have also been directed to probing what areas of the brain are involved in creative or insightful solutions to reasoning problems and the timing of the activity involved. Thus (Kounios et al. 2008) have observed differences in levels of EEG frequencies (in the alpha, beta and gamma ranges) across cortical areas when insightful solutions were being obtained in solutions of anagrams; in particular, there was an increase in the level of gamma oscillations (in the range of 30–80 Hz) in the right hemisphere as compared to the left. In Christoff et al. (2009), considerable activity was observed by fMRI in the brain during creative phases. Similarly, in Bhattacharya et al. (2009), strong gamma activity in the right prefrontal cortex was reported as being observed up to 8 s before the creative solution to a problem.

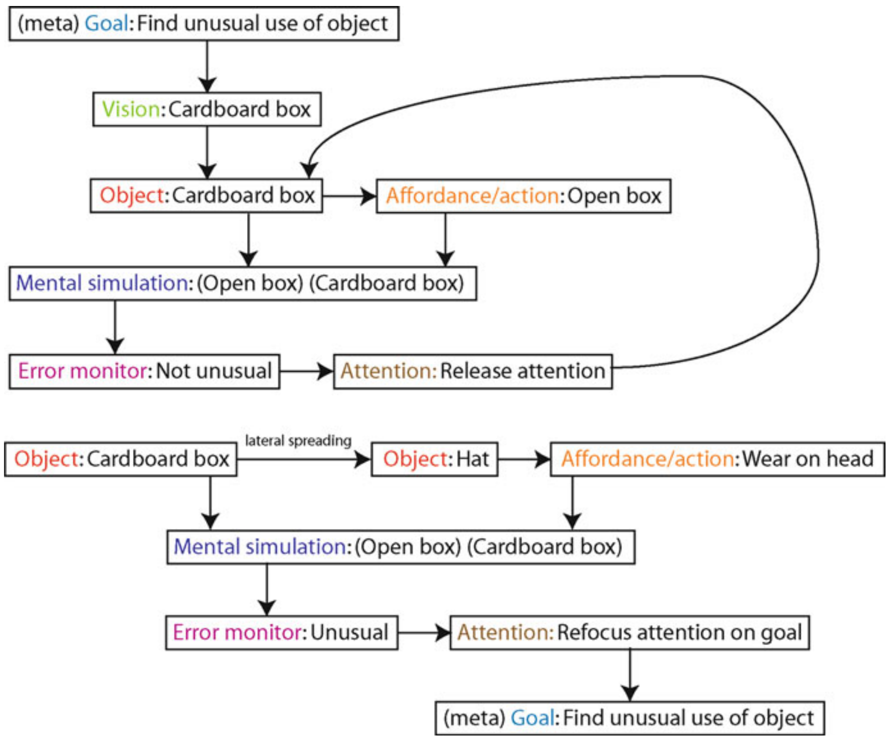

Fig. 8.9 The information flow during the creative act

These results support the overall architecture of Fig. 8.8 and the dynamical flow of the processes as shown in Fig. 8.9. Thus the right hemisphere gamma activity of (Kounios et al. 2008), observed as occurring about one third of a second before the subject's conscious experience of insight, is expected to occur in the information flow of Fig. 8.9 during the process of lateral spreading from the object representation for the cardboard box to one for hat. This use would have attention drawn to it when the error monitor showed the use as a hat was unusual. Consciousness of such a use would then arise accordingly, and the attention circuitry correspondingly re-activated. The observation of (Bhattacharya et al. 2009) of prefrontal activity up to 8 s prior to reaching a creative solution could then correspond to various alternative solutions being tried but failing, as shown by the error monitor activity. There may have been associated prefrontal goal activity to hold tentative solutions as goals for trying their usage out. Finally, the (Christoff et al. 2009) fMRI activity observed in a number of different brain area is more difficult to pin down due to the lack of accurate temporality of the observed activity but is also to be expected from the overall architecture of Fig. 8.7 when extended by Fig. 8.8 to the attentive and creative circuitry.

