Memory as the substrate of cognition: a developmental cognitive robotics perspective

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Abstract

Recent developments in neuroscientific theory have suggested that cognition is inherently memory-based, where memory is fundamentally associative. The application of this perspective to cognitive robotics is not well developed, especially in the context of the constraints and structure afforded by the embodiment of the agent. This paper seeks to describe the foundation of an approach that incorporates this memory-based perspective, by presenting a theoretical framework that incorporates the necessary aspects. A computational implementation of this framework is described, and a low-level application case study is discussed, which validates this memory-based approach. This implementation emphasises the necessity of environmental interaction in the ongoing development of behavioural competencies, and the central role that a value system plays in this process.

1. Introduction

The aim of the present research is to explore the application of principles of cognition derived from biological agents to artificial agents. In particular, the focus is on low-level, fundamental aspects: the intention is to examine the principles themselves rather than how a particular implementation may produce an artificial agent behaviour that slightly exceeds that which is currently possible. One such principle is that cognition should be considered to be fundamentally memory-based. The aim of this paper is to describe the motivation and basis for a memory-based approach to cognitive robotics, and builds upon previous work (Baxter and Browne, 2009a). This approach takes inspiration from a biological account of cognition, but it enables a conceptual integration of neural- and non-neural-inspired mechanisms to an extent lacking in other frameworks. Furthermore, it is proposed that this memory-based account is only relevant to autonomous cognitive robotics when it is considered within the framework of ongoing development through sustained environmental interaction.

Principles of operation and structure underlying complex and autonomous behaviour are frequently drawn from biological systems as they currently provide the best examples of the desired functionality (i.e. existence proofs). As such, the type of principle used has changed over time in accordance with the prevailing views of biological cognition. For example, traditional artificial intelligence approaches are inspired by the 'mind as computer' metaphor, e.g. as described by Bickhard (2009b), leading to a prevalence of logical and mathematical modelling implementations. More recent approaches have tended to emphasise computational models and architectures that are directly inspired by biological neural structures and functionality e.g. McKinstry et al. (2008). In parallel with this, the developmental robotics paradigm has received increasing attention, based on the recognition that the manner in which the cognitive control systems are created (through development) have profound implications on the functionality of these systems (Weng et al. 2001). It also enables a potential level of autonomous and flexible behaviour not otherwise possible, due to a high degree of adaptive coupling with the environment, and a desired minimisation of information designed *a priori* into the system.

One principle that is becoming increasingly apparent from neuroscientific integrative models is that cognition may be fundamentally considered to be the manipulation and utilisation of memory, e.g. (Fuster 1997, Postle 2006). Memory is in this context considered to be fundamentally associative, following Hebbian principles (Fuster, 1997), and in the low-level sense, rather than at the level of, for example, episodic memory. This principle emphasises the distributed nature of cortical organisation as the substrate for cognitive behaviours, rather than the competing modular view: in so doing it provides the basis of a common framework for both perception and action. The application of this framework to artificial cognitive systems is thus a promising avenue of exploration, as it allows the integration of a number of aspects central to autonomous robotic systems, including embodiment, developmental processes, and ongoing environmental interaction.

The memory-based cognition approach described in this paper seeks to incorporate aspects of both the top-down (psychologically-inspired) and bottom-up (neuroscience-inspired) approaches to cognitive robotics. It is acknowledged that the behaviour of the agent is the important issue - the focus of the present work is on low-level behaviours, upon which more complex behaviours may subsequently be bootstrapped. While abstracting away from the low-level biological detail of neural processes (including neurotransmitters etc.), the memory-based framework seeks to describe the distributed 'computational' [1] substrate of these foundational agent-level behaviours. There is thus a distinction between the present work and the dynamical/complexity theoretical approach to neural functionality. Whilst it may be argued that it is precisely the fundamental dynamics that are of importance, the starting position taken in the present research is that associative memory can be accounted for by these processes, but that they can be assumed, and built upon. This approach is intended to be complementary to these existing approaches rather than to supersede them, by forming a possible conceptual bridge between the bottom-up and top-down approaches.

