DAC

Distributed Adaptive Control: Theory and Practice

Paul Verschure & Armin Duff Eds.

CSN Book Series

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1 | Preface

I Acknowledgments

We would like to thank the Convergent Science Network for Neurotechnology and Biomimetic systems project CSN II - FP7 601167 for supporting the publication of this ebook on the biologically-inspired cognitive Distributed Adaptive Control (DAC) architecture. This DAC architecture is one of the very few examples of biomimetic architectures of perception cognition and action that has been applied to a range of artificial behaving systems i.e. robots, while having a strong grounding in the pertinent neuroscience of both invertebrate and vertebrate systems.

As a subject for teaching material DAC will introduce researchers and students to key concepts of minds and brains, at both the functional level and at the level of how the physiology and anatomy of brains shape and realise these functions.

We are grateful to the laboratory of Synthetic, Perceptive, Emotive and Cognitive Systems (SPECS), which was involved in the development of the different versions of the DAC architecture. We also wish to express our gratitude to all the students that successfully used DAC in their studies and research projects and have thus helped to improve it further.

Finally we would like to thank the Book Sprints team and the FLOSS Manuals team for making this book possible!

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http://booksprints-for-ict-research.eu

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http://www.csnetwork.eu

FLOSS Manuals Foundation

FLOSS Manuals creates free documentation about free software. It is an online community of some 4-5000 volunteers creating manuals in over 30 languages.

http://www.flossmanuals.org

Book Sprints

Book Sprints is a rapid development methodology for producing books in 3-5 days. The methodology was founded by Adam Hyde of BookSprints.net.

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Two EU Projects at Work in a Creative and Collaborative Writing Effort

The publication of this book on the Distributed Adaptive Control theory (DAC) is part of the CSN Book Series and is a collaborative effort between the EU coordination action CSNII - Convergent Science Network for Neurotechnology and Biomimetic systems, and the EU project Book Sprints for ICT Research.

The goal of CSN is to contribute and advance the training of future generations of researchers who will shape the field of biomimetics and biohybrid systems by producing teaching materials (e.g. video lectures, podcast interviews, tutorials and books) and also by providing visibility and access to all of the material produced in the context of the CSN educational objectives. Through these dissemination actions CSN hopes to further enhance the impact of the field.

The goal of Book Sprints for ICT Research project is to adopt and test the Book Sprints methodology within the context of academic ICT research. This means that Book Sprints will apply their method of collective writing to the CSNII group formed by the authors of the DAC book.

www.booksprints.net
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According to the Book Sprints method, the authors of the DAC book worked closely together with a facilitator, a professional editor and a designer, who helped with the overall production of the book. The duration of a Book Sprint writing event is normally 4-5 days.

The resulting book was finished at the end of this event with the goal to be made available as both printed and electronic publication.

On the one hand CSN profits from this collaboration because it has been able to deliver a book in a very short period of time, and on the other hand, the Book Sprints for ICT Research project has had the opportunity to evaluate the Book Sprints method for an academic publication with an ICT research group such as CSN.

Location of Event

This event took place in the spring of 2014 at the coast of Barcelona in Spain.

Book Theme

CSN teaching material and the 2nd CSN book series on the Distributed Adaptive Control theory (DAC).

Book Authors

A group of 8 scientists agreed to participate in this book endeavour. These are experts (PhDs, postdocs, professors) from different disciplines such as neuroscience, psychology, biology, physics and engineering.

Paul Verschure is an ICREA professor and director of the Center of Autonomous Systems and Neurorobotics at Universitat Pompeu Fabra where he leads the SPECS Laboratory. With a background in psychology and AI he aims to find a unified theory of mind and brain using synthetic methods, and to apply it to quality of life-enhancing technologies. He is the founder of the DAC theory. **Co-author of the chapters 'The Science of Brain and Mind' and 'Distributed Adaptive Control: A Primer'.**

Tony Prescott is Professor of Cognitive Neuroscience and the Director of SCentRo at the University of Sheffield, UK. He has worked since 1992 on investigating parallels between natural and artificial control systems. **Co-author of the chapters 'The Science of Brain and Mind', 'Distributed Adaptive Control: A Primer', and 'Rehabilitation Gaming Systems'.**

Armin Duff is a visiting professor at the Universitat Pompeu Fabra Barcelona, Spain, and a senior researcher at the SPECS laboratory. His main research interest is how intelligent systems extract and learn the rules and regularities of the world in order to act autonomously. In particular he evolved the Distributed Adaptive Control (DAC) architecture proposing a new learning rule called Predictive Correlative Subspace Learning. **Co-author of the chapters 'DAC5', 'DAC Tutorial on Foraging' and 'DAC Simulation Environment: iqr and Gazebo Setup'.**

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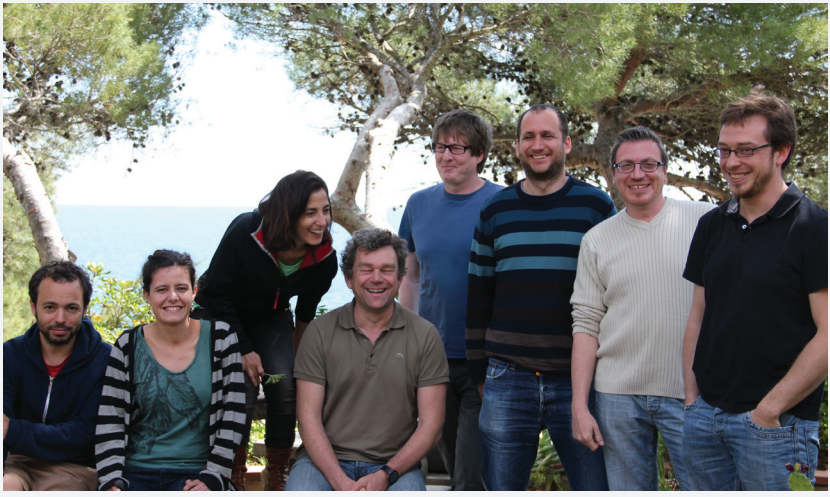
Anna Mura is a biologist with a PhD in natural sciences and is a teaching professor and senior scientist at the SPECS laboratory, Universitat Pompeu Fabra, Barcelona. Presently she is dealing with science communication and outreach activities in the field of brain research and creativity. **CSN book series editor, author of the chapter 'ADA: A Neuromorphic Interactive Space Based on DAC', and co-author of the chapter 'Rehabilitation Gaming System'.**



Abstract

Distributed Adaptive Control (DAC) is a theory of the design principles underlying the Mind, Brain, Body Nexus (MBBN) that has been developed over the last 20 years. DAC assumes that the brain maintains stability between an embodied agent, its internal state and its environment through action. It postulates that in order to act, or know how, the brain has to answer 5 fundamental questions: who, why, what, where, when. Thus the function of the brain is to continuously solve the so-called H5W problem with 'H' standing for the 'How' an agent acts in the world. The DAC theory is expressed as a neural-based architecture implemented in robots and organised in two complementary structures: layers and columns. The organisational layers are called: reactive, adaptive and contextual, and its columnar organisation defines the processing of states of the world, the self and the generation of action. Each layer is described with respect to its key hypotheses, implementation and specific benchmarks. After an overview of the key elements of DAC, the mapping of its key assumptions towards the invertebrate and mammalian brain is described. In particular, this review focuses on the systems involved in realising the core principles underlying the reactive layer: the allostatic control of fundamental behaviour systems in the vertebrate brain and the emergent non-linearity through neuronal mass action in the locust brain. The adaptive layer is analysed in terms of the classical conditioning paradigm and its neuronal substrate the amygdala-cerebellum-neocortex complex together with episodic memory and the formation of sense-act couplets in the hippocampus. For the contextual layer, the ability of circuits in the prefrontal cortex to acquire and express contextual plans for action is described. The general overview of DAC's explanation of MBBN is combined with examples of application scenarios in which DAC has been validated, including mobile and humanoid robots, neurorehabilitation and the large-scale interactive space Ada. After 20 years of research DAC can be considered a mature theory of MBBN.

2 | DAC Theoretical Framework

1 The Science of Brain and Mind

This book describes an approach to understanding the human mind and brain that the authors have been developing for more than two decades. In this opening chapter we try to explain the motivation for our approach by placing it in a wider context. Specifically, we explore how the different sciences of mind and brain—from neuroscience and psychology, to cognitive science and artificial intelligence (AI)—stand in relation to each other at this moment in the 21st century. Our aim in doing so is to persuade you that despite the fact that our knowledge is expanding at ever-accelerating rates, our *understanding*—particularly of the relationship between mind and brain—is, in some important sense, becoming less and less. An explanatory gap is building that, for us, can only be bridged by a kind of multi-tiered and integrated theoretical framework, Distributed Adaptive Control (DAC), which is developed and described in this volume.

A second goal of this chapter is to show that, in bridging this explanatory gap, we directly contribute to advancing new technologies that improve the human condition. Indeed, our view is that the development of technologies that instantiate principles gleaned from the study of the mind and brain, or *biomimetic* technologies, is a key part of the validation process for the scientific theory that we will present. We call this strategy for the integration of a science and engineering 'Vico's loop' after the 18th-century Neapolitan philosopher Giambattista Vico who famously proposed that we can only understand that which we create: 'Verum et factum reciprocantur seu convertuntur.' We aim to show both here, and in the 'DAC Applications' section of this book, that following the creative path proposed by Vico can lead not only to better science (understanding), and useful engineering (new life-like technologies in form and function), but can also guide us towards a richer view of human experience and of the boundaries and relationships between science, engineering and art.

Matter over Mind

To begin, let us consider some concrete examples of how the science of the mind and brain is currently being pursued. Since mind emerges from brain, an important trend that we have noticed is increasing the focus of resources and efforts towards the brain side of the mind-brain duality, seemingly in the hope that this will unlock the secrets of both. We call this trend 'matter over mind' because we feel that it is drawing attention towards things that can be measured—brain processes—but in a manner that risks losing sight of what those processes achieve—instantiating the mind.

Two concrete and significant examples of this trend are as follows. In 2013, the European Commission initiated the Human Brain Project (HBP)—a decade-long, €1 billion effort to understand and emulate the human brain. In the same year, the US Government announced the BRAIN Initiative—projected to direct funding of $3 billion to brain research over a similar ten-year period. With this level of investment and enthusiasm you would hope that great advances in brain science are surely just around the corner. Knowing so much more about the brain, we should surely also know much more about the mind and thus about ourselves.

However, although this increased international enthusiasm for brain science is exciting and in many ways welcome, there are some niggles. Looking at these flagship projects we are struck by how both initiatives are convinced that an understanding of the brain, and hence the mind, will proceed from a very large-scale, systematic approach to measuring the brain and its physical properties. More precisely both of these projects intend to leverage powerful 21st-century technologies—such as the latest human brain imaging, nanotechnology and optogenetic[1] methods—that can make the connectivity and activity of the brain more apparent. They will then apply the tools of 'big data', such as automated reconstruction and machine learning, powered by the accelerating power and capacity of computers, to help make sense of what will amount to a tsunami of new measurements.

While all of this is well and good, we see a significant gap. Will we know ourselves once we have all the facts in our database? Where are the theories of brain function that are going to explain all of this new anatomical detail? How are we going to make the connection between the understanding of the brain at a tissue level and the understanding of mind at a psychological level? In this fascination with the brain as the physiologically most complex organ in the human body, are we losing sight of what is needed to understand and explain the role of the brain in guiding and generating behaviour and shaping experience? While many have argued that we need better data to drive theory building, we contend that there is already a mountain of unexplained data about the brain, and what is needed are better theories for trying to make sense of it all.

Part of the solution to the challenge of connecting brain physiology to behaviour is—as we explore further below and throughout this book—computational modelling, either using computer simulation, or, to understand the link between brain and behaviour more directly, by embedding brain models in robots. Naturally these large-scale projects that are exploring the human brain will apply and extend current computational neuroscience models and methods so, on the surface, all seems well. In particular, they will develop computer simulations that seek to capture rich new datasets at an unprecedented level of accuracy using hugely powerful massively parallel machines (HBP, for instance, will invest heavily in building these

on neuromorphic principles), in an attempt to show how interactions among the microscopic elements that constitute a brain can give rise to the global properties that we associate with the mind or its maladies. One of the goals of these projects is to better understand/treat mental illness, thus showing societal relevance. Indeed, this programme of brain simulation has ambitions to match those of the corresponding endeavour of brain measurement, so why worry?

Well, our concern lies in the observation that the technical possibility of amassing new data seems to have become the main driving force. The analogy is often made with the human genome whose decoding has unlocked new avenues for research in biology and medicine. However, whilst the genome is large (3 billion base pairs) it is finite and discrete (each pair can only be one of a fixed number of known patterns), and the case could be (and was) made that deciphering it would concretely and permanently address a key bottleneck for research. With the brain, on the other hand, there is no equivalent target to the genome—no template for brain design that once we have described it we can say we are finished. There will always be another level of description and accuracy that we can strive for and which, for some, will be the key to unlocking the brain's secrets from microtubules and CAM kinase to gamma range oscillations and fMRI scans. Further, whilst the new tools of 21st-century brain science are attractive in terms of their greater accuracy and power, what we see with many of their results is confirmation of observations that had already been made in previous decades albeit in a more piecemeal fashion. To unlock the value of these new datasets, we believe, will require the development of multi-tiered explanations of brain function (of which there is more below), and data analysis tools will help, but the theory-building activity itself will largely be a human endeavour of which abstraction will remain an important part.