8.7 Reasoning as Rewarded Mental Simulation

8.7.1 Non-linguistic Reasoning

We present in Fig. 8.10 a simple modular architecture for reasoning in the two-stick paradigm, used on chimpanzees. There are two sorts of sticks: S1 (short) and S2 (long), which are present on a given trial.

A chimpanzee wants to reach the food, but cannot do so by stick S1 alone; it can only be reached by using S2. However, S2 can only be reached by use of S1 (since the chimpanzee is in a cage).

The relevant neural architecture is proposed to be as in Fig. 8.10. The modules are as follows:

(a) *Drives*: Basic drives that cause the system to attempt actions; in the present case: hunger (satisfied by pressing button on distant wall, so food delivered).
(b) *Goal list*: Goals are available to the system (independent of available actions within simulated world). Goals for us are represented by stimuli. For this paradigm, have three goals: button/S1/S2.
(c) *Vision*: This module provides the simulation with information about current state of the world. An IMC can then calculate movements to achieve selected goals, or it returns "NOGO" if not achievable.
(d) *Motor IMC*: The IMC (inverse model controller) allows simulation to determine if goals are achievable or not, given current state of world.

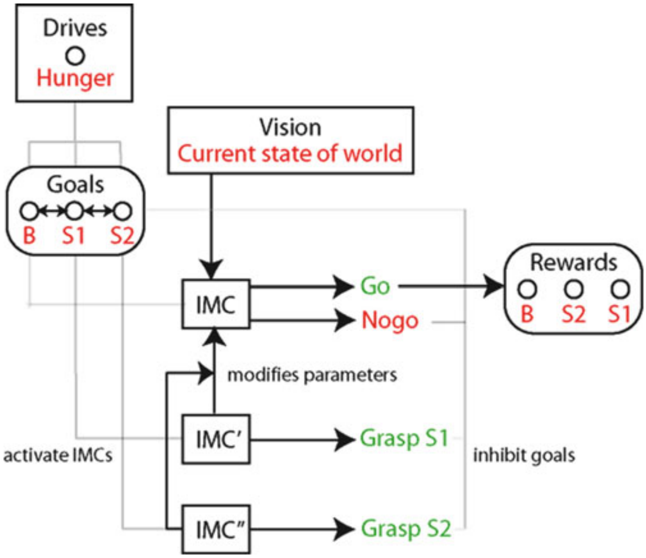

Fig. 8.10 The architecture for non-linguistic reasoning. See the text for details

(e) *Rewards*: System's reward values are modified by the results of mental simulation, and this modification allows correct actions to be executed to solve the paradigm.

(f) *Forward models*: We have not included these specifically in the architecture of Fig. 8.10. Each IMC will have an FM associated with it, which is easier to train than the IMC. This is because the FM has an immediately generated error as comparison of predicted next state (after an action) and the actual state as determined by sensors. This error can be used to train both the FM and IMC.

We present also in Fig. 8.10 a list of available actions (which may or may not be physically possible – for example, grasping the food reward initially can be attempted, but is not attainable) as goals within the goals module (so in this case, goal "B" represents the action "Push Button"). The model is composed of a drive module (a continually active node) representing continued hunger causing persistent activity emitted from it to activate the motor drive, and hence other module (until the hunger node is satisfied and turned off by obtaining the reward by pressing the button). There is a goals module coding for the three stimuli of button, stick S1 and stick S2 (to press the button, pick up the stick S1 and then the stick S2, respectively). There are three IMC modules, the first (denoted IMC) being for pushing the button by the gripper, the second is for grasping stick S1 (and denoted by IMC′, with consequent alteration of the length of the gripper in IMC to correspond to carrying stick S1), and the third (denoted IMC″) is for performing a similar action with stick S2 (and consequent change of parameters using in the gripper IMC). There is also a reward module in which there is modifiable steady activity corresponding to the current reward value of either the button B or the sticks S1 and S2 (all the observable objects in the environment).