This paper will cover the following. After overviewing the neuroscientific and psychological evidence underlying the proposed shift towards a robotic memory-based cognition (section 2), a theoretical framework is described that formalises this proposition (section 3). The application of this framework to a robotics problem highlights the necessity for a developmental approach, and the central role of a value system, in the development of a set of basic behavioural competencies (section 4). The manner of the computational implementation of the theoretical framework enables different aspects of the developmental memory-based system to be highlighted than existing approaches would, particularly the interplay between neural- and non-neural-inspired mechanisms (section 5).

2. Memory-Based Cognition for Autonomous Agents

The view that brain function (and so cognition) may be divided into functional modules, and even that these modules may be mapped onto specific regions of the brain, is being increasingly superseded by an emphasis on distributed organisation and functionality, e.g. (Fuster 1997, McIntosh 2000). The case of Working Memory (WM) forms a pertinent example of this trend for the present research, since its proposed functionality is as the interface between memory and cognition. WM has been defined as a functionally distinct part of the human memory system that temporarily stores information in an accessible state relevant to a current task (Cowan, 1999), and has generally been modelled and studied as functionally separable from both long-term memory and cognition (Repovs and Baddeley, 2006). However, recent theories and models have focused on the distributed nature of functionality. For example, (Postle, 2006) argued that WM should be seen as an emergent property of the brain, being the temporary reactivation of already existent long-term memory representations.

One particularly relevant model of cognition based on the structure of distributed cortical organisation is the Network Memory theory (Fuster, 1997). This wide-ranging theory of human cognitive functionality proposes that distributed networks of neurons form the common substrate of memory, perception and action. Each of these distributed networks encode associative relationships, which may be considered as basic neural elements, and are termed ‘cognits’ (Fuster, 2006). These are proposed to be arranged in two informal and overlapping hierarchies, the first founded in primary sensory cortical regions, and the second founded in primary motor regions. Behaviour emerges from this system through the activation-based interaction of cognits across, and at all levels of, these hierarchies – this active process may be described as cognition.

Memory may therefore be described as being fundamentally associative, with cognits from the Network Memory theory formed and associated with one another through Hebbian processes of activity dependant synaptic plasticity. This is in accordance with neuroscientific theory, in particular the mechanism of Long-Term Potentiation (LTP), which has been proposed to be responsible for long-term memory processes (Cooke and Bliss, 2006). The use of the term ‘memory’ in the present paper reflects this view, and does not intend to imply the involvement of the abstract concept of episodic memory. However, since it is fundamentally associative, and created in response to that which has occurred (either through the recurrent connectivity of networks, or as resultant from sensory input), this view of memory may be described as ‘proto-episodic’, since it is an encoding of previous activity, but without conforming to the characteristics of human episodic memory (such as conscious recall of previously experienced episodes).

Current implementations of memory systems in cognitive robotic implementations have not yet moved towards this distributed representation and process perspective. A functional separation of memory and cognition has led to discrete computational structures for each: cognition as active processing, and memory as a passive storage device, which may be divided into further functionally specific memory types. A memory-

1 The term 'computational' is used for convenience - it is not suggested that the processes fundamental to biological cognition are inherently the result of Turing machine-like information processing, rather it is used since it provides a useful descriptive metaphor.

based approach to cognitive robotics architectures (where memory is an active process primary to cognition rather than a mere passive adjunct) will have profound implications for the type of computational implementation used, most notably the commitment to a common structural and functional substrate for perception, action and cognition. This commitment allows the memory-based approach to satisfy the requirements of a number of theoretical frameworks. For example, the active perception paradigm, e.g. (Noe, 2004), and the principle of sensory-motor coordination, e.g. (Pfeifer and Scheier, 2001), both require the integration of perception and action, with ongoing interactions between the two. Furthermore, the associative processes underlying memory are ongoing and adaptive, and used in the ongoing production of behaviour, and so may be seen as being in accordance with the principle of anticipation from the interactivist framework (Bickhard, 2009a). In the memory-based framework then, learning should be considered as the adaptation of memory rather than a distinct process.