A key point for us is that description and measurement whilst vital to doing good research are not the ultimate goal of science. Rather, we describe in order to explain. As the physicist David Deutsch noted in 1997, there are an infinite number of facts that we could collect about the natural world (and this will include a countless number of brain facts), but this kind of knowledge is not, by itself, what we would call understanding. The latter comes when we are able to explain the amassed data by uncovering powerful general principles. In astronomy, for instance, Ptolemy, followed by Copernicus, Galileo, Newton, and then Einstein all developed theories that sought to explain observations of the motion of stars and planets. Each new theory succeeded in explaining more of the assembled data and did so more accurately and more succinctly. For instance, Copernicus explained data that had been problematic for Ptolemy's geocentric cosmology by replacing the earth with the sun as the centre point around which the planets turn. Einstein showed that Newton's law of gravitation breaks down when gravity becomes very strong, and was thus able to better (or more succinctly) explain some data on planetary orbits. In physics the search for a theory with more explanatory power than general

relatively continues, with the hope to one day explain the origin of everything, beginning with and including the Big Bang, according to a single set of over-arching principles.

In comparison to astronomy, how far have we come in developing powerful theories for understanding brain data? The answer is not very far yet. With the current focus on large-scale datasets there is an interest in discovering principles for sure, but there also seems to be an expectation that these will bubble up through the accumulation of observations; a process of induction if you will, powered by the tools of data mining and computational modelling. Moreover, in place of striving for the kind of compact theoretical description seen in physical science, there is an increasing focus on models that can capture more of the potentially relevant detail. The boundary becomes blurred between capturing principles and what can become, in the end, an exercise in function fitting. In our admiration of the elegance and beauty of brain data, and with the power of modern ICT systems to simulate it, we can come to believe that the best model of the brain is the most exact model. Following this path, however, can only lead to the conclusion that the brain is its own best explanation, an idea satirised by Rosenbleuth and Wiener in their comment that 'the best material model for a cat is another, or preferably the same cat' (Rosenblueth & Wiener, 1945), and reminiscent of Borge's famous story of the cartographical institute whose best map was identical to the landscape it described and thus lost its usefulness.

A second way of summarising this concern is that the zeitgeist seems to favour more reductionist descriptions rather than theoretical explanations. The logic appears to go that we still don't know enough of the key facts about the brain—cells, circuits, synapses, neurotransmitters, and so forth—therefore lets go and find out these details. Once we know these things we will necessarily better understand both brain and mind. However, while neuroscience tilts towards more data gathering, it is interesting to note that other areas of biology are becoming more holistic in their approach, adopting what is often described as a 'systems' view. Indeed, in systems biology, explanations are sought that go across levels from the molecular through, the cellular, organismic, and the ecological. No one level of explanation (or description) is privileged, and understanding at each level informs and constrains understanding at the levels above and below it. In much the same way, and within the sciences of the mind, parallel complementary explanations can be sought at the psychological level (mind) and at the biological level (the brain), and we can allow that there may be other useful explanatory levels between these two. Indeed, we contend, as do many others, that useful theories of mind and brain can be motivated that abstract away from the biological details of the brain but at the same time capture regularities at a level below that of our direct intuitions (what some have called 'folk psychology'), and that in this area some of the most powerful explanatory ideas might lie.

Cognitive Science Turf Wars

The notion of a multi-tiered understanding of the mind and brain is of course nothing new. Indeed, in many ways it is captured in a research programme that since the mid 20th century has gone by the name of cognitive science (e.g. Gardner 2008). Acting as a kind of scientific umbrella, cognitive science has fostered interdisciplinary dialogues across the sciences of the mind and brain for the last seventy years, promoting the complementarity of explanations emanating from neuroscience, psychology, linguistics, philosophy, and computer science. At the same time, however, cognitive science has never really succeeded in building a consensus around a core set of scientific principles. Instead, it has seen struggles between different communities as to what should be the preferred level of description of mind and brain and it has hosted heated debates over the meaning and relevance of central concepts such as representation and computation. Perhaps this is the nature of a healthy science, however, unlike neuroscience, for instance, which holds a successful annual conference for more than 30,000 delegates, the focus of cognitive scientists is dispersed across dozens of events each favouring a particular perspective or approach. Moreover, despite its potential relevance to both the scientific understanding of brain disease and the development of new smart technologies it has surrendered much of its ground on the former to neuroscience and on the latter to robotics and AI. Finally, whilst neuroscience as a community has been able to mobilise support at the highest levels for endeavours such as HBP and the Brain Initiative, funding for cognitive science appears to be flagging at least momentarily (the EU, for example, recently scrapped its Robotics and Cognitive Systems programme in favour of one solely focused on robotics, partly due to the failure, as they saw it, of cognitive systems to address society-relevant challenges). Standing back for a moment, we wonder if the current resurgence of a more reductionist brain science programme is, at least in part, due to the failure of cognitive science to really capitalise on the great start that it made more than half a century ago. A commitment to interdisciplinarity has till now failed to lead to powerful interdisciplinary theories that command broad assent, leaving a vacuum to be filled by explanations couched at only one level.

A further way to look at the current status of the field is to recognise that, in terms of the sociology of science as described by Thomas Kuhn, cognitive science sometimes appears to be ‘pre-paradigmatic’. For Kuhn, work within any given domain of science begins with multiple competing general theories, or ‘paradigms, but then progresses to a point where one of these is clearly more successful than the rest, comes to dominate the field, and attracts more and more supporters to work within it—this then is the normal state for a mature scientific field. According to this narrative, it is possible for an alternate paradigm to arise building on any weaknesses in the current dominant general theory, such as a failure to adequately explain key data, and questioning some of its core precepts.

If sufficiently persuasive, such an alternative can provoke a 'scientific revolution' in which the current dominant paradigm is overthrown to be replaced by a new orthodoxy. Whilst a scientific revolution can come about because the new paradigm is more explanatory (in the sense discussed above), a key element of the Kuhnian analysis is that trends in scientific research are partly determined by social and political forces rather than purely scientific ones. The dominant paradigm might crumble, for instance, not simply because it is weaker but because it has become unfashionable, conversely an alternate paradigm might fail to thrive not because it does not offer better explanations but simply because it fails to attract enough supporters, or resources, to mount a serious challenge—as in politics, the incumbent can have power and influence that allows them to suppress contenders at least for a while.

The Kuhnian narrative appears to work well in physics, a domain that Kuhn was trained in, and where the Newtonian view succeeded the Galilean view then to be replaced by the special relativity/quantum view. Applied to sciences of the brain and mind, the picture is more complicated. From one view, cognitive science stands as a distinct scientific domain still looking to find its feet (i.e. pre-paradigmatic), with symbolic AI, connectionism, dynamic systems, and perhaps cognitive neuroscience, all vying as competing paradigms within it. Within the field, the navel-gazing continues but with the vague assumption that eventually a consensus will emerge and cognitive science will have come of age. From an alternative view, cognitive science is itself a paradigm competing within the broader domain of the natural sciences to be *the* approach to understanding the mind and brain. From this perspective, cognitive science replaced behaviourism as the dominant paradigm in the mid-20th century and has succeeded to hold its ground till now despite a lack of consensus and internal division. At this point we might ask if cognitive science is now at risk, in Kuhn's sense, of being overthrown and, if so, who would be the contender? Surveying the landscape, does the new breed of assertive reductionist neuroscience have, as its ambition, the desire to replace the cognitive science consensus in favour of multidisciplinary explanations? Could neuroscience potentially succeed in eliminating cognitivist theories, and all their conceptual intermediaries, in favour of explanations couched directly in terms of brain states and dynamics? Will a future retelling of the history of science conclude that cognitive science was a useful approximation, like Newtonian physics, effective in plugging the explanatory gap left by predecessors such as behaviourism, but ultimately not as powerful as a fully-formed 'quantum' neuroscientific theory of the relationship between mental phenomena and brain activity (note that this analogy has been suggested before in relationship to Connectionism (Smolensky, 1988), which now might be viewed as another partial step to a full neuroscientifically-grounded account)?

We describe this scenario not because we think it is likely, or because we think an eliminativist neuroscience really is the better paradigm. However, we recognise, with Kuhn, that science is a societal activity, and that the field of cognitive science could wane, or perhaps is already waning. We would like cognitive science to wake up, move its focus away from turf wars about privileged levels of explanation, and get back to its core agenda of building powerful multi-tiered theories of the mind and brain. We worry that a neuroscientific agenda that increasingly sees the brain as the best theory of itself is actually a retreat from properly advancing the sciences of the mind or any science for that matter. Like behaviourism seventy years ago, the brain again becomes a box whose contents is ultimately unanalysable; this time we can describe what is inside, but we surrender the hope of a theoretical explanation of the emergence of the mind in favour of the aspiration that if we copy it accurately enough we will somehow replicate interesting aspects of mental function.

Towards a Multi-Tiered Theoretical Framework

So what *should* a 21st-century approach to understanding the mind and brain look like? In the study of mind and brain there is currently no accepted general theory and the last attempt to define one came to a halt in the early 1950s with Clark Hull's theory of the behaving system that followed the logical-positivist school. Since then, it has gone relatively quiet in terms of attempts to postulate theories that show how a physical system like the brain can give rise to mind and behaviour; at best we have seen micro-theories that are highly specialised. This is the explanatory gap that needs to be filled—a general theory, or framework, connecting brain and mind.

In broader terms, what should we look for in such a theory? First, as we discussed above, a theory must *explain*, in this case, the scientific observations that constitute the relevant 'facts' of empirical science concerning measurement of the brain and behaviour, and this data must be interpreted in such a way that provides an explanation of human experience. Second, a theory must make testable *predictions* that can be validated with available methods and technologies (making predictions that require measurements to be made with science fiction technologies cannot be taken too seriously). Third, a scientific theory must be able to *control* natural phenomena. This means, for instance, to be able to define a set of manipulations that constitute an experiment or the principles on the basis of which a useful artefact can be constructed. In addition to these primary requirements, we can include that it must be supported by a broad base of observations, generate multiple predictions in a range of areas, and display continuity with pre-existing knowledge and theories. Furthermore, it must follow Adelard of Bath's dictum that nature is a closed system and all natural phenomena must be explained as caused by other natural agents (formulated in the 12th century) and Occam's razor, which asks for parsimony in scientific theories.

Our commitment value of models, particularly those that make useful impact in the world, derive from the dictum 'verum et factum'—we understand by making. Another way of expressing this idea is that the machine *is* the theory concretely embodied and observable. We can contrast this view with 20th-century notions of how science should work. Specifically, in the first half of the 20th century, the notion of scientific theory was strongly dominated by a syntactic formal interpretation where a scientific theory comprised axioms that allowed the deduction of observations, which upon being tested against reality would lead to an update of the axioms. In this logical positivist view a language of science could be constructed that would specify an ordered way to shape scientific progress. In the second half of the 20th century, however, there was a shift to a so-called semantic, or model-based, interpretation where a scientific theory describes aspects of reality not unlike a map describes a physical landscape. However, theories and models face the problem of being under-constrained. From this view, there are many possible ways to interpret observations. We can think of the model as a fit of a curve through a cloud of data points. There is a practically infinite number of lines we can draw; which ones to retain and which to ignore? In the study of mind and brain we consider that we can reduce this search space by imposing the requirements that theories of mind and brain must be able to relate to multiple levels of description—minimally the structure and function of the brain, or to its anatomy and physiology, and the behaviour it generates. This method is called *convergent validation.* In more practical terms our strategy is to build computational models to emulate the brain's anatomy and physiology and to embody these models using interfaces to the physical world (for instance, via a robot). In this form our theory as a model can explain anatomy, physiology and behaviour, make predictions at multiple levels of description and control a physical device. In addition, it instantiates Vico's loop: we have made an artefact with life-like capabilities that can potentially be deployed in a useful task.

An additional form of constraint and a critical aspect of understanding the mind, and not just its parts, is that we need to develop theoretical frameworks that have the potential to inclusively explain all of the interesting capabilities of mind and brain including, but not limited to, perception, sensorimotor control, affect, memory, learning, language, imagination, creativity, planning, consciousness, etc. In short, work within particular subdomains, and most work in cognitive science, is necessarily of this character, must have the potential to be incorporated within the bigger picture, and this evolving idea of the full architecture of the mind and brain should reveal how underlying principles operate across these subdomains at the same time as identifying that specific subdomains may also have their own specialisms. Occam's razor—the requirement to have an overall succinct theory—should be applied, with the aim that this framework is assembled at a high level of abstraction whilst retaining the possibility to be a complete explanation of how the brain gives rise to mind. Naturally, the framework we are assembling does not adopt an a priori view about privileged levels of explanation. Indeed, it is a

requirement of our commitment to convergent validation that we should generate models at multiple levels of abstraction—some very close to mechanisms revealed through the microscope of neuroscience, others very high-level and connecting to principles identified in engineering or computer science. Finally, we recognise the value of different methodologies for acquiring explanatory concepts. For instance, we can work inductively and bottom-up, using the powerful data analysis tools now being developed, to identify the 'good tricks' (Dennett, 1995) that have been discovered in the evolution of nervous systems. Likewise, we can work top-down and deductively, going from computational analyses (in the sense of David Marr) of the functions of mind to ideas about the mechanisms that can give rise to them. Here advances made in engineering and AI furnish us with candidate principles that could be instantiated by the brain and mind. We do not prefer bottom-up or top-down approaches, but rather strive for the completeness of our theory, and to have elements of both in order to have strong constraints in these two directions.