At each stage of the simulation, the system is presented with a range of possible actions and must choose an action to perform. The IMC and FM (the latter not shown in Fig. 8.10) allow the system both to mentally simulate these actions (with no external actions) or alternatively to instantiate the actions (the former by inhibition of any output from the IMC, the latter when this input is allowed to activate the effectors by switching off the inhibition).

In Fig. 8.11 we show the flow of goal and reward activation within the system. After an initial attempt to press the button, a NOGO result is obtained. After this, but with the hunger drive still activating motor activity, S1 is attempted to be gripped, which, having been achieved, still fails to allow the button to be reached. After S2 is attempted, however, the button is now reachable. This causes S2 to be rewarded and moves the goal backward to achieving S2. This requires S1 to be gripped, so once that is obtained, S1 is rewarded and the simulation has correctly rewarded all of the potential goals and hold their relative activities with r(S1) > r(S2) > r(button).

There are two key features critical to the operation of our model – the ability to rapidly transfer rewards between goals and the capacity to consider both spatial and spatially invariant goal representations. In any system in which in-

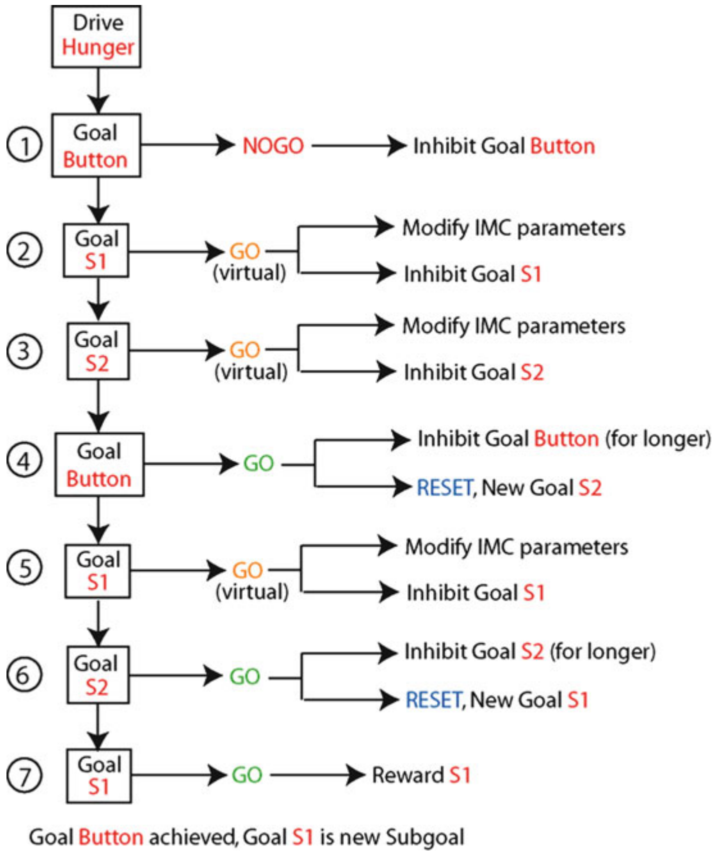

Fig. 8.11 Flow of information during reasoning in the two-stick paradigm. See text for details

termediate goals must be used to reach an ultimate goal, some mechanism must exist to make the reasoner want to perform the intermediate goals. We suggest that rapid movement of reward can do this, by attaching higher rewards to subgoals, which then gives reason to perform them. Without this movement of reward, some other mechanism must fulfil the same function – otherwise, the original maximally rewarded task (such as pushing the button, in our example paradigm) would be continually attempted, neglecting all sub-tasks. It is possible that the brain can do this in some other way. However, rewarding these intermediate actions provides a relatively simple mechanism. It may be possible to examine this hypothesis experimentally by observing neurotransmitters and neuromodulators known to be related to reward (such as dopamine) within the brain during reasoning (as in OFC or amygdala) or by seeing how agonists/antagonists to these neuro-chemicals affect reasoning.