3. Synthesis of a framework for cognitive robotics

A theoretical framework has been developed – the Memory-Based Cognitive Framework (MBCF) – to address the considerations discussed above (Baxter and Browne, 2009a). The present paper further characterises the MBCF, and provides a real-robot evaluation of its computational implementation. A fundamental assumption of the present work is that it is concerned with embodied autonomous agents. This has the practical consequence of providing the sensor and effector spaces of the agent, which completely encompass the interfaces between the agent and the environment. There are a number of other central aspects of the theoretical framework that are based upon this foundation: associative memory formed through constructivist processes, activation-based functionality, and a value system as the driver for the development of coherent agent behaviours. These aspects are characterised in the following paragraphs, and a basic formalisation is introduced, which forms the basis of an application to a robotic platform (section 4).

The sensory space of an agent completely encompasses the effect that the environment has on the control system of an agent: the potential flow of information from environment to agent is accounted for in this space. Similarly, the effector space encompasses all possible changes the agent can directly effect on the environment. As such, it is necessary that the behavioural competencies and the cognitive architecture that support them must be grounded in these spaces. The associative memory-based structure must therefore also be grounded in this manner (figure 1). A discretisation of the sensor and effector spaces of both individual sensors/effectors and of the information accounted for by these sensors/effectors (e.g. the discrete return values from ultrasonic sensors), is assumed[2]. These discrete elements may then form the basis for the explicit associative relationships.

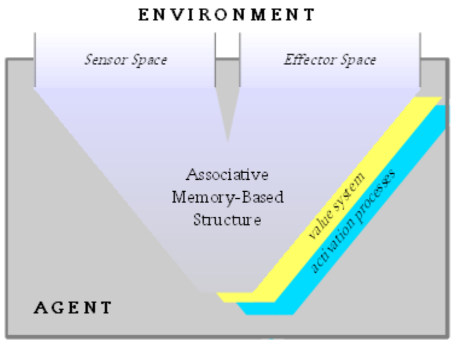

Figure 1: Functional overview of the proposed Memory-Based Cognitive Framework (MBCF). This framework assumes an embodied agent in an environment.

These sensor/effector base elements are not necessarily associative in themselves, but rather encode specific perturbations resultant from, or enacted on, the environment. Each of the individual discrete states may be associated with one another as a result of temporal or spatial co-occurrence – thus establishing the requirement for ongoing environmental interaction for the 'construction' of associative information. If these resultant associations are considered to be explicit units, then a spatial associative unit, u_a^t (at an instant in time *t*), may be defined as:

$$u_a^t = [e_1, e_2, A_t] \quad (1)$$

Where e_x correspond to sensory or effector space states (or other associative units) that are associated, and A_t is the activation level of this associative unit at time *t*. The formation of these associative units over time results in the networked memory system (figure 1). This memory-based setup is thus responsible for perception and action, acting as a common framework. Note that the effect of the physical morphology of the sensors and effectors is not explicitly incorporated into this constructivist account. However, it has been generally acknowledged that physical embodiment has fundamental consequences for cognition, e.g. (Lungarella et al., 2003), and it has been shown that this is likewise the case for the MBCF (Baxter and Browne, 2009b), where embodiment provides a set of constraints on the creation and use of these constructivist associations.

Another important aspect of these associative units is that each unit has an activation level which may vary

2 It is acknowledged that this is no small assumption to make for biological systems – however, given that the target domain is cognitive robotics, this assumption is held to be justified, as it is in the vast majority of other robotics implementations.

over time. Given that links exist between the associative units, activation may spread across the memory network. There are two sources of activation: the first is due to random fluctuation (which is especially apparent in the effector space, as seen in foetal motor babbling behaviours for example), and the second is due to the sensory system being influenced by the environment. The activation level of an individual associative unit, a scalar $A(u_a^t)$, is a function that may be described as follows:

$$A(u_a^t) = f\left\{A(e_1^t), A(e_2^t), A\left(u_a^{t'}\right), A(X)\right\} \quad (2)$$

Where $A\left(u_a^{t'}\right)$ denotes the previous activation of this associative unit, $A(e_n^t)$ denotes the activation of the units linked to it, and $A(X)$ denotes a level of random activation. This concept of activation and flow through the network is very simplistic compared with biological systems, but is a frequently used abstraction. The action performed by the agent at any time is determined by the resultant activation levels in the effector space, with the motor command for each effector chosen on a winner-takes-all basis. In order for this process to produce coherent behaviours, there must some mechanism that can bias the activation flow through the memory system, so that the action performed is not simply that which has occurred before (due to the retrospective formation of the associative units). It is proposed that the value system, as a fundamental evaluation mechanism, takes on this role.