It is important to build on previous scientific attempts at a general theory of the mind and brain. In this book you will find ideas that originated with the invention of control and information theory in engineering, digital computers in ICT, and systems theory in biology. Amongst these we would highlight the insights of the early cyberneticians such as Norbert Wiener, Warren McCulloch, Rosh Ashby, and William Grey Walters who combined the theory of feedback-based control from engineering, with the notion of homeostasis from biology, to produce a theory of the brain as a mechanism for maintaining balance that can be applied to diverse areas of brain function from autonomic function (the regulation of bodily processes such as breathing, circulation and metabolism) and motor control, to cognitive processes such as learning and memory. During the emergence of cognitive science in the 1950s, leading figures were also concerned with general theories of the mind. For instance, building on attempts to understand decision-making, Alan Newell and John Anderson both elaborated general theories of cognitive architecture using if-then rules (productions) as their primary building block. These models explored and demonstrated the power of a simple principle, recursively applied, in generating mind-like properties, but they also revealed some of the limitations of prematurely settling on a specific level of analysis, or computational primitive. Indeed, partly in reaction to this model of the brain as a symbol-cranking system, a view which emerged from computer science and rather arrogantly declared the independence of theories of mind from theories of brain, namely, the connectionist architectures developed by David Rumelhart, Jay McClelland, Geoffrey Hinton, Terry Sejnowski and others, looked much more at the specific structural properties of the brain, particularly its massively distributed nature, as inspiration for their models of brain architecture. The excitement around these models, which had the capacity to explain facets of learning and memory that were problematic for symbol-based approaches, encouraged claims to be made that this was *the* privileged level of explanation at which theories of mind should be couched. This is one

of many examples in cognitive science where success in applying one particular kind of explanatory principle in a number of subdomains led to premature conclusions of this nature. Looking back, thirty years on from the connectionist 'scientific revolution', that approach has succumbed to the same criticism, but this time from computational neuroscience—that the more abstract version of brain architecture favoured by the connectionists overlooked critical details. But the answer is not to go deeper and deeper to find the perfect model, but to recognise that different scientific questions can be addressed at these many different levels (Churchland & Sejnowski, 1992). A dynamic systems view, emerging in the 1990s, and championed by Scott Kelso, Esther Thelen, Jeffrey Elman, and others attempted a synthesis between connectionist theory (or 'new' AI more broadly) and systems biology. However, once again, the effort to distinguish itself from what had gone before, in this instance by declaring itself to be non-computational, limited the impact of the approach. More recently, new bandwagons have emerged based on the notion of the brain as a machine for doing Bayesian inference, or prediction (minimising its own ability to be surprised by the world). The most ambitious versions of these theories hope to be full accounts of how mind emerges from brain. The attraction that we have as scientists to the possibility of uncovering core principles that succinctly explain many of the things we want to understand (as the physicists managed to do in explaining the motion of the stars and planets), must be tempered by the recognition that such notions have so far only captured a small fraction of the competencies of the human mind and so have a very long way to go before they can make any claim to theoretical completeness. As an evolved system that must solve many different types of challenges in order to survive and thrive, we must also be open to the possibility that there is no one principle, or even a small cluster of principles that will explain the mind/brain. We certainly hope for a theory that is much simpler than the brain, but we expect, nevertheless, that it will be extremely complex.

As we have explained in this chapter, we consider that an important element of theory development and testing is its instantiation as a machine; this allows us to achieve a level of completeness not possible at the purely theoretical level or even in simulation, and allows us to test theories whose complexity we cannot easily entertain in our own minds. More emphatically we consider, following Vico, that a mark of a good theory of the human mind and brain is that it can be instantiated in this way, and an advantage of this approach is that it can also lead to the develop of new biomimetic technologies that have value to society. The remainder of this book describes an attempt at a framework that seeks to address this challenge, and its instantiation in multi-tiered models (some embodied) as a means of testing/refining the framework. Finally, in the applications section we show how this approach is beginning to lead to technologies for/of rehabilitation, neuroprosthetics, and assistive robots, that we hope will show how our approach to the science of the mind and brain can lead to useful innovation and ultimately to broad societal benefit.

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Footnotes

1 Optogenetics is a technique that uses genetic manipulations to make neurons in animal brains emit light when they are active, thus offering exciting new ways of finding out how cells connect to each other and of identifying how and when particular types of cells are active during behaviour.

Distributed Adaptive Control: A Primer

'Won't somebody tell me, answer if you can!
Want somebody tell me, what is the soul of a man?'

Blind Willie Johnson—1930s blues song

The Greek rationalist philosopher Plotinus asked, in about 250BC: 'And we, who are we anyhow?' 'Zombies' we are told by Daniel Dennett, one of the leading philosophers of the 20th-century cognitive era, or 'Meat Machines' according to Marvin Minsky one of the founding fathers of artificial intelligence. Is that it? Is that what the *soul* of humans has become? Reduced and brushed away into a mechanical universe. Here, 'soul' is referred to as synonymous with the more modern construct of mind (Blind Willie Johnson, however, would disagree with that). To become even more specific we can define 'mind' as the functional properties of brains that can be expressed in overt behaviour. 'Behaviour' is defined as autonomous changes in the position or shape of a body or soma. Once behaviour serves internally-generated goals we can speak of 'action'. The 'brain' is defined as a distributed, wired-controlled system that exploits the spatial organisation of connectivity combined with the temporal response properties of its units to achieve transformations from sensory states, derived from the internal and external environments, into actions. The core variable this mind/brain maintains in a dynamic equilibrium is the integrity of the organism in the face of the second law of thermodynamics, the organism's needs and environmental changes that continuously challenge this integrity and threaten survival, and thus compromise reproduction. The mind/brain is the result of a centralisation of mediation following the increasing complexity of the morphology, sensory repertoire, sensorimotor capabilities and the niche organisms that emerged during the Cambrian explosion about 560M years ago. The incrementally tighter bi-directional coupling between the organism and its environment we observe through the progression of phylogeny, implies that in order to answer Plotinus with respect to us humans and other animals, we do have to consider as our explanandum the nexus of mind, brain, body and environment.

The Distributed Adaptive Control theory of mind and brain (DAC) is formulated against the backdrop of the main developments in psychology, artificial intelligence, cognitive science and neuroscience during the 19th and 20th century. It aims at integrating across the dominant paradigms and approaches, as opposed to a priori

negate any of them. The story of the study of mind and brain is essentially one of a sequence of paradigms that are defined by negating their predecessors. This trend starts with the focus on the study of consciousness in the nascent continental school of the psychology of Fechner, Helmholtz, Donders and Wundt in the second half of the 19th century. Structuralism was followed by behaviourism that saw its heydays during the first half of the 20th century and constituted a direct reaction to structuralism by negating its core dogmas. With the wish to develop a rigorous experimental science of adaptive behaviour, behaviourism largely rejected the use of constructs that were not directly observable, leading to the extreme position of Watson and Skinner that constructs related to 'mind' had no place in a science of psychology. Important sources of inspiration for this approach were the pragmatism of Peirce, James and Dewey, which anchors knowledge in practical outcomes and a simplified interpretation of the developments of physics, the most successful science of that era and its method of operationalisation: the definition of phenomena through the operations deployed to make measurements on them. Behaviourism in this extreme form rejected mind in favour of the study of an empty embodied organism. Behaviourism advanced important experimental paradigms and insights in the study of learning, in particular the paradigms of classical and operant conditioning introduced by Pavlov and Thorndike respectively in the early 20th century. Behaviourism served the agenda of the ideal of a unity of science where the psychology of adaptive behaviour could be reduced to the biology of the brain, which would map to chemistry and physics. However, after about half a century of trying, behaviourism failed to deliver on its promise of identifying universal principles of adaptive behaviour grounded in the 'atom' of the reflex that would be isomorphic with their physical instantiation in the brain, and to scale up to more advanced forms of behaviour beyond salivating, twitching, freezing, pushing levers or pecking targets. Most importantly, organisms were not enslaved by the reinforcement they received from the environment, as the empty organism dogma prescribed, but rather involved with self-structured learning and behaviour. Fuelled by the development of adaptive control systems during the Second World War, the movement of the cybernetics of Wiener, Rosenblueth, McCulloch, Pitts, Grey Walter and Ashby emerged that proposed a multidisciplinary approach towards adaptive behaviour, centring on the mathematical and engineering principles of control and interaction such as homeostasis, feedback control and neuronal operations. Cybernetics included a synthetic component where the emulation of these principles was sought using artificial systems, most notably the homeostasis of Ashby and the robot turtles of Grey Walter. In parallel, a second contender was based on the advances in computing machinery in breaking codes and sorting large amounts of information, leading up to the computer metaphor of mind pursued in artificial intelligence and the cognitive science of the second half of the 20th century. Pioneers of this movement starting with Alan Turing had shown that machines could display functional properties that resembled human problem solving. This analogy inspired a young generation of upcoming researchers in the US bolstered by

generous government support, to declare the computer metaphor a new science of the mind, and giving rise to the artificial intelligence (AI) of Newell, Simon and Minsky, and the linguistics of Chomsky. AI overshadowed cybernetics and heralded a brave new world of the study of the logical operations performed by the disembodied mind, which negated behaviourism and its link to empirical investigation at the level of brain and behaviour. This so-called functionalist view, where explanations of mind focused on the rules and representations of the software of the mind, ruled for a few decades. It was exactly this functionalist view and the so-called multi-instantiation it implied, that severed the link to the study of the brain in order to explain the mind: logical operations can be implemented in various physical substrates and the latter does not inform on the properties of the former. AI and the computer metaphor stumbled over its own claims of being able to synthesise intelligence, largely due to a critical dependence on the human programmer and the knowledge they implanted in the AI system leading to what has been called the symbol grounding problem, or in more general terms, the problem of priors: a system can follow predefined rules operating on predefined representations and not 'know' what it is doing, thus lacking the ability to understand and adapt to the real world in which it is embedded. Lacking impact in the real world, the disembodied mind of AI was followed in the 1990s by a period of research in which biological metaphors guided the construction of artificial systems and their associated claims on the mind, such as in behaviour-based AI, artificial life, genetic algorithms and neural networks and connectionism combined with a philosophy of eliminative materialism, where the whole human experience would be described in 'brain speak'. The 'new' AI directly negated its predecessor by proposing a non-representational behaviour-based explanation of mind, while connectionism was seeking out the 'subsymbols' that would link substrate to mind. Neither of these approaches have had a lasting impact on the study of mind and brain beyond facilitating the advancement of computational modelling in the life sciences, such as computational neuroscience. The last step in this regression of the study of mind and brain is the surrender to the seduction of big data or a bottom-up modelling approach driven by the force of data. The human mind dissolved into petabytes of data.

DAC aims at reintroducing necessary theoretical considerations into the study of mind and brain and to combine these with a well-defined synthetic method: the machine is the theory. It is from the perspective theory that we investigate nature and answer Plotinus' challenge. Data as such is meaningless and if pursued in its own right will solely generate more noise in our understanding of reality. DAC is defined with the ambition to explain the conscious, embodied mind, or the MBBN, thus connecting it to 19th-century structuralism and its explanandum. Furthermore, DAC adopts from behaviourism the objectives to develop an objective multi-scale science of mind and brain starting from its key paradigms of classical and operant conditioning, in realising its theories in an embodied quantitative form starting from the perspective of control links DAC to the agenda of cybernetics, while scaling

up towards high-level cognitive functions such as problem solving, language and decision-making incorporating the agenda of traditional AI. Hence, DAC takes the obstacles faced by preceding paradigms as the objectives of its research programme with the goal to unify them rather than negate the preceding paradigm. The latter would be difficult at this stage because there is currently no dominant paradigm, but the study of mind and brain exists in a highly fragmented conceptual world of micro-theories, relatively small research communities pursuing highly specialised questions all glued together by the drive to generate more and more data. DAC is taking the explicit and firm position that if we want to answer Plotinus we have to get back to theorising about mind and brain.

Given DAC's research agenda of solving the challenges faced by the different attempts to explain mind and brain, the question is what should our explanandum be, the phenomenon that we want to specifically explain? DAC proposes that this should again be the structuralist goal of developing a science of consciousness. Given that consciousness lacks a clear definition, this might sound surprising, so lets spend a few words on why this is a good choice. The explanandum of behaviourism, also inspired by the Darwinian revolution and the specific dynamics of the 19th-century society of the developing new world, was adaptive behaviour or learning. With the switch to the computer metaphor the explanandum changed to reasoning, reflecting the outcome of the symbol manipulation that computers are built for or artificial intelligence, a label coined by one of its first researchers John McCarthy for a 1956 seminal conference at Dartmouth College co-organised with Claude Shannon and Marvin Minsky. With the choice of the naming of the field and implicitly its objectives, the machine mind of AI would target a rather ill-defined and relatively suspect construct. Intelligence became a concept of great interest to the science of the mind due to the work of Galton in the late 19th century. Seeking a single scale with which to quantify human mental capabilities, he settled on the notion of intelligence as measured through a self-devised test battery and reflecting a single inherited factor, also called *g*. This operational approach, also adopted by the behaviourists, was further expanded by Binet who settled the debate on intelligence by equating it with a more elaborate test battery that became of great practical value in the large-scale assessment required for the assimilation of hundreds of thousands of recruits in the armies that fought the First World War. By resorting to a pure operational definition of intelligence its ontology was murky and presumed to reside in the single underlying *g* factor with unknown and assumed irrelevant links to natural processes, thus challenging the dictum of Adelart of Bath. Artificial intelligence set itself up for a research programme anchored to an ill-defined construct, thus making it very difficult to assess success or failure. Indeed, now we know by using brain imaging techniques on humans performing intelligence tests that as opposed to a single *g* factor, intelligence appears to depend on a number of interaction cognitive processes (Hampshire, Highfield, Parkin & Owen, 2012). Hence, this raises the question of whether the target of the field designated by 'artificial intelligence' should

be rephrased in order to align it with the natural processes underlying perception, cognition, emotion and action in a more general sense. Indeed, this drift to a more fragmented view of 'intelligence' and its possible deconstruction is also reflected in the current standards of diagnosing mental deficits in DSM5 which, as opposed to a single factor as used to be the case, stresses a number of capabilities including: verbal comprehension, working memory, perceptual reasoning, and cognitive efficacy. Combining these observations it would seem foolish to insist on developing a science and technology of intelligence.