8.7.2 Setting Up the Linguistic Machinery

Non-linguistic reasoning employs most of the important components of the brain. However, there is one missing, that of language. This is a very complex faculty, involving many of these same brain components but now with different coding. We can envisage parts of how this works through our ability to create neural networks of self-organising maps. Sets of these, learnt in conjunction with the associated visual stimulus representations, and with appropriate lateral connections learnt through the similarity of feature maps of similar stimulus inputs, leads to somewhat similar representations maps as expected to arise in the word semantic maps in the brain.

Maps for action representations require the object being acted on or its associated affordances to be defined as part of the representations. This requires suitable connections from the site for action coding to that for affordance coding. Such action codes are very likely in prefrontal cortex (especially in the premotor area) so as to allow for recurrent activity, leading to a succession of movements in effectors. Finally, verbs would then be similarly encoded, connected specifically to the action they represent.

Language coding requires mechanisms to extend beyond the initial one and two-word stumbling statements of the infant ("kick ball", "more cereal") to the much more complex phrase-inserted and grammatically correct sentences such as those in the papers in this book. Such grammar has been supposed by some to be impossible for a child to learn, leading to the idea of the "language instinct" encoded in the brain.

However, more recently, there has been an upsurge of a naturalistic approach to language that supposes that the language faculty is learnt gradually by children, given a general recurrent structure of the frontal lobes, along with crucial sub-cortical sites such as cerebellum and basal ganglia. Various models have been developed of how insertions may be constructed so as to change singular nouns into plural ones or change the tense of a verb, or even insert a given phrase grammatically correctly into a developing sentence. These processes specifically involve structures such as the cerebellum, hippocampus and basal ganglia. These latter systems are known to be involved in such activity, and their loss causes deficits in learning these various parts of grammar.

8.7.3 Linguistic Reasoning

There are several types of linguistic reasoning, such as logistic reasoning, spatial reasoning, induction (deducing laws from a finite set of events) and various others. Logistic reasoning is exemplified by syllogistic reasoning:

$$\text{“}p \text{ implies } q.p \text{ is true. Therefore } q \text{ is true.”} \tag{8.5}$$

This can be solved in at least two different ways, by rote learning or by spatial maps.

Rote learning involves being able to manipulate the symbols p, q, "implies" and so on so as to be able to rewrite (8.5) as

$$\text{“All } p\text{'s are } q\text{'s. } Z \text{ is a } p, \text{ therefore } Z \text{ is a } q.\text{”} \tag{8.6}$$

This can then be used by the identification of p, q and Z with specific cases. For the old stand-by: p = men, q = "mortal" and Z = Socrates, then there results the expected syllogistic argument "All men are mortal. Socrates is a man. Therefore Socrates is mortal". We need to consider how that, and similar syllogisms, could be implemented in a neural architecture.

The spatial approach would be as follows: rapidly to introduce a spatial activation neural disc (on a suitable spatial map) with the disc identified as the set of all men, and another such disc as the set of all mortals. The basic premise of the syllogism is that the space of all men is contained in that of all mortals. This can be coded by enclosing the first set inside the second (by suitable flexible movement of the discs). Then any particular man, whatever his name, would be a local region set inside the set of men, and hence inside the larger set of mortal animals. Thus spatial reasoning approach to logic, where possible, can be implemented in a spatially distributed set of neural modules.

The linguistic approach is not so obvious. Its main steps involve the neural architectures to:

(a) Identify Socrates as a man
(b) Transfer the "man" property to the property of "mortality"
(c) Identify Socrates thereby as possessing the property of mortality.