The necessity for a value system in developmental systems is well established (although different terms are frequently used – such as emotion, drives and intrinsic motivation – in a similar manner), although the manner of implementation varies widely, e.g. (Oudeyer and Kaplan, 2007). Biological theory suggests that while there are certain brain regions with particular involvement in this evaluation mechanism (Baxter and Murray, 2002), there is a high degree of distributed organisation and emergent functionality (Pessoa, 2008). The value system for the MBCF is similarly distributed (figure 1), forming an intrinsic part of the associative memory system. In terms of the developmental processes, the value system takes inspiration from the development of the pain system in the human foetus (Lowery et al., 2007), which may help to guide the initial development of sensory-motor coordinations. The value system, V, may be visualised as a multi-dimensional function:

$$V = f(s_{t'}, s_t, m_{t'}, m_t, I) \quad (3)$$

Where $s_{t'}$ and s_t are the past and present sensory states respectively, $m_{t'}$ and m_t are the equivalent effector states, and I represents somatic states (e.g. hunger or tiredness levels). This function is used to modulate the activation levels in the memory system at the level of individual associative units, thus driving the system as a whole towards producing useful (as externally interpreted) behaviours.

4. A robotic problem case study

In many cognitive robotics applications, basic behavioural competencies are set *a priori*, upon which further behaviours may be bootstrapped or developed. Basic competencies in this context refers to very low level coherent agent behaviours, such as the ability to move forwards in a straight line, or obstacle avoidance when moving in an environment. For example, in (McKinstry et al., 2008), a comprehensive and complex simulation of the mammalian cortex controls the behaviour of a mobile robot by choosing the appropriate motor behaviours at any given time. Including commands such as move forwards, turn and reverse, these motor behaviours are coherent at the level of the agent, and are implemented *a priori*. A similar situation exists in developmental/epigenetic robotics. For example, in schema approaches, e.g. (Chaput, Kuipers and Miikkulainen, 2003) and (Guerin and McKenzie, 2008), rules defining behaviours and competencies are implemented *a priori*, upon which more complex behaviours are bootstrapped through environmental interaction. The question of the origin of these basic behaviours themselves has been addressed using evolutionary methods for example, over the course of multiple generations, e.g. Floreano and Mondada (1998).

In this case study, it is shown how such behaviours may be developed in a memory-based system, on an ontogenetic, rather than phylogenetic, time-scale. It should be noted that the emphasis of this case study is on the manner of the development of a coherent agent behaviour, and not on the complexity of the resultant behaviours themselves, on the basis of associative memory only. The memory-based computational architecture used is closely based on the description given of the MBCF (section 3), particularly regarding the explicit representation of associative units, but is only one possible means of implementing the theoretical framework in a computational architecture.

When the computational architecture is implemented in combination with a mobile robot platform, the system as a whole is termed an Embodied MBCF Agent (EMA). The mobile robot platform defines the sensory and effector spaces (in terms of the number of sensors and effectors, and the resolution thereof), in this case a differential wheeled Merlin Robotics Miabot Pro mobile robot with ultrasonic sensors. Three sensors are used in this case study (N, NW, NE), each with four states corresponding to a detected distance to nearest object range of 0cm – 40cm, and both of the motors have five possible states, for reverse and forward motion (from -2 to +2).

Based on these spaces, three association layers are implemented (figure 2). In the sensory association layer association units form links between sensory space elements, likewise in the effector association layer with effector space elements. Associative units in the cross-over layer link one unit in the sensory association layer with one unit in the effector association layer.