Despite these concerns about the mind as a computation school of thought, a message is propagating through different media that we are reaching the limits of human-driven advancement and that we are facing a post-human era that essentially follows the dystopic scenario of the *Terminator* movie series (Kurzweil, 2005). As with the Skynet AI systems in the movies, machine intelligence is predicted to reach a point where machines will become autonomous and outsmart humans, leading to the realisation of the former that the latter are obsolete and/or a hindrance to the propagation of intelligence and computation into the universe (Kurzweil, 2005). After this 'intelligence explosion' or 'singularity' as it is oft-called, Cyber Armageddon is upon us and robosapiens will emerge and supersede homosapiens terminating the progression of biological evolution and thus forcing biological life forms like ourselves to co-opt into a union with machines, which will in return provide us with eternal existence. Although the estimates of when this will happen exactly have been gradually shifting further into the future, the day of its revelation, or 's-day' ('singularity day') is now set to occur around 2045. The conviction about this coming singularity has also been called 'technologism' because of its merging of anticipated technological capabilities, proposed to be the ultimate operationalisation of intelligence, with religious motives such as divine power of a future technology, the redefinition of nature and the revelation of a route to reach eternal existence (e.g. Noble, 1997). The evidence upon which the plausibility of these beliefs is based is scant and usually points to Moore's law, our putative rapidly-increasing understanding of the brain and assumed unstoppable advances in AI research. Indeed, a brave new world awaits us once our minds are all downloaded to the matrix. However, why would one believe these claims, what is its utility and most importantly how will this be realised? Having ever-increasing computer processors as such does not answer Plotinus: we have observed the deterioration of brain science into a mindless collection of ever-increasing amounts of data and the failure of the AI research programme pursuing the mirage of 'intelligence'. In this respect the singularity movement aims at giving itself plausibility by 'defending' humanity from cyberdoom, but it makes the question of which natural phenomenon to target in a science of mind and brain more salient, and in addition, raises the fundamental question: for what purpose do we develop such a science?

Through integrating across all prevailing paradigms in the study of mind and brain, DAC seeks to explain a specific natural phenomenon that many brains share: consciousness. It translates this explanandum into a very concrete research programme by linking it to the multi-faceted nature of consciousness and its realisation in brains. Let's first take a look at the mind/brain and inspect the question of how it serves fitness in an evolutionary sense, or as Dobzhansky phrased it: 'Nothing in biology makes sense except in the light of evolution.' DAC starts with the fundamental consideration, following Claude Bernard and Ivan Pavlov, that brains evolved to act, establishing a metastable equilibrium between the organism and its environment. But what does it take to act? DAC assumes that the *how* of action is realised through five fundamental processes that brains implement:

1. **Why:** the motivation for action in terms of needs, drives and goals.

2. **What:** the objects in the world that actions pertain to as they can be perceived.

3. **Where:** the knowledge of the location of objects in the world and the self.

4. **When:** the timing of action relative to the dynami CS of the world and the self.

5. **Who:** the inferred hidden states of other agents.

This defines the so-called H5W problem (five questions, all starting with 'W') shortly, where each of the Ws designates a larger set of sub-questions of varying complexity. The H5W problem is hypothesised to be an exclusive and solitary animals engaging with the physical world solve the H4W problem excluding 'Who'. This implies that the more standard constructs inherited from psychology such as motivation, perception, emotion, cognition, memory and action are now reorganised in the context of the top-level functional goal functions that brains optimise: H5W.

DAC proposes that the unifying phenomenon we should focus on both to explain mind and brain and to construct it in artificial systems is consciousness. This phenomenon has become part of the neuroscience agenda due to the initial but separate efforts of Nobel laureates Francis Crick and Gerald Edelman. The DAC theory proposes that consciousness is a key component of the solution to the H5W problem, especially dealing with 'Who', and that it emerged during the Cambrian explosion 560M years ago when suddenly many animal species had to co-exist and the 30 basic body plans defining phylogeny, and their nervous systems, emerged. Essentially the proposal is that the interaction with the social real world requires fast real-time action that depends on parallel control loops. The conscious scene in turn allows the serialisation of real-time processing, its valuation, and the subsequent

optimisation of the parallel control loops underlying real-time action.

Irrespective of the validity of this H5W hypothesis on consciousness it is a concept that can drive a more integrated approach towards mind and brain. In particular, if we look at the state of the art of the study of consciousness we can observe that it is organised around five complementary dimensions. More specifically we can say the content of conscious states or qualia are:

1. Grounded in the experiencing physically- and socially-instantiated self (Nagel, Metzinger & Edelman; Damassio).

2. Co-defined in the sensorimotor coupling of the agent to the world (O'Regan).

3. Maintained in the coherence between sensorimotor predictions of the agent and the dynamics of the interaction with the world (Hesslow, Merker).

4. Combine high levels of differentiation (each conscious scene is unique) with high levels of integration (Edelman, Tononi).

5. Consciousness depends on highly parallel, distributed implicit factors with metastable, continuous and unified explicit factors (Baars, Changeux Dehaene).

These core principles of theories of consciousness are called the Grounded Enactive Predictive Experience (GePe) model. We propose that by moving from the explanandum of intelligence to that of consciousness, a new and integrated science and engineering of body, brain and mind can be found that will not only allow us to realise advanced machines, but also to directly address the last great outstanding challenge faced by humanity: the nature of subjective experience[1] and Plotinus' challenge.

Now that we have the preliminaries out of the way we can turn to the actual DAC theory, its structure and relation to the processes of H5W and GePe.

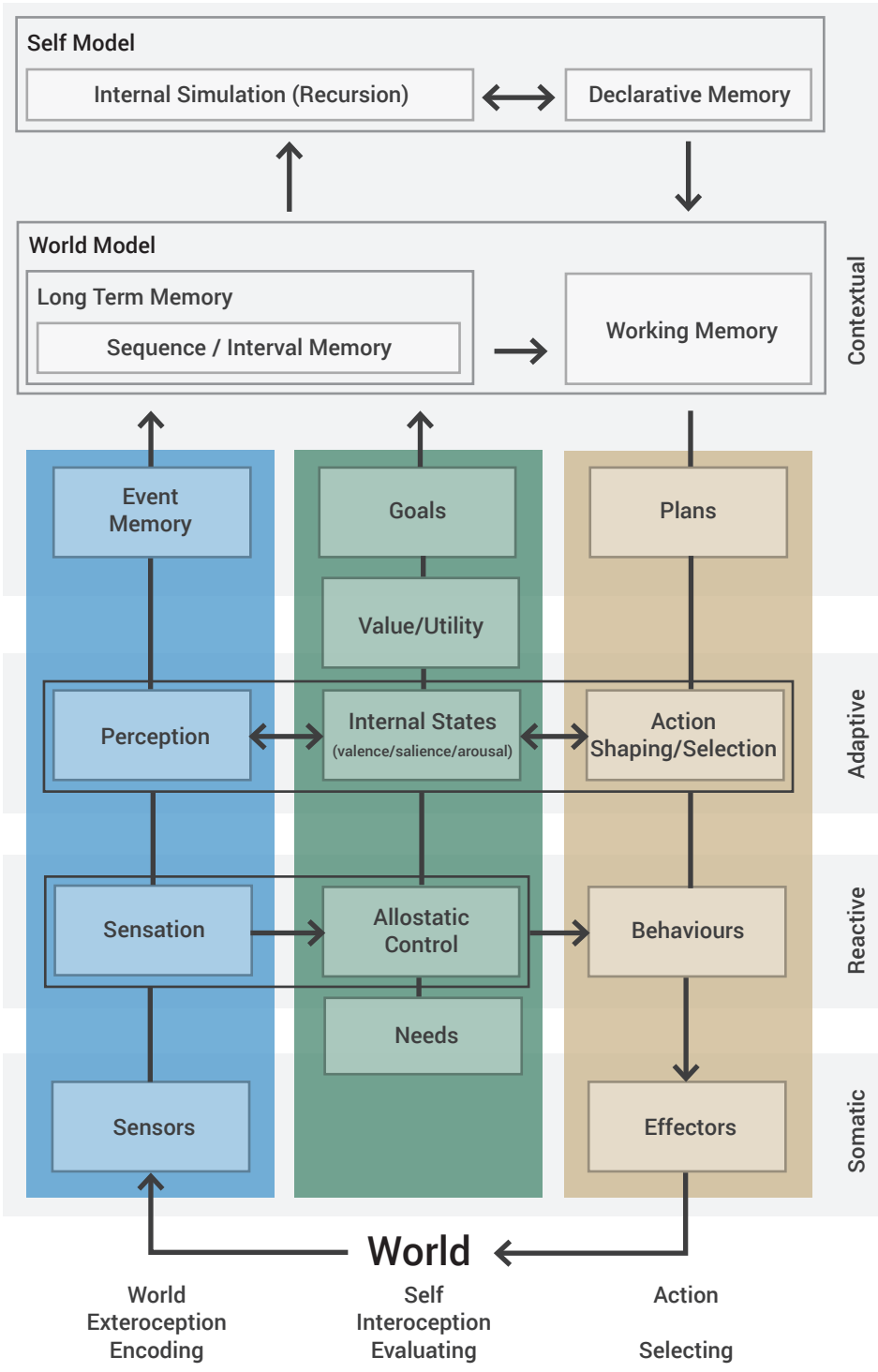
Self Model
Internal Simulation (Recursion)
Declarative Memory
World Model
Long Term Memory
Sequence / Interval Memory
Working Memory
Contextual
Event Memory
Goals
Plans
Value/Utility
Perception
Internal States
(valence/salience/arousal)
Action Shaping/Selection
Adaptive
Sensation
Allostatic Control
Behaviours
Reactive
Needs
Sensors
Effectors
Somatic
World
World
Exteroception
Encoding
Self
Interoception
Evaluating
Action
Selecting

Figure 1. *The DAC theory of mind and brain and its components proposes that the brain is based on four tightly coupled layers called: soma, reactive, adaptive and contextual. Across these layers we can distinguish three functional columns of organisation: exosensing, the sensation and perception of the world (left, blue); endosensing, detecting and signalling states derived from the physically instantiated self (middle, green); and the interface between self and the world through action (right, yellow). The arrows show the primary flow of information mapping exo- and endosensing into action defining a continuous loop of interaction with the world. At each level of organisation, increasingly more abstract and memory dependent mappings from sensory states to actions are generated.*

DAC proposes that solving H5W depends critically on the interaction between several layers of control that continuously cooperate and compete for the control of action (Fig.1). The s*omatic level* (*SL*) of DAC designates the body itself and defines three fundamental processes: *exosensing* of states of the environment, *endosensing* of states of the body and its essential variables of survival, defining *needs* and *actuation* through the control of the skeletal-muscle system. The r*eactive* layer (*RL*) comprises fast predefined sensorimotor loops, i.e. reflexes and stereotyped behaviours that support the basic functionality of the *SL*, together with the control signals that drive and modulate the engagement of higher control layers and their epistemic functions. These sensorimotor loops are organised in fundamental and opposing behaviour systems that can be characterised as the 5Fs of fight, flight, freeze, feed and fornicate (Gray), and others would include seeking, care and play (Panksepp). These basic behaviour systems encapsulate sets of essential variables defined by the *SL* and put in place operational procedures to maintain them in dynamic equilibrium-supporting survival. DAC proposes that the fundamental organisation of these basic behaviour systems is along two dimensions of attraction and aversion and that they are differentiated in terms of their specific triggering stimuli and specific motor programmes. Each of the *RL* reflexes is triggered by low complexity signals largely, but not exclusively, conveyed through proximal sensors, to ensure fast operation and genetic prespecification. In addition, each reflex and behaviour system is directly coupled to specific internal affective states of the agent or valence markers. In this way reactive behaviour serves not only the reduction of needs as proposed by Hull but is also labelling events in affective terms to serve epistemic functions such as the tuning of perceptual systems to pertinent states of the world, shaping action patterns and composing goal-oriented behavioural strategies realised at subsequent levels of the DAC architecture. Hence, the primitive organisational elements of the reactive layer are *sense-affect-act* triads and the activation of such a triad triggers action and carries essential information on the interaction between the agent and the world that is a key control signal for subsequent layers of the architecture.