The first of these stages (a) is a problem of categorisation of a visual object and its categorical name (in Socrates case a "man"). We assume that there is a well-developed visual system and its associated semantic map to achieve that. Similarly, the third stage (c) should be achievable by given connectivity, with the ability to set up a lateral connection from Socrates to the adjective "mortal". It is the second stage (b) that is less obvious. It could be achieved by laying down the syllogism in long-term memory, having a permanent connection from nodes coding for "man" in the appropriate semantic map to the region coding for "mortal" in the region of the semantic map for adjectives. But such a possibility does not possess the flexibility that we observe available to us in arguing on the syllogism.

An alternative is to use prefrontal to posterior connectivity rapidly to lay down activations for "man" and "mortal" in that brain region, well connected to the relevant nodes in their appropriate posterior semantic maps. The syllogism would then arise by again rapidly setting up connections from the prefrontal nodes for "man" to those for "mortal". The realisation that "Socrates is a man" would then cause some activation of the "mortal" prefrontal region. This prefrontal activation would then be carried back to suitable semantic maps and hence ultimately lead to the activation of the "mortal" adjective. It is more likely that the second prefrontal route is used, as follows from numerous brain imaging results.

8.8 Overall Results of the System

So far, we have described the separate components of the GNOSYS/MATHESIS system and their response results for two reasons:

(a) To support their intrinsic value to the system (such as allowing the creation of an attention feedback-controlled visual system able to handle visual detection in noisy environments).
(b) Allowing relation to results from brain observations, thus showing how our system can reproduce these, and thus justify the use of the epithet "brain guidance".

However, all of these separate components have to be fused together into the overall GNOSYS software system or the "brain". In this section, we present the results obtained when the whole GNOSYS system was used to solve the various tasks it had been set.

The GNOSYS system has been tested using a number of scenarios in order to establish its capabilities in each cognitive faculty separately and in unison. From all these experiments, we describe next a set of tests that we find as most interesting in showing the reasoning capabilities and especially the tool construction strategy that it used.

8.8.1 Experiments

In simple environments furnished with the appropriate objects, we have tested the system with the "Trapping Groove" and "N-sticks" reasoning paradigms among other things. To use both paradigms together we asked the agent to retrieve a ball from a table that has a trapping groove in its middle (as shown in Fig. 8.12). The size of the table is such that the robot cannot accomplish this task directly when the ball is placed at its centre: it has to search for a tool of appropriate size. This can take place either by searching the spatial memory or by simply exploring the environment. At the same time the agent reasons as to whether it is possible to construct a tool of appropriate size by using components that have been found during mental or physical search. What solution will be selected depends on which solution's pre-requisites are fulfiled first. In Fig. 8.12 (bottom) we see a situation where the robot uses two small red sticks to construct a longer one and then uses the latter to retrieve the ball. If a longer blue stick blue is found first it is used instead (top).

Other complex commands were also given. An example is the request for the construction of a stack of cylinders at a specific point on the floor when the initial conditions of the environment were similar to those shown used in Fig. 8.13. This task required the ability to develop a high-level plan of forming a stack by the development of sub-plans such as finding and transporting appropriate cylinders to the neighbourhood of the target point before attempting the stacking action. To achieve this, the system had to either retrieve from (spatial) memory the location of