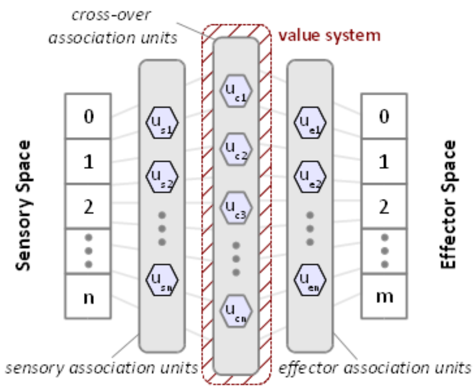

Figure 2: Description of the computational architecture. Three layers of explicit associative units are implemented (sensory association units, effector association units, and cross-over association units), with the cross-over layer under the influence of the value system.

An activation value is added to the relevant sensory space element (for each sensor), and to a randomly selected effector element (for each effector, a simulation of a motor babbling mechanism), at the start of each time step. Activation spreads through the network layers to the effector space (figure 2). The effector space element with the highest activation value at the end of each time-step is executed, for each effector individually.

Each unit in the cross-over layer has a value tag, which is a single scalar, updated on each time-step in response to a measure of success of the previously executed behaviour (a basic measure based on the change in distance to a detected obstacle), and the individual associative units contribution to that behaviour (in terms of activation level) – essentially a basic reinforcement learning implementation of the value system as described in equation 3. These value tags act as scalars of the activation level of the cross-over associative units, and thus have a different effect on different units, allowing the behaviour of the agent to be altered. The function was implemented to increase the value tags of those association units which promoted a continuous forward movement obstacle avoidance behaviour.

The initial condition of every run is the robotic agent located in a simple square environment (measuring 0.9m by 0.9m) bounded on all sides by immovable barriers detectable using the robots ultrasonic sensors, with the start location at (0.15m, 0.15m) from one of the corners. The EMA computational architecture is initialised with no associative links present in any of the associative layers (i.e. there is no memory structure present), and so also with an uninitialised value system (i.e. no predefined value tags). Two setups of the EMA computational architecture are used: the first with the value system as described, and the second in which the value system has no effect (i.e. there is no scaling of individual associative units activation levels). As a benchmark comparison control system, a random walker was implemented, where a random motor command was selected on every time-step, for each motor, from among the five states available to the EMA's. Each run consists of 3000 time-steps (approximately 35mins real time), and ten repeat runs were conducted for each of the three controllers.

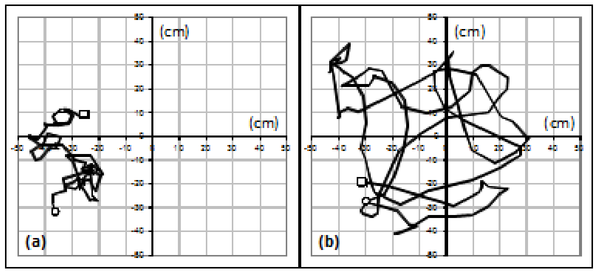

Figure 3: Path plots from a sample 3000 time-step run of the EMA; (a) the first 200 time-steps, (b) the final 200 time-steps. Circles denote the starting point in the time window, and squares the end point.

Sample path plots for the EMA are shown in figure 3. These representative examples show that at the start of a run, the EMA moves around the arena in a random-like manner, whereas by the end of the 3000 time-step run, it is exhibiting the type of behaviour that was desired, and demonstrating the ability of the memory-based architecture to develop these: straight line forward movement in open space (in the middle of the square arena), whilst turning away from the environment boundaries.

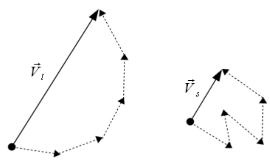

Figure 4: Derivation of the concatenated vector. Five consecutive time-step movement vectors are concatenated; see text for details. Even though the constituent vectors of $\vec{V_l}$ and $\vec{V_s}$ are the same length (i.e. the agent has travelled the same absolute distance), $|\vec{V_l}| \gg |\vec{V_s}|$.