The *adaptive layer* (*AL*) extends the predefined sensorimotor loops of the reactive layer with acquired sensor and action states. Hence, it allows the agent to escape from the strictly predefined reflexes of *RL* through learning. The *AL* is interfaced to the full sensorium of the agent, its internal needs and effector systems receiving internal state information from *RL* and in turn generates motor output. The *AL* constructs a state space encoding of both the external and internal environment, together with the shaping of the amplitude-time course of the predefined *RL* reflexes. It crucially contributes to exosensing by allowing the processing of states of distal sensors, e.g. vision, haptics and audition, which are not predefined, but rather, are tuned in somatic time to properties of the interaction with the environment. The acquired sensor and motor states are in turn associated through the valence states signalled by the *RL*, following the paradigm of classical conditioning where initially neutral or conditioned stimuli (*CS*) obtain the ability to trigger actions, or conditioned responses (*CR*), by virtue of their contiguous presentation with intrinsically motivational stimuli or unconditioned stimuli (*US*) as introduced by Pavlov. The *AL* expands the sensorimotor loops of *RL* into sense-valence-act triplets that are now augmented through learning to assimilate a priori unknown states of the world and the self (affect and action). In this way the *AL* allows the agent to adapt to and master the fundamental unpredictability of both the internal and the external environment.

Overall, the *AL* allows the agent to overcome the predefined behavioural repertoire of the reactive layer and to successfully engage an a priori unpredictable world. The behaviour systems of the reactive layer combined with the perceptual and behavioural learning mechanisms of the adaptive layer allows the DAC system to bootstrap itself to deal with novel and a priori unknown state spaces, in this way solving the notorious symbol grounding problem that lead to the demise of classical artificial intelligence and a range of other approaches (Searle, 1980). However, the adaptation provided for by the *AL* occurs in a restricted temporal window of relatively immediate interaction, i.e. up to about one second. Thus, in order to escape from the 'now', further memory systems must be engaged that are provided by the contextual layer of DAC.

The *contextual layer* (*CL*) of DAC allows the development of goal-oriented behavioural plans comprising the sensorimotor states acquired by the *AL* (Fig. 1). The contextual layer comprises systems for short-term, long-term and working memory (STM, LTM and WM respectively). These memory systems allow for the formation of sequential representations of states of the environment and actions generated by the agent. The acquisition and retention of these sequences is conditional on the goal achievement of the agent as signalled by the *RL* and *AL*. *CL* behavioural plans can be recalled through sensory matching and internal chaining among the elements of the retained memory sequences. The dynamic states that this process entails define DAC´s WM system.

The *CL* organises LTM along behavioural goals, and we have shown, that this together with valance labelling of LTM segments is required in order to obtain a Bayesian optimal solution to foraging problems. Goals are initially defined in terms of the drives that guide the behaviour systems of the *RL*, such as finding a food item (i.e. feed) or solving an impasse (i.e. flight). Goal states, as termination points of acquired behavioural procedures or habits, together with the behavioural sequence itself, exert direct control over how decision-making and action selection are performed. DAC realises this so-called goal and sequence fidelity by including a memory-based bias term in decision-making: if segment *n* of sequence *k* is associated with the executed action it will reduce the activation threshold of its associated segments in order to influence their perception-driven activation.

DAC proposes that the H4W challenge is solved through a multi-layer architecture that increasingly depends on memory to bootstrap predefined need reduction reflexes to acquired goal-oriented behaviours. These layers are tightly coupled and cannot be seen as independent encapsulated modules. Rather, each layer is predicated on the semantics and/or control signals generated by the other layers. As such we can see that 'what' and 'where' span a column of processing stages across the layers of the architecture that all deal with states of the world. 'Why' spans across the layers reflecting states of the self, from needs to goals and utility. 'When' is encapsulated within the learning and memory mechanisms of *AL* and *CL* supporting timing and sequencing. Finally, 'how' defines a last column of processes across the layers of the DAC architecture that define action orchestration and selection.

How can this proposal of layers and columns be a theory of consciousness? Well now we are in a position to map GePe to DAC:

1. Grounded in the experiencing physically and socially-instantiated self: the *SL* constitutes the foundation of the embodied hierarchy.

2. Co-defined in the sensorimotor coupling of the agent to the world: the *RL* and *AL* both establish immediate sensorimotor loops with the world.

3. Maintained in the coherence between sensorimotor predictions of the agent and the dynamics of the interaction with the world: the *AL* relies on prediction-based systems for both perceptual and behavioural learning.

4. Combines high levels of differentiation (each conscious scene is unique) with high levels of integration: the *CL* integrates across all sensory modalities and memory systems and provides selection mechanisms to define a unique interpretation of the state of the world and the agent.

5. Consciousness depends on highly parallel, distributed implicit factors with metastable, continuous and unified explicit factors: the *CL* integrates memory-dependent implicit biases in decision-making and interpretation of states of the world with explicit perceptual states.

It would be premature to say that DAC has *explained* consciousness but we can observe that it does capture the main components of an integrated theory of consciousness while advancing a concrete research agenda that poses specific questions on perception, emotion, cognition and actions structured along H4W.

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Footnotes

1. The other two being the origins of the universe and of life on which significant progress has been made in the 20th century.

Cybernetics

Control

Cybernetics was originally defined by Wiener (1948) as 'the scientific study of control and communication in the animal and the machine'. In this sense, DAC belongs to the cybernetic field as it aims at explaining behaviour generation in embodied agents, be it to understand the brain of animals or to build sentient artefacts. By building control systems that allow a sensorimotor device (i.e. a robot) to react to environmental changes or to reach a specific state, we are borrowing principles about how such things are achieved in biological beings. We are also challenging our standpoint in this domain by proposing alternative and improved models that may bring additional hypotheses and constraints to our view about wet brains. Specifically, this deals with adaptive control, which builds upon reactive control mechanisms in order to provide an increase of the control quality through experience. In order to reach a system that can experiment and learn from its own actions, a more basic level of control is required. From an evolutionary point of view many behaviours that facilitate survival (e.g. motor reflexes, contact avoidance, foraging) could be achieved in simple 'hard wired' ways that would require none or few learning capabilities. However, learning from experience at the lifetime scale is a feature that offers an even greater ability to survive, especially combined with mechanisms such as teaching and learning from observation. Without entering any consideration between innate and acquired mechanisms, it is reasonable to assume that the combination of both control system levels allows an overall improvement of the sustainability of the agent.

Perception-Action System

The main point of any control system is to create a transformation from a perceptual input to a command that is addressed to an effector. An effector can be a muscle/motor, the release of a chemical substance, or whatever leaves a signal in the world (e.g. physical contact, light, sound signals, chemicals). The perceptual side can be decomposed into:

1. Exteroception: perception of signals originating from the outside world, including from other agents.

2. Interoception: perception of signals originating from the agent's own body, such as physiological substances (e.g. hormonal levels, sugar level), as well as the whole limbic system describing the emotional state.

Through action, the agent in the world will produce a mixture of interoceptive and exteroceptive signals. The term perception refers to a generic combination of exteroception and interoception, and represents a generic signal to be used as an input by a control system. With all its simplicity, the combination of elementary perception action loops can give rise to what will appear as complex, goal-oriented behaviour. The Braitenberg vehicles are a famous example (Braitenberg, 1986). The simplest kind of Braitenberg vehicle had just two perception-action loops, where a light sensor was coupled to a motor controlling a wheel. Having the light sensors in opposite sides of the vehicle's front, and the wheels set up in parallel, very simple arrangements of the control loops resulted in the robots moving towards or away from a light source or even circling around it. An external observer would then attribute special characteristics to each vehicle, for instance, the characteristic of 'fear' to the vehicle that when it perceives a light will escape in the opposite direction, since it will appear that this vehicle prefers to remain unnoticed in dark places (see Fig. 1).

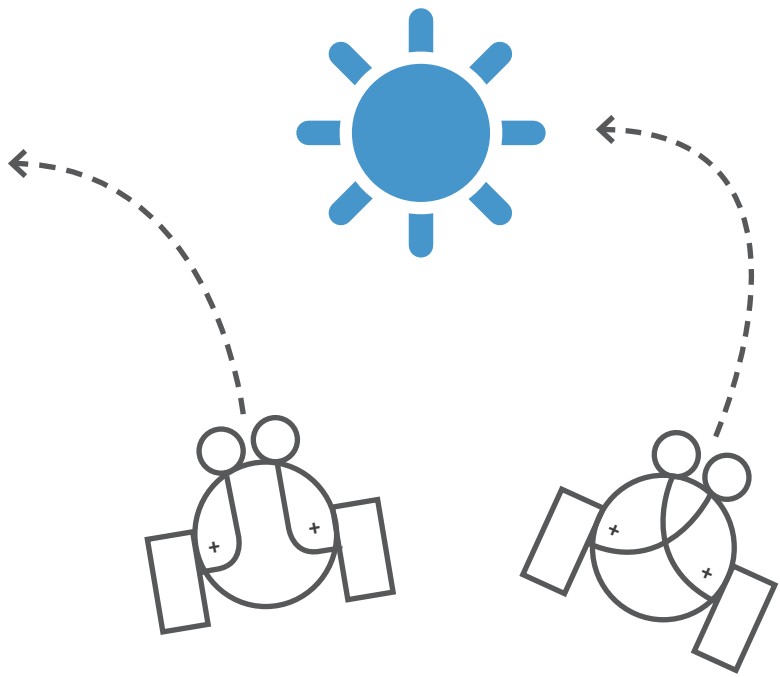

Figure 1. *Example of Braitenberg vehicles expressing 'fear' and 'love'.*

These synthetic examples of direct sensorimotor coupling driving navigation has its biological counterpart in bacterial chemotaxis. Bacteria can orient themselves towards food sources or flee poison provided that chemical receptors result in the excitation of their ipsilateral or contralateral motor effectors, the flagella.

Perpection-Action-Feedback Loop

During the Industrial Revolution arose the problem of needing to automatically regulate the performance of machines. An earlier example of automatisation was posed by the steam engine machine which was used to power factories. The power was delivered via a spinning wheel and it was desirable that the amount of power stayed as consistent as possible, that is, that the wheel rotated at a consistent speed. For this, the machine had to sense its own speed and adjust the amount of fuel needed to increase or decrease it within a narrow range. This was achieved by a centrifugal governor, a mechanical device that solved this sense-act problem. The proliferation of these types of automatisation problems, sadly fuelled by the technological developments occurring during the Second World War, gave rise in the 20th century to the control engineering discipline and a body of theoretical work known as control theory. From a control perspective the solution to the problem of the steam engine machine relies in the so-called feedback control. A feedback controller compares the actual performance with a desired one and applies a corrective action to reduce the mismatch.

The minimal requirement for setting up a feedback controller is knowing in which direction to act in order to reduce the mismatch between the desired and actual state. In control theory terms, this mismatch is referred to as the error. Likewise, once we detect that we are in an undesired state, we can react to avoid it. For instance, if an object burns the tip of our fingers, flexing the arm will help to avoid the contact with the source of heat whereas if the heat is felt in the back of the hand, extending the arm will be the correct action. Another example of this mechanism is found in the pupillary light reflex (PLR) which adapts the diameter of the pupil in order to maintain the quantity of light hitting the retina and balances the levels of lightness/darkness of a scene. This example also introduces the concept of homeostasis which is the act of maintaining a system in a desirable state through action upon effectors that have direct consequences at the input level. In the case of the PLR, a specific range of luminosity is acceptable and desired. If the input sits outside of this range the reflex will either dilate the pupil in order to allow more light in, or on the contrary contract it to reduce exposure.

By comparing the perceived state to the target state a feedback controller gets an estimation of the error, and subsequently acts to minimise it. If the variable being regulated is an internal state of the agent, like body temperature, blood sugar concentration, or emotional state, the act of maintaining this process within a physiologically adequate range is known as homeostasis. A living organism, as well as complex artefacts, have many homeostatic modules, each one controlling different variables. This type of formalism, depicted in Figure 2, is present at multiple behavioural levels that can be extended beyond the simple reactive mechanism. In particular it also defines the formulation of the drives mechanism that acts as the root for motivation of autonomous living systems.

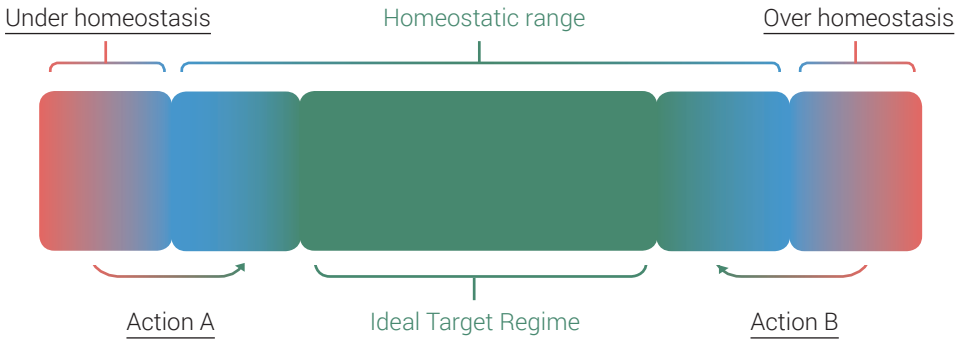

Figure 2. *Homeostatic range.*

The feedback control scheme is applied by engineers to deal with many automation problems, but more importantly, it is used by living organisms at multiple levels of behaviour. For instance, when we ride a bike, or when we stand upright, we have the goal of maintaining a vertical position and we apply corrective actions, through the bike handles, or activating our muscles, to stay in that position. Another example is when the level of blood glucose rises, the pancreas releases a hormone, insulin, which causes the liver to take up glucose from the blood and store it as glycogen. Likewise, the blood glucose level is maintained in a desired level. Each of these reflex arcs is an example of a perception action loop, where a perceived state (contact with an intense heat source) causes an action (withdraw the limb) that at its turn changes the perceived state (diminution of the heating sensation). It is the assumption in feedback control that the action affects the perception that caused it. The relation between these homeostatic loops may be independent, and thus feedback loops will be arranged in parallel, with minimal interaction or conflict between them, or in contrast in a hierarchical manner, where a general state of equilibrium is achieved when a set of subsystems are themselves at equilibrium. It is also possible that a same effector will be included in different loops, and in that case there can be conflicts where two homeostatic goals require contradictory actions. Say, that an animal is both tired and cold. For the subsystem regulating body temperature, it will be convenient to increase the metabolic rate, for instance through an increase of the amount of physical activity. However, at the same time the system controlling the energy storage will push towards the diminution of energy consumption by triggering resting activities like laying down or sleeping. This type of situation illustrates the necessity of what we will discuss later in this book as allostatic control: how to orchestrate the agent objectives in order to maintain a good global inner state over time.