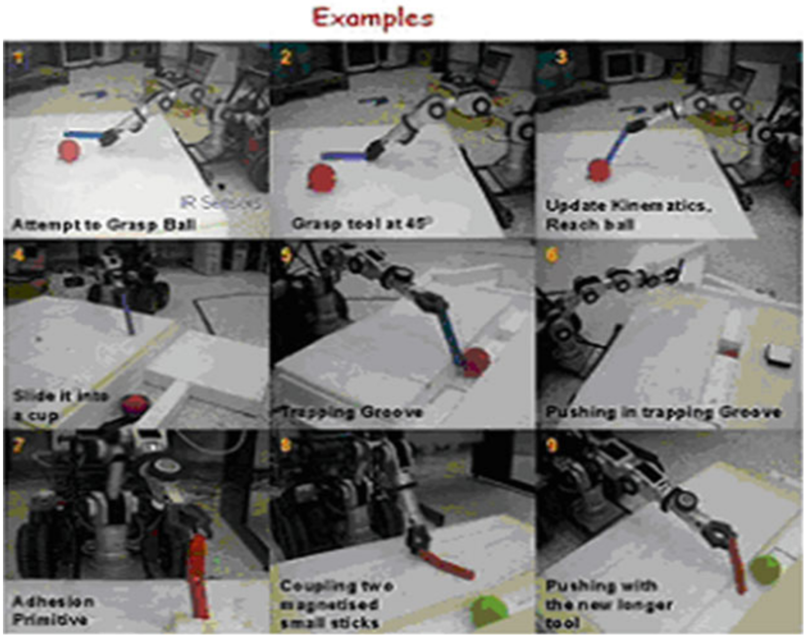

Fig. 8.12 Solution of the trapping groove paradigm and retrieval of a ball. The agent has first constructed a stick and then used it for reaching successfully the ball. The tool construction process is not hard-wired but rather is the result of reflections during "mental imagination". What is known are the forward/inverse model pairs for various objects. These have been acquired during training and familiarisation with the objects

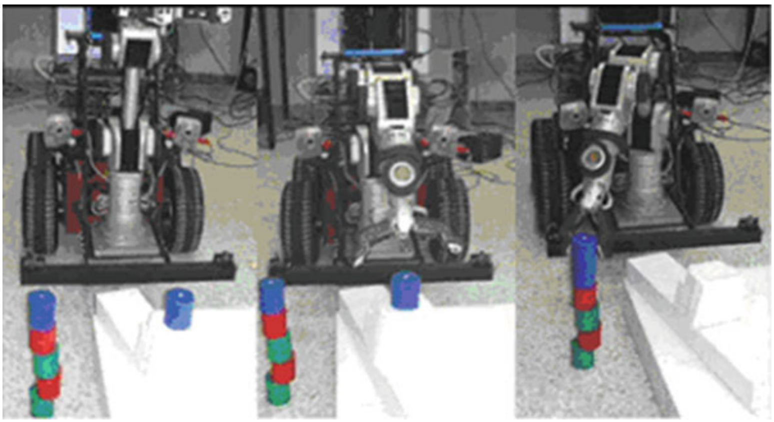

Fig. 8.13 Stack of six cylinders. Five cylinders were initially fetched in the neighbourhood of the target location of the stack from various initial locations on the floor. The last cylinder positioned to a nearby table. The robot collects the last cylinder and completes the stack

appropriate cylinders or to enter in an exploration phase, where it was surveying the space in order to locate the needed objects (the actual system used to achieve these results was that of UGDIST, which is very similar to that of KCL outlined earlier). Figure 8.13 (third panel) shows a typical stacking situation where the accuracy of the forward/inverse model for the arm can be seen in action.

8.8.2 Results

The aforementioned experiments and their variations were conducted as described above. In all cases, the system performed successfully in solving various reasoning problems. The GNOSYS system had a high success rate (>80%) in object recognition tasks from various viewpoints. This was achieved using the two-stage visual processing system mentioned earlier (first the coarse system and then the fine one), where in the second stage attention was applied to the visual input, in order to infer the class of occluded or badly illuminated objects, combined with the goal-biassing influence coming from the concept system. Activated concepts (either due to current reasoning processes or due to activation arising from previous stimuli) modulated the attention mechanism present in the fine visual-processing module. It is important to note that the visual system was based on two off-the-shelf web cameras operating at 160×120 pixel resolution. The only visual pre-processing that took place was cleaning up the camera image by using a colour segmentation algorithm. Object manipulation performance was very accurate (>90%) due to the highly accurate forward-inverse models (Morasso et al. 2005). Recognition of concepts was also highly accurate (>90%) as well as detecting novel objects (Taylor and Taylor 2007) in the environment (>70%).