Whilst the path plots qualitatively show that the EMA has developed a straight-line movement obstacle-avoidance behaviour from initially random movement, a more objective measure is required in order to objectively compare behaviours. A basic statistical method has been proposed to achieve this (figure 4): the concatenated vector mean length method. Making the assumption that the movement of the robot from one time-step to the next can be represented as a single vector (which, given that each time-step is short, is held to be justified), then a concatenated vector is the addition of a number of consecutive such vectors. For the present study, this number is five. The length of this concatenated vector gives an indication of the behaviour of the agent: at its longest, the agent has travelled in a straight line with maximum speed. If the mean of the lengths of concatenated vectors in a specific time window is taken, then this gives an indication of the behaviour of the agent over the course of this time window.

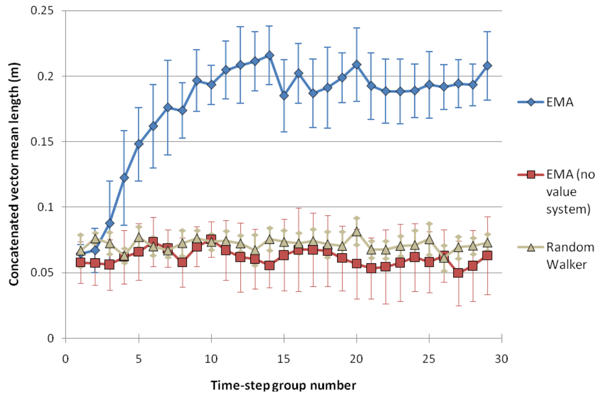

Figure 5: Concatenated vector mean length results for the low-level behaviour development case study, demonstrating the development of a continuous movement obstacle avoidance behaviour for the EMA. Each plot is the mean of ten runs, and each data point is the mean length of the concatenated vectors in a 100 time-step window (a time-step group); error bars show the 95% confidence interval of the mean.

The results of the application of the concatenated vector mean length method showed that the EMA does exhibit a clear progression in the acquisition of these behavioural competencies (comparing the performance in the 29th time-step group using a one-tailed t-test, $p<0.01$), compared with the random walker controller (figure 5), although the EMA starts at the same level of performance (in time-step group 1, two-tailed t-test, $p=0.7$). Furthermore, the results demonstrate the importance of the value system: without the fundamental evaluative mechanism provided by the value system, the agent never progresses beyond a random-like behaviour.

5. Discussion

5.1 The computational implementation

The behaviours the subject of the case study (straight line forward movement and obstacle avoidance) are low level in comparison with the types of behaviour usually the focus of developmental cognitive robotics work. However, it has been shown how a memory-based architecture, where the interaction of associative processes with a value system is the central mechanism, may be used to develop these low-level competencies. The developmental process is clear: ongoing interaction with the environment[3] is necessary both for the creation of the associative memory links, and for updating the effects of the value system. In this way, it can be classed as development rather than learning since the memory structure is itself formed, rather than simply being the optimisation of an existing structure. Furthermore, in this context, learning may be described as the process by which the memory system adapts in response to changes in the conditions and context in which it operates, rather than an optimisation processes.

For the memory-based approach described here, it is important to note that there is no explicit separation between the representations of the different behaviours exhibited by the robotic agent. The production of behaviours can only be understood when the memory system as a whole is considered. Whilst this is a feature of artificial neural-based approaches (where the output of a network is determined by the combined action of the entire network), the memory-based approach described here requires the additional context of the value system. Where the implementation of the value system is inspired by non-neurally-inspired mechanisms, this account is in accordance with biological theory, where neurotransmitters complement the activity of neural systems for example.

The explicit representation scheme used in the computational implementation (i.e. where each associative unit is a discrete object) enables a degree of interrogation of internal processes not possible in artificial neural networks. This is because nodes encode an actual relationship, and so the flow of activation through the network can be interpreted directly in terms of the agents environment and behaviour, whilst maintaining the distributed nature of perception for action. Furthermore, this enables the value system to differentially modulate the flow of activation through the network based on the specific properties of individual nodes, rather than at the level of the entire network, as in artificial endocrine systems, e.g. (Neal and Timmis, 2003). One drawback to the explicit representation implementation used is the potential for a combinatorial explosion in the number of associative units formed as the sensor and effector space sizes increase. However, it is argued that the explanatory advantages that this approach affords justifies its use in this context - particularly regarding the developmental process, and the integration between neural- and non-neural-inspired processes.