Predictive Control

Reactive controllers perceive the world and react to it in a predetermined way in order to maintain their perception in an optimal regime. They can also use an error signal as feedback information in order to adapt to dynamic environments. However, the most successful control can be achieved by acting in anticipation, instead of in reaction, to error. If a system can predict its own error in the future, it can act pre-emptively to avoid it. We refer to this as anticipatory or predictive control.

Coming back to the spinal reflex that reacts to pain perception with a flexion or an extension of the limbs—the spino-nociceptive withdrawal reflex—the goal of this reflex is to maintain a state of no-pain. As such, even better than reacting rapidly to the pain perception is to avoid pain altogether. For instance, if a heavy object is falling to your feet you will respond by retracting the feet before the object hits them. This action, which can be subjectively experienced as a reflex, is anticipatory because it minimises the error by avoiding its arise, and to do so, uses information coming from outside of the reflex arc. In this case, the visual information is used to avoid a pain perception that otherwise would have caused the activation of the spino-nociceptive withdrawal reflex. From a control perspective, this type of control scheme is considered feedforward since it predicts evolution of the world state in the future.

Indeed, anticipatory actions can be considered as reactive actions to predicted states: as much as a reflex is a reaction to a perceived stimulus, an anticipatory reflex is a reaction to a predicted stimulus. Indeed, in this case, the neurons that would have been activated by the pain stimulus, and causing an activation of an agonist-antagonist set of muscles, are driven by a neural activity, that coming from a higher level area, can be interpreted as predicted pain. The forward model, given the current state and its previous dynamic, predicts a signal that can then be used by the reactive controllers mentioned above.

The very first sensorimotor contingencies upon which anticipatory actions can be learned compose the peripersonal space of the agent. Through motor babbling, even in pre-natal conditions, an agent is able to perceive the effects of its effectors on its own body: through self-touch the initial body schema necessary for control of the limbs and localisation of tactile stimuli are built. This phenomenon in humans has been called ‘primary circular-reaction hypothesis’ by Piaget (PIaget & Cook, 1952), it also includes the early interaction of visual and proprioceptive modality. Indeed, this self-oriented exploration provides the learning system with very regular sensorimotor patterns that are fully observable as they depend only on the agent status (even in the visual case if we consider a static environment not involving much movement in the landscape). Many of the elements composing the peripersonal space are learned early on in development, and are therefore acting as core reactive mechanisms, thus they blur the limit between reflexes and acquired actions.

Whereas many of the reactive feedback actions can be innate, anticipatory actions are acquired through experience, even in cases where they are apparently universal. For instance, the well-known system of regulation of blood sugar also has anticipatory components. Eating sweet food directly triggers the release of insulin into the blood stream that occurs before the autonomic nervous system has time to measure the increase of glucose in the blood. So, even though this is a response common to all animals it is not a reflex arc or a feedback control system. The response, insulin release, does not affect the triggering stimulus, sweet taste in the tongue, but instead it allows a more successful control of the glucose level in the blood.

Other types of anticipatory control will differ markedly between individuals since these associations are built based on regularities occurring in the environment they experience and those may not be the same. For instance, one can imagine that an animal living in an environment where sweet taste only comes from artificial sweeteners will lose the anticipatory release of insulin since now the sweet taste will no longer be predictive of an increase in blood sugar. For an agent to acquire adaptive anticipatory responses it needs to have the capacity to capture regularities in the environment, that is, to act in the environment and experience how to change the world.

Learning

Learning in animals is mainly achieved by a neural substrate that provides an interconnected network of cells that can adapt to external stimuli. The parallel researches in brain learning mechanisms and their algorithmic counterparts converge by categorising learning into different subclasses with different requirements and fields of application.

Three Different Categories of Learning

Computer science defines three different categories of learning processes according to the nature of the information available and to the goal of the task. These are unsupervised, supervised and reinforcement learning. Such a division can guide the implementation of the learning mechanisms of a cybernetic system and can also help to understand the components of animal learning.

We can first introduce the different types of learning intuitively with an informal example: consider the enormous endeavour of learning a language by being immersed in it, as a child learns it or as an adult moving to a foreign country. Such a task involves all three learning strategies at different stages.

The first task we are faced with is the identification of those meaningful sounds that are the constituents of the languages, the phonemes, from what initially constitutes a seamless stream of speech. This will pave the way for identifying some basic words of the language. The most important requisite for achieving this is to simply be exposed to the speech, to hear it. Likewise, the learner will incrementally acquire a better representation of the language sounds, which will enable identification of them in a stream of speech. This process is an instance of an unsupervised learning task since there is only one type of data available, the inputs, and the goal is simply to acquire representations that will later assist in categorising them. For instance acquiring sufficient representational accuracy to later distinguish a ‘t’ from a ‘d’. An important phenomenon to take into consideration at this level is the simultaneous learning of motor representation regarding how to produce these sounds. As the infant experiments in sending commands to its vocal apparatus, he will produce and hear sounds. This will provide the required material for learning a mapping between a motor command and the phoneme it produces. Thus, we can see that unsupervised learning can take place either in the pure sensory domain or in the sensorimotor one.

Secondly, as the learner begins to speak a new language, other speakers, or teachers, will eventually correct them by explicitly providing the correct output. This may happen at many levels, for instance, correcting pronunciation or a verb inflection. Consider the case of verb inflection, the learner will know the correct form to use the next time that same or a similar verb needs to be used in the same grammatical context. In computational terms this process would be classified as supervised learning. In supervised learning the learner is provided with examples of how to map from the input to the output. In this example, we have the verb (e.g. 'to eat') and the grammatical context (e.g. third person singular, past tense) as the input and the target inflected form as the output (e.g. 'ate' instead of 'eated').

Finally, the use of language has the pragmatic value of achieving a communication goal. If this goal is achieved, e.g. the kid gets her baby bottle, that success will reinforce the learner to repeat that same communication when a similar situation reoccurs. On the other hand, if the communication fails, she will be motivated to try a different strategy. This is an example of a reinforcement learning process. In this case, given a certain state and a goal, he or she will produce an output, for instance an action. Subsequently, the learner will evaluate the outcome as a success or a failure, or more generally, in terms of reward, lack of reward or loss.

One should not confuse these computational descriptions of the general learning categories with their particular implementations or algorithms proposed in the machine learning literature. From a DAC framework perspective, and more in general from a cybernetics perspective, these descriptions anticipate the types of problems that an autonomous system will have to solve, but not all algorithmic solutions are relevant for our approach.

Indeed, one can recast some animal learning processes, such as classical conditioning or perceptual learning, in terms of supervised and unsupervised learning, and then, more importantly, one can ask how does the neural substrate implement the required learning mechanisms? What follows is a description of the three types of learning, and how they are used within different components of DAC.

Unsupervised Learning—Perceptual Learning—Cortex

Unsupervised learning involves only inputs, without feedback. Essentially, it extracts the prototypes that best represent the input space in terms of its statistical properties. Unsupervised learning has been proposed to occur mainly at the cortical level and creates abstract representations of concepts ranging from pure sensorimotor units (e.g. a hand posture, a circular shape, etc.), to higher-level amodal concepts (e.g. a tool, an animal, etc.).

Following these learning processes, a learner can efficiently represent a high-dimension input space (i.e. perceptual world) by compressing it into a low-dimension representation space. This low-dimension space can be excited by bottom-up perceptive input, therefore activating a specific perceptual archetype (i.e. concept) or used in the top-down direction by recreating the sensory signal associated with a specific archetype.

One can formulate the goal of unsupervised learning as the minimisation of a loss function that is defined as the mean distance between the input data sample (e.g. words, faces, abstract concepts, etc.) and the representations of the items stored in the system (these representations are referred to as prototypes). As an abstract illustrative example, one can imagine that both the input stimuli and the prototypes are coded as vectors, such that we can define a distance between inputs in the same way that we can define a distance between two points in a map. The smaller the distance, the more faithfully the stored prototype represents that item. As a further example, consider the difference, between, say, individual perceptions of the phoneme /t/ and the internal representation (or representations) of the /t/ phoneme.

In neural terms, we can informally interpret that the prototype(s) of a given input are encoded in the neurons that activate the input stimulus. In general, the larger the neural response to a stimulus, both in number of neurons and in the intensity of their response, the larger the stimulus representation in the brain (or, in abstract terms, the smaller the distance between the input stimulus and its closer prototype). However, the capacity of the brain is bound, not allowing it to store an accurate representation of all the stimuli perceived through life. Thus, stored representations are generalisations that mostly reflect the regularities in the input domain. Indeed, minimisation of the average loss function suggests that more

frequent items should be more faithfully represented. In other words, a supervised learning process will provide more representational resources, memory or neural tissue, to the more frequently encountered stimuli.

The process known as perceptual learning, which consists of increasing the granularity of the sensory representations, is underpinned by an unsupervised learning process. Clearly, an animal recognises stimuli that it has previously experienced more accurately, than the ones it has not. In humans, we can come back to the language example: when we listen to some speech, we do not recognise the phonemes of a second language as distinctly as we do with the ones of our first language. And, obviously, we have been exposed more often to the phonemes of our own language than from another language learned later in life.

However, frequency alone might be a poor indicator of what needs to be stored in memory. Indeed, some relevant but infrequent stimuli should nonetheless be faithfully represented. To address this issue mathematically, we can set a loss function where the mean distance between input and prototype is weighed by a relevance factor. Then, our perceptual knowledge will not only reflect our sensory history in terms of frequency, but also in terms of the relevance of the stimuli.

In computational neuroscience, the cerebral cortex has been associated with unsupervised learning processes. Especially in the early sensory cortices, extracting perceptual archetypes, but also arguably in the cortical motor areas, such that recurrent patterns of coactivation can be stored as motor primitives.

Back to perceptual learning, the phenomena of the reorganisation of the cortical sensory areas, can be seen as a vast unsupervised learning process. For example, the A1 area of the auditory cortex is tonotopically organised according to the stimulus frequency, in other words, neighbouring neurons respond to stimulus of similar frequencies. Different animals, mice, monkeys and humans cover different ranges of the frequency spectrum, likely reflecting both evolutionary and environmental constraints. But this organisation is not static and can rapidly adapt, reflecting sudden changes in the animal's environment. For instance, a mother becomes rapidly attuned to the sound frequency of her newborn's cry.

Experimental psychologists have reproduced this process of retuning the auditory cortex to increase the response to stimuli that suddenly become more relevant. For example, in the paradigm of fear conditioning an animal, such as when a rat hears a pure tone sound—the conditioning stimulus (*CS*)—which precedes an electrical footshock. Using electrophysiological measurements, it has been shown that after very few trials of paired stimulation, the rat's neural response to the *CS* increases dramatically. i.e. both the response of individual neurons and the number of neurons attuned to the *CS* increase.

This mechanism of the relevance-modulated building of sensory representation, or sensory maps, has been reproduced in several works inspired by the DAC framework, for instance, the reorganisation of the auditory cortex in response when a neutral conditioning stimulus is associated to a naturally aversive one. As the machine learning field grew, several unsupervised learning models have been proposed which all follow the same principle. The historical example and most simple instance of learning implementation is the Hebbian rule which is based on the observation that two neurons firing together tend to facilitate the synapse between them in order to increase their coactivation over time. Mathematically, the simplest formalisation of this principle is as described in Equation (1) where W_{ij} represents the connection weights between neurons *i* and *j*, X_i represents the activity of neuron *i* and X_j the activity of neuron *j*.

$$\Delta W_{i,j} = x_i x_j$$

Equation (1)

Assuming that a group of neurons is wired together and receive input from external sources, this learning rule will tend to create clusters of neurons that will be simultaneously active for specific input patterns. These clusters will adapt as much as possible to fit the statistical properties of the input space and to categorise it into classes. A simple example of this principle is the Hopfield network: by observing the receptive field of a specific neuron it is also possible to recreate the input signal prototype that it is encoding for, therefore allowing the example retrieval of the whole signal from partial cues.

Supervised Learning—Classical Conditioning—The Cerebellum

Mathematically, supervised learning aims to fit a function that maps elements from an input to an output space. Given an input *X* and an output *Y*, the goal of supervised learning is to approximate *F* such that *Y = F(X)*. As in the previous case of unsupervised learning, for supervised learning we define a loss function that measures the difference between the output produced by the system and the correct output, that is *given* to the system. The goal of the learning process is to minimise that mean difference.