8.8.3 Extensions Needed

There are numerous directions in which extensions to the system could be taken:

1. Addition of more detail in the motor system, using the known recurrence in the frontal system (frontal cortex, basal ganglia, cerebellum) to enable both attended and automatic actions to be learnt, with a smooth transition from the former to the latter.
2. Extension of the linguistic component to an enlarged semantic net, with learnt connections between the word codes and the action and object representations. This would thereby ground the words in the models of the world built in the GNOSYS brain. Note that we are only ever able to ground language that far, and not in the outside world, since the words can only be used to represent the outside world through the objects and actions, and more generally, the concepts that the words are trying to replace. The verbs, in particular, can only be represented

by the syntactic structures given by the representations of the action sequences carried by the frontal lobes and by the objects on which the actions are being taken.
3. A more complete version of the hippocampus, allowing both memory codes in the well-connected CA3 component (through learning lateral connections) and the resulting download (through learning) onto the neural modules nearby, representing neural structures in nearby cortical sites (temporal and related lobes).
4. More complex attention control circuitry, especially in the addition of a corollary discharge of the attention control signal (as in the CODAM model), so as to make attention control faster and more efficient.
5. The neural coding is developed by space–time-dependent learning, using the neuronal spiking transfer of information between modules. Such learning allows in particular the learning of the causal structure of inputs as well as in the use of causal flows of neural spikes in the attention control system of CODAM.

We discuss possible further work in Sect. 8.10.

8.9 Relation to Other Cognitive System Architectures

We have already noted the specific components of the GNOSYS Cognitive System, which, in general, distinguishes it from many other Cognitive System Architectures. Most specifically, it crucially depends on an attention control system both for its sensory input processing (presently specifically for vision) and for its motor action responses. The sensory attention system also allows for the learning of new concepts of objects in its environment, which can then be extended by abstraction into higher level concepts, connected by a web of lateral connections so as to enable reasoning and stimulus meaning to be extended almost in a symbolic manner (although no explicit symbols are employed in the GNOSYS system).

The system also crucially possesses a set of internal motor models (arising from fused work of the GNOSYS and MATHESIS projects, although we will still term the system the GNOSYS system for simplicity) enabling it to perform virtual (internal "mental") processes in which the results of the various steps of the internal models' activity do not cause any internal responses but modify internal state values so as most specifically to achieve desired goals. Such desire is itself set up by a set of predicted reward values encoded for each of the external stimuli the GNOSYS system has already encountered in its intercourse with its environment. Thus the GNOSYS brain possesses cognitive powers of perception and concept formation, learnt sensory and motor attention, goals creation in a given environment, reasoning and internal "mental simulation". Finally, we should add that we have implemented these powers in a robot embodiment so that they are observed in action in the robot itself.

We tabulate these powers and compare them with other leading proposals on cognitive systems in the table. We only consider in our comparison those architectures that are purely connectionist, since the symbolic or hybrid systems bring in symbolism, which is not clearly related to the sub-symbolic activities of the overall system, and limit the possible learning capabilities of the system as well as the use of brain guidance. This latter aspect is particularly important if we are considering those cognitive architectures that have a chance, at some later date, of the inclusion of a conscious component. This is, as we noted in the introduction, a crucial component of cognition but one mainly ignored so far in the AI/Machine intelligence approach to cognition. We also leave out the important and influential SOAR/EPIC/ACT-R/ICARUS class of models, since these use production rules and a symbolic component as well as not possessing suitably adaptive dynamics and active perception.

We have not considered more brain-based architectures such as Cog, Kismet or Cerebus, since these are still in developmental stages (as in Scassellati's Theory of Mind for Cog) or have a strong symbolic component (as in the case of Cerebus and Kismet).