Regarding the behaviour of the agent, the incremental development of the low level sensory-

3 Since the agent is embedded in a perception-action cycle, as the constructivist architecture develops, so the coherency of the behaviour increases, and thus also the control over the sensory input received.

motor competencies from random exploratory movements can be observed. Once a certain level of competence has been acquired, a plateau is reached (figure 6). It is hypothesised that this, or rather an internal indicator thereof (such as a plateau in the rate of change of the value system tags), may be used as the trigger for structural changes for the development of further behaviours, for example the lifting of constraints (Lee, Meng and Chao, 2007).

5.2 Related approaches and implementations

Despite the differences, the computational implementation described in the case study exhibits a number of similarities with artificial neural network approaches. For example, information in a neural network is encoded in the weight of the links between the nodes, and the behaviour exhibited by the network (i.e. its outputs) is encoded in a distributed manner. In the computational approach taken in the present work, nodes are used to represent associative relationships, but the behaviour of the network (i.e. the motor outputs produced) is similarly resultant from distributed information.

The explicit manner of encoding relationships in the MBCF/EMA is conceptually similar to the manner in which sensory-motor competencies are learned and encoded by the robotic motor-mounted camera setup reported in (Chao, Lee and Lee, 2010). In this setup, cross-modal associations are formed by explicitly linking elements in a sensory space and a motor space, so that the system can learn to move the camera so that an object of interest lies in a foveal region. A single explicit link in this implementation is responsible for the behaviour of the agent at any given time, which contrasts with the distributed nature of behaviour representation in the present research.

In another related approach, explicit constructs encoding anticipatory associations are used in a constructivist framework, thereby explicitly merging the constructivist and interactivist frameworks (Quinton and Buisson, 2008), where the present work only explicitly incorporates aspects of constructivism. This is seen by comparing the contents of a construct: in the constructivist/interactivist framework encode temporal associations (i.e. *A* followed by *B* in a given spatial location), whereas in the present work a construct encodes a spatial association (i.e. temporal co-occurrence of *A* and *B*).

The value system is effectively implemented as a reinforcement learning algorithm (Sutton and Barto, 1998), where the reinforcement is resultant from the change in sensory state, and the effector commands that resulted in this state, rather than from explicit reward feedback from the environment. Although initially inspired by mechanisms of foetal pain, in the reinforcement learning context, it is thus also comparable with theories of dopamine-based learning in biological systems (Suri, 2002).

5.3 Implications

The implementation of the memory-based approach presented above minimises the amount of domain specific information implemented *a priori*. A consequence of this is that a great deal of importance is placed on the drivers of development. For the memory-based approach described here, this role is fulfilled by the value system. Since the value system and memory structure are both distributed systems, this allows the opportunity to incorporate principles of organismically embodied robotics (Ziemke, 2002), as the value system may be rooted in the embodiment of the agent through the use of mechanisms inspired by, for example, homeostatic systems (Di Paolo and Iizuka, 2008). This is not possible to the same extent in current systems where modular and functionally specific structures are implemented. The hypothesis that the present research is working towards is that this memory-based approach will ultimately lead to more cognitively flexible agents, since there is no such explicit division between the underlying representation of behaviours, with an emphasis on the unification of cognition and memory.

A memory-based approach to cognitive robotics architectures would also be able to more readily incorporate developmental processes than a competing modular implementation, precisely because of the common substrate for cognitive functionality. This common substrate means that the same developmental processes would necessarily apply to all aspects of functionality, thus requiring less function-specific *a priori* information on the part of the system designer, which increases the biological plausibility and autonomy of resultant implementations.

6. Conclusion

This paper has described how a developmental memory-based approach to cognition provides a solution to a number of outstanding problems in the understanding of cognition, and shown how this principle may be applied to robotics. In this view, cognition should be interpreted as being the manipulation and utilisation of memory rather than being a function dissociable from memory. An explicit representation computational implementation has validated this approach, and demonstrated the interplay between embodiment, value system and memory for the development of behavioural competencies. While only low-level functionality has been explored, this paper presents an important further step on the path towards a memory-based cognitive robotics.

Acknowledgements

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