Learned anticipatory control can, in some cases, be understood as the outcome of a supervised learning process. Consider the case of classical conditioning introduced previously. In a classical conditioning setup, the neutrality of the *CS* causes the naive animal not to respond to it. In other words, he implicitly produces an output to the *CS* stimulus that is a no-action. However, as the animal closes the eye to minimise

the disturbance caused by the introduction of a puff of air pointed directed towards it, such activation of the sensorimotor loop becomes an error signal indicating that the eyes should have been closed at the arrival of the Unconditioned Stimulus (*US*). With this in mind, we can interpret the eyeblink conditioning setup as a supervised learning problem where the input is provided by the CS, the agent's output is whatever action is taken or not taken in response to that *CS*, and the *US* presence dictates that the correct output should have been to close the eye. Therefore, we can see that acquiring an anticipatory avoidance reflex can be seen as the result of a supervised learning process. The DAC framework situates this kind of process in the adaptive layer.

In classical conditioning, learning occurs principally in the cerebellum which suggests that the cerebellum should implement a supervised learning algorithm. Indeed, in the cerebellar cortex it is possible to identify all the information pathways that would be necessary for carrying all the inputs and outputs involved in a supervised learning problem. Coming back to the eyeblink example, there is an area in the cerebellum where the output of a particular class of neurons, the Purkinje cells, controls the eyelid closure. These neurons are powerfully innervated by the climbing fibres, originated in the inferior olive. These climbing fibres signal the activation of the reactive loop of the eyelid closure, that is triggered by the *US*. The *CS* stimulus information reaches these same cells via the parallel fibre, a different and segregated pathway. From a supervised learning perspective, the Purkinje cells receive an input (the *CS*—via the parallel fibres), produce an output (through their axons) and receive an additional input signal that indicates the correctness of the output (via the climbing fibres). Over trials, the climbing fibre signal will adjust the transformation of the parallel fibre input into an output such that the cell will respond to the *CS* with a timely command to close the eyelids.

In this case, by having provided the desired output, it is possible to adapt the transformation in the right direction, using gradient descent for example. At the lowest level it allows the agent to learn the sensorimotor changes induced by a motor command.

In general, a supervised learning system can be used to predict the consequences of a specific action given a specific context. This predictive mechanism can then be used in the context of forward chaining (i.e. predicting the consequences of several successive actions) or backward chaining (i.e. inferring the goal, or initial state that led to plan the execution).

The artificial neural implementation of supervised learning, extends unsupervised learning principles such as the Hebbian rule. Layout of neurons and connections can lead to a situation where the activity of certain neurons depends only on other neurons of the network and not directly on the input to the system. Such an organisation is typically the multilayered architecture deployed by multilayer perceptron (MLP) or Deep Learning models. In such a case the neurons are segregated into two categories: the one activated by the external input to the system (Input layer, X_i), and the one receiving

pre-synaptic activity from the input layer (or a hidden layer) and post-synaptic activity from a desired output (Output layer, Y_j). Following, the predicted activity of the output layer $\hat{Y}_j$ can be formulated as in Equation (2) with *f()* being the activation function of the neuron (e.g. sigmoid). The learning mechanism lies in the adaptation of weights as expressed in Equation (3)

$$\widehat{Y} = f(\sum_{i=0,n} W_{i,j} X_i)$$

Equation (2)

$$\Delta W_{i,j} = \lambda(\widehat{Y}_j - Y_j) X_i$$

Equation (3)

The main difference with the previous case of unsupervised learning is the apparition of the teaching signal as a difference between the current prediction computed from the input and the current real signal observed. The coefficient λ represents the speed of adaptation of the weights and is a parameter common to most of the supervised learning algorithms. It can be set either in a fixed or adaptive manner, as a way for example to emulate neuromodulators of learning like dopamine or acetylcholine.

Reinforcement Learning—Operant Conditioning—Basal Ganglia

Reinforcement learning is different from other types of learning in the sense that it does use feedback about the prediction, but it is only qualitative (i.e. good or bad) and therefore does not have explicit access to the optimal direction to follow in the landscape of possible transformations. It is tightly linked to the concept of reward, which we frame as the general improvement of the inner state of the agent. More than the sensorimotor consequences of an action, reinforcement learning can be used to predict an expected reward, making it the ideal candidate to deal with action selection at the behavioural level. The main brain structure dealing with reinforcement learning is the basal ganglia, especially the striatum, which receives input from the substantia nigra and occurs in dopamine release, therefore increasing or decreasing the plasticity of synapses.

Reinforcement learning is the main way of dealing with action selection. Considering that an agent's goal is to maximise the overall reward it will get from its actions in the future, reinforcement learning provides the predictive mechanism necessary to select actions in order to achieve such a maximisation.

Another crucial part of reinforcement learning lies in its ability to work on the output of supervised learning; since you can consider the quality of a prediction an intrinsic reward, it allows you to select the action that will make you learn the most. Such a process can be used to guide exploratory behaviours like motor babbling to portions of space that are more likely to benefit the agent in terms of its representation and prediction capabilities. This has been used to make behavioural patterns such as walking emerge from motor babbling.

Machine Learning and the Behavioural Feedback

Historically, machine learning did not evolve to explain the generation of adaptive behaviour in autonomous agents. Its goal instead was centred on the practical development of information processing applications that, for instance, classify images automatically, forecast the evolution of the stock market, and produce automatic translations, among others tasks. Indeed, the idea that embodiment imposes constraints for a learning algorithm is not usually considered in the machine learning literature, and, on the other side, the use of machine learning techniques usually assumes requirements not met by a behaving agent.

For instance, an agent's learning depends on its experience, but since an active agent determines his experiences through behaviour, the shaping of the behaviour through learning will change the agent's experiences. Such a tight link between the structure of perception and behaviour is referred to as behavioural feedback. In an adaptive system, by way of behavioural feedback, the inputs at the onset of a learning process will differ from the ones received by the end of it. This observation, which might seem completely trivial for the layman, violates one of the assumptions usually taken in the machine learning connectionist literature, that is, that input samples are independent and identically distributed (i.i.d.). This is, that the algorithm draws input samples as though they were lottery pellets randomly extracted from a bag. Violation of the so-called i.i.d. assumption does not immediately disqualify connectionist solutions as an explanation of learning in biological systems. However, it does implicate that the findings or constructs from the machine learning connectionist literature may not be translatable to the domain of embodied adaptive systems.

Behavioural feedback affects even the simplest learning paradigms. For instance, in an avoidance learning paradigm, such as the conditioning of the eyeblink response with a puff of air, an animal learns to produce an adaptive response that anticipates a perturbation. However, classical conditioning is an unconscious learning process that is driven by the sensory perception of the airpuff alone, not by a categorical knowledge about the stimulus presence, and learning affects the perception of the airpuff. In the naive animal the puff of air reaches the unprotected cornea, causing

a strong pain perception, but as the animal learns to anticipate it, the closing eyelids protect the eyeball lessening the pain perception. Thus, even in this elementary case of supervised learning, there is a sensorimotor contingency that makes it so that the sensory state successfully predicted at the end of learning is not the same sensory state that was experienced at the beginning.

Two Phase Model of Classical Conditioning

Even the simplest processes of animal learning might involve different types of computational learning processes. So far, we have separately introduced relevance-modulated unsupervised learning in the context of fear conditioning, and supervised learning in the context of classical conditioning, but a finer analysis will reveal that in classical conditioning we can already individuate both learning processes.

In the 1960s the Polish psychologist Konorski proposed that the associative processes underlying classical conditioning can be separated into a fast non-specific learning system and a slow specific one. He proposed that after just a few trials of paired tone-airpuff stimulations, the non-specific learning system will indeed acquire the knowledge that the *CS* precedes a motivationally relevant event. This first process will result in a non-specific preparatory response to the *CS*, such as freezing the body position. As paired stimulation trials accumulate, the animal gradually builds a specific motor response tuned to counteract the *US* effect, which in the airpuff case is the eyeblink response.

In general, the more salient a stimulus is, the higher its capacity to induce plastic changes; this is, the faster it drives learning. Thus, besides eliciting a non-specific response, the first phase of learning boosts the internally attributed saliency of the *CS* stimulus, increasing the neural response to the tone. This increased response may enable learning in cases where the initial response of the sensory cortices to the *CS* was insufficient to recruit the plasticity mechanism of the cerebellum.

Whereas the cerebellum interprets the *US*-evoked activation of the climbing fibre signals that a concrete motor action should have been produced, activation of the nucleus basalis, evoked by the same *US*, broadcasts to the cortex the message that a relevant stimulus was received. This message is coded by the unspecific release of the acetycholine a neuromodulator, that once reaching the sensory cortices, will converge with *CS*-evoked activation.

Therefore, the acquisition of an adaptive reflex requires two concurrent learning processes. This is captured by the different levels of implementation of the DAC framework, as described in the 'Tutorials' section of this publication.

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3 | DAC Tutorial on Foraging

DAC5

DAC is based on the fundamental assumption that foraging can be explained on the basis of the interaction of three layers of control: reactive, adaptive and contextual. DAC5 was proposed as a model for classical and operant conditioning (Pavlov, 1927; Thorndike, 1911; Verschure, 1998). The reactive layer provides a set of reflexes allowing the system to interact with the environment—unconditioned stimuli (*US*) to unconditioned response (*UR*). The adaptive layer is a model of classical conditioning and fulfills a two-fold task. On the one hand it learns to associate the conditioned stimuli (*CS*) to the *UR*, forming the conditioned response (*CR*). On the other hand, it forms internal representations of the *CS* used by the contextual layer. The contextual layer is a model for operant conditioning; it provides the system with short- and long-term memory structures. The sensorimotor contingencies formed at the level of the adaptive layer are acquired and retained in these memory structures, forming behavioural sequences. The representations stored in the contextual layer are constantly matched against the ongoing perceptions allowing for the retrieval of successful behavioural sequences in similar contexts.

The prototypical robot test case for DAC5 is a foraging task in an open arena. In this task, the robot, equipped with proximal and distal sensors, explores the arena in search of light sources while avoiding collisions with the surrounding wall. Coloured patches scattered on the floor serve as landmarks for the navigation. In the framework of classical conditioning, the proximal (e.g. distance and light) sensors serve as aversive and appetitive *US*s. Close to the light or at a collision a *UR* is triggered such that the robot approaches the light or turns away from the wall. The coloured patches serve as *CS*s.

Reactive and Adaptive Layer

In DAC5, the adaptive layer learns sensorimotor contingencies generated by the reactive layer and forms internal representations of the environment based on the classical conditioning paradigm (Pavlov, 1927). An unconditioned stimulus *US* triggers an unconditioned response *UR* (see Fig. 1). A *US* event also induces activity in populations of units which reflect an internal state (*IS*). Learning consists of associating a conditioned stimulus *CS* to the *US* such that after learning, the *CS* on its own can trigger a conditioned response *CR* (see Fig. 1). In doing so it combines perceptual and behavioural learning. Behavioural learning associates the different *CS*s to the correct *CR*s. Perceptual learning compresses the higher dimensional *CS* to the lower dimensional *CR*.

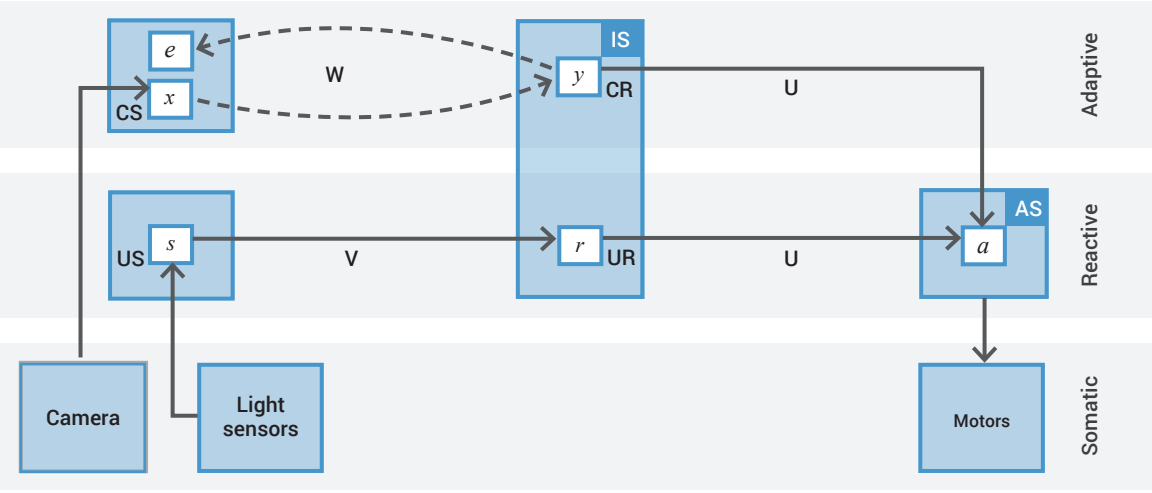


Figure 1. *The Adaptive and the Reactive layer: squared boxes stand for neuronal groups, arrows stand for static (solid line), and adaptive (dashed line) synaptic transitions between the groups.*

We define the following abbreviations for the activities in the different cell groups:

$$
\begin{aligned}
s &= \text{Activity of the } US \text{ cell group} \in \mathbb{R}^M \\
x &= \text{Activity of the } CS \text{ cell group} \in \mathbb{R}^N \\
z &= \text{Activity of the } IS \text{ cell group} \in \mathbb{R}^K \\
V &= \text{weight matrix from } US \text{ to } IS \text{ cell group} \in \mathbb{R}^{M\times K} \\
W &= \text{weight matrix from } CS \text{ to } IS \text{ cell group} \in \mathbb{R}^{N\times K} \\
r &= \text{Contribution of the } US \text{ to } IS \in \mathbb{R}^K \\
y &= \text{Contribution of the } CS \text{ to } IS \in \mathbb{R}^K \\
m &= \text{Activity in the } MM \text{ cell group} \in \mathbb{R}^L \\
U &= \text{weight matrix from the } IS \text{ to the } MM \text{ cell group} \in \mathbb{R}^{K\times L}
\end{aligned}
$$

Usually the dimensionality *N* of the *CS* is higher than the dimensionality *K* of the *IS*. The dimensionality *M* of the *US* is in general but not necessarily similar or equal to the dimensionality *K* of the *IS* cell group. In the general case the activity of the *US* and the *CS* cell can be a nonlinear function of the sensor readings. Usually, however, the function is the identity function. With these definitions the forward dynamics of the adaptive and reactive layer can be written as:

$$
\begin{aligned}
r &= V^\mathsf{T} s \\
y &= W^\mathsf{T} x
\end{aligned}
$$

The *US* cell group can be comprised of neurons for different values of *US*s such as appetitive and aversive stimuli. To simplify the notation they are all represented in the vector *s*. The predefined weight matrix *V* determines what actions are triggered by the different states of *US*. It connects the elements of *US* to specific elements of *IS* and thus via the action selection *AS* sets specific actions. *W* describes the association of *CS* to *IS* and is subject to learning.