8.10 Conclusions

In this chapter, we have attempted to address the tasks raised by the title to this paper: to create a neural architecture able to carry out the perception–conceptualisation–knowledge representation–reasoning–action cycle. It is possible to recognise such a cycle as indeed being carried out in the human brain: the flow of input into the brain leads to the generation of a set of percepts of objects in the environment being viewed, concepts in the knowledge representation system are then activated, and reasoning can be carried out as to the various action solutions to possible tasks that might be carried out to gain rewards from the objects. Actions to achieve such rewards are then determined and can be carried out.

We attacked this daunting problem by recognising that brain guidance in constructing an effective neural network architecture for this task would be appropriate. From that point of view, we then noted that the overall cycle involves brain processes at different levels:

(a) At the lowest level: perception, concept formation and action were involved, all under the control of attention.
(b) At a second level: the creation of knowledge representations, including internal models based on them, all under attention control. At the same time, reward prediction models are created for biassing the importance of perceived objects.
(c) At the highest level: the use of the lower and second level faculties to enable reasoning to take place for the solution of suitably rewarded tasks.

It can be seen from the different levels (a), (b) and (c) above that the two lower level faculties can be treated as being able to be learnt separately, without the need for consideration of reasoning proceeding. Such were the methods used to develop the GNOSYS architecture.

The final problem of higher cognitive processing is that there is a lack of experimental data on brain processes involved in non-linguistic reasoning. There is a growing literature on cortical areas involved in linguistic reasoning, including, as expected, numerous linguistic sites through the brain as well as those involved in executive functions. However, these do not necessarily move forward the architecture involved in the critical stages of reasoning, involved in setting up sub-goals. The manner of involvement of value map adjustment, as proposed in the model described earlier, needs careful discussion alongside augmented brain data to begin to validate it.

Finally, we consider points where further work needs to be done (emphasising and extending points already made in Sect. 8.3):

(a) Extension of the above architectures for thinking, reasoning and creativity explicitly to language. This has already been done implicitly, in terms of using words to code for given neurons in the simulations; details of how these word codes might arise through learning need to be explored.
(b) However, there is the more important question as to how language itself is learnt. Is that through more of the same sort of architectural components (attention using object and action codes, value maps, internal models)? Or are there different mechanisms at work to achieve a full linguistic repertoire? Given the rather different architectures of cerebellum and basal ganglia, it is very likely that the latter is true (although the former has been suggested as using internal models, and the recurrence of the frontal lobes using the basal ganglia has been used for forward model construction as sequence learners, as discussed earlier). Then what are the new principles involved, if any?
(c) In relation to the further analysis of the nature of linguistic processing of (b), are there similar coupled forward-inverse models in language that are developed especially by those who think linguistically rather than those who think visually? Or is inner speech driven, in all humans, by sequences of inner visual thoughts, but clothed in language after the event? This latter possibility does not seem likely but may occur in lower animals. How would that be tested?
(d) Further development of the internal model structures to enable thinking to be achieved at a non-attended level when the initial learning was at an attended level. This has been discussed in the chapter under the heading of creativity, but aspects such as associations between internal models and their extension to linguistic codes needs to be more fully explored as does the question of the details of the switches between the attended and unattended levels to allow for unconscious thoughts.
(e) Further development of the creativity switching architecture, especially the monitor system for assessing the value of a new concept activated by lateral connectivity in the manner suggested in the discussion in the chapter.
(f) Further exploration of the manner in which learning of lateral connections can be achieved so as to allow for creativity itself to be most effective. This is a basic question of creativity research: how best to study so that a deep problem can most efficiently be solved using the lateral connections thereby created? But how were these lateral connections created? If under attention, then taking

attention away from any concept map might allow lateral spreading, and so reasoning by analogy. But how had the lateral spreading been achieved during the learning under attention in the first place? Was it during gaps in the attended learning process when the hard work was being done? Or was it during the attended learning process itself where suitably widespread reading brought these lateral connections about?

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