The slow dynamics describing the change of the weights *W* follow the learning rule called correlative subspace learning (*CSL*) (Duff et al., 2011):

$$\Delta W = \eta(x - Wy)((1-\zeta)y + (1+\zeta)r)^{\mathsf{T}}$$

The parameter η is the learning rate and may vary with time. Learning is driven by the two product terms $\mathrm{xy}^{\mathsf{T}} \propto xx^{\mathsf{T}}$ and $\mathrm{x}\,\mathrm{r}^{\mathsf{T}}$. The parameter ζ varies between -1 and 1 and balances the influence of the two terms xx^{T} and xx^{T} on learning. With a ζ of -1 only xx^{T} drives learning and for a ζ of 1 the learning dynamics are determined by $\mathrm{x}\,\mathrm{r}^{\mathsf{T}}$ only. The term xx^{T} is related to the auto-correlation of the *CS*. With the assumption that the learning rate η is small and the mean of *x* over time is zero, we can regard xx^{T} as the instantaneous estimate of the real auto-correlation. Thus, we can identify this term with perceptual learning as it depends only on the *CS*. The term $\mathrm{x}\,\mathrm{r}^{\mathsf{T}}$ relates to the correlation of the *CS* and the *UR*. Again it can be seen as the instantaneous estimate of the real correlation. We identify this term with behavioural learning as it contributes to learning the association between the *CS* and the *UR*. However, with only these two terms the weights would grow exponentially and never converge. The negative normalisation term *-W y* depresses the weights and assures convergence.

The parameter ζ allows to control the influence of the terms xx^{T} and $\mathrm{x}\,\mathrm{r}^{\mathsf{T}}$ on learning, and thus allows to balance perceptual and behavioural learning. With a ζ of -1 learning is only driven by the *CS* and the learning rule corresponds to the subspace learning algorithm proposed by Oja. A ζ of -1 corresponds to purely perceptual learning.

The perceptual representations defined by the extracted subspace are the so-called prototypes defined as $\mathrm{e}{=}\mathrm{W}\ \mathrm{y}{=}\mathrm{W}\mathrm{W}^{T}x$. The prototypes are the basic elements used to store and recall action sequences in the long-term memory of the contextual layer (Verschure, 2003; Verschure, 2003a). The prototype corresponds to the linear projection of *x* to the learned subspace defined by the weight matrix *W*. Thus the prototypes directly depend on the extracted subspace and the parameter ζ allows to control if the prototypes are defined more by the auto-correlation of the *CS*s or by the correlation between the *CS* and the *UR*. What is the optimal balance between perceptual and behavioural learning, i.e. what is the optimal value for ζ is not clear in advance and will strongly depend on the task at hand and the statistics of the *CS* and

the *UR*. In this way, the adaptive layer fulfills its twofold task of learning the sensory motor associations and forming internal representations, i.e. the prototypes *e* for the planning system of the contextual layer.

Contextual Layer

The contextual layer provides mechanisms for memorising and recalling behavioural sequences. It comprises two memory structures: a short-term memory (STM), and a long-term memory (LTM) for the permanent storage of information (see Fig. 2 below**)**. These allow the system to acquire, retain and express sequences of the sensorimotor contingencies the adaptive layer generates. The acquisition of information into memory is done in two steps:

1. Sensorimotor events generated by the adaptive layer are stored in the STM, forming a behavioural sequence.

2. When a goal state is reached the sequence of sensorimotor events stored in the STM are copied into the LTM and the STM is initialised.

The information stored in the LTM is then recalled to reach goal states, as follows:

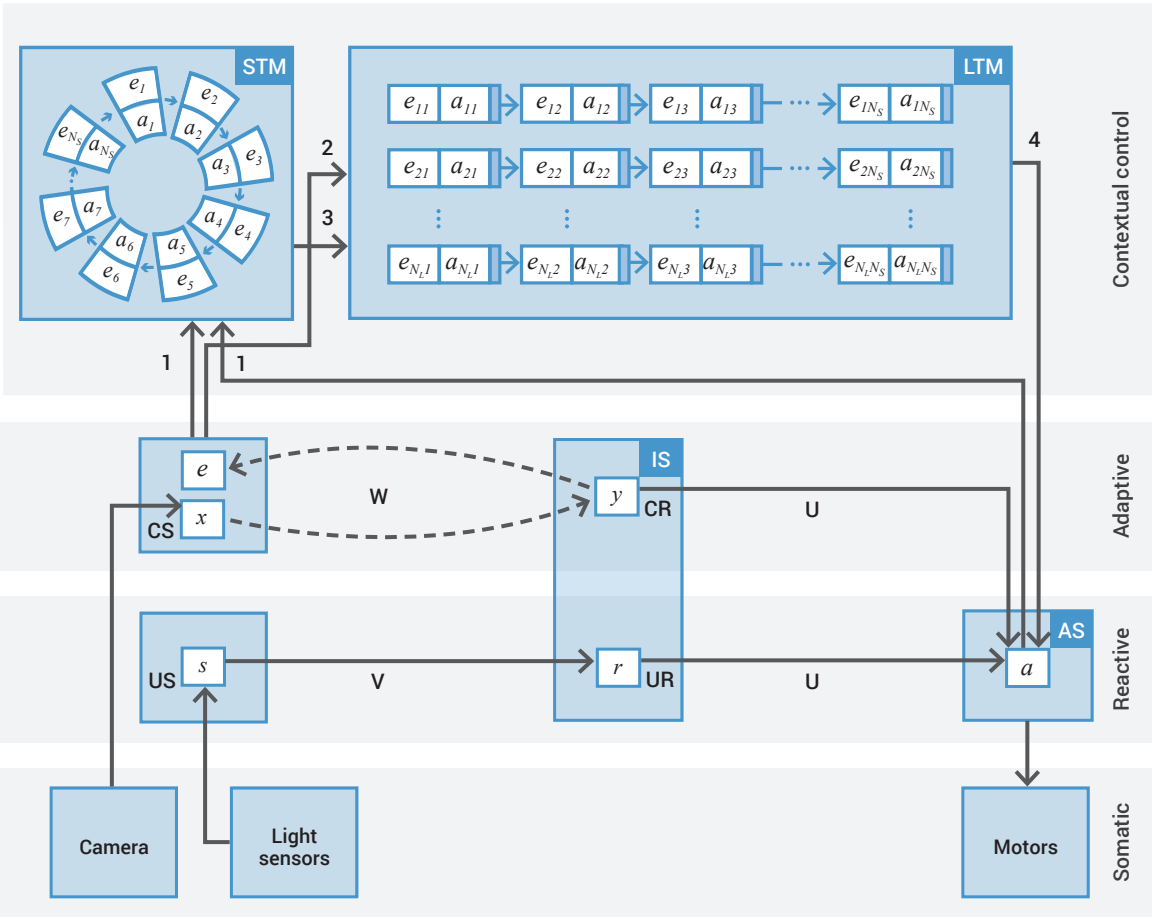
1. Whenever a new sensory event is generated it is compared with all the ones stored in the LTM.

2. The segments of the LTM that are similar enough (similarity defined by a matching criteria) to the generated one are retrieved.

3. Retrieved segments from memory contribute to compute the selected action.

4. The selection of segments from the LTM is biased by previous experience to achieve sequential chaining

Figure 2. *Contextual layer: (1) The generated CS prototype e from the adaptive layer and the executed action a are stored as a behavioural couplet in the STM. (2) When a goal state is achieved the information stored in the STM is copied into the LTM as a sequence and the STM is initialised. (3) The generated CS prototype e is compared with all the prototypes e stored in the LTM. (4) The action a proposed by the contextual layer is calculated as a weighted sum over the actions associated with the sensory events selected from the LTM.*



The STM is the structure that temporarily stores the behavioural sequence that is being experienced by the robot and that did not lead to a goal state yet. It is a ring buffer formed by a sequence of *NS* segments. Each segment contains the action executed *a* by the robot together with the *CS* prototype *e* that was generated at that time. When a goal state is reached the content of the STM is copied into the LTM and the STM is initialised. The LTM contains *NL* sequences of maximum size

of *NS* segments. Each sequence stored in the LTM has a value that relates to the goal states they lead to (e. g. +1 for an aversive state such as collision, +1 for an appetitive state such as reward).

The retrieval of the proper action from memory is based on the similarity between the current *CS* prototype *e* and the *CS* prototypes e_{lq} previously stored in the LTM. This similarity is calculated using a distance measurement as follows:

$$d(e, e_{lq}) = \frac{1}{N}\sum_{j=1}^{N}\left|\frac{e_j}{max(e)} - \frac{e_{lqj}}{max(e_{lq})}\right|$$

The degree of matching of segment *l* in sequence *q* determines the input to its so-called *collector*:

$$c = (1 - d(e, e_{lq}))t_{lq}$$

The collector determines the contribution of the segment to the final proposed action by the contextual layer. Its activity depends on the distance *d(.)* between the current generated *CS e* prototype and the *CS* e_{lq} prototype stored in segment *l* and sequence *q* and on a so-called *trigger value t* that is associated with each segment *lq* in memory.

The trigger value is used to ensure chaining through a sequence. Its value depends on whether the segment that temporarily precedes it in a sequence was selected in the previous cycle. If it was not selected the trigger has a default value of 1 and therefore it does not bias the selection of the segment. However if segment *l-1* in sequence *q* was selected then the trigger value of segment *l* in sequence *q* is set to a higher value than 1. This means that the collector unit associated with that segment will increase its value and that therefore the segment will have more probability of being selected in future decision-making. The trigger value decreases asymptotically as:

$$t_{lq}(t+1) = \alpha_t + (1 - \alpha_t)t_{lq}(t)$$

where $\alpha_t \in [0; 1]$. When a segment is selected its trigger value is reset to 1.

The action proposed by the contextual layer is calculated using the activity of the collectors, but only if these collectors satisfy two criteria: (1) Its activity is above a predefined threshold (θ^C); and (2) Its activity is inside a predefined percentage range from the maximum collector's activity, e. g. the collectors compete in an E%-Max Winner Take All (WTA) mechanism (Almeida et al., 2009) in which only the

collectors inside with an activation equal or greater than E% from the maximum collector's activity contribute to the action. These two criteria can be dynamically adjusted so that they change their value according to the certainty or uncertainty of the robot, e. g. when the robot is still learning it will have a low value of θ^C and E% so that it can take into account a greater number of proposals. The selected collectors contribute to the contextual action as:

$$a_c = \sum_{l,q \in LTM} \pm \frac{c_{lq} H(c_{lq} - \theta^C)}{\delta_{lq}} a_{lq}$$

where δ_{lq} is the distance measured as the number of segments needed to reach the goal state from the current state, i. e. distance between selected segment and the last segment in the sequence. The plus sign means that the selected segment corresponds to an appetitive goal state sequence whereas the minus sign means that it belongs to an aversive goal state sequence. Only if the computed action a_c is positive it is executed. In this way, backwards actions are avoided.

The activation of the contextual layer depends on the quality of the generated prototypes *CS e* from the adaptive layer. This quality is assessed by using a discrepancy measure that runs an average distance between the predicted prototypes *CS e* and the actual *CS x* value:

$$D(t+1) = \alpha_D D(t) + (1 - \alpha_D) d(x, e)$$

where α_D defines the integration time constant and the distance *d(x,e)* between actual *CS x* and estimated *CS e* prototypes. Only when this discrepancy measure falls bellow a certain threshold (*confidence threshold*) the contextual layer is enabled.

An action selection mechanism receives three actions, one from each layer of the architecture: reactive action (a_r), adaptive action (a_a) and contextual action (a_c). The final action executed by the robot is selected through a priority mechanism in which the most priority action is the reactive action, then the contextual action, and finally the adaptive action.

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Tutorial 1: Getting Started

Foraging

Foraging, i.e. the capability of an animal to search and find food, critically determines its evolutionary fitness as it plays an important role in its ability to survive and reproduce. In behavioural terminology, foraging represents a goal-oriented exploration for resources normally motivated by food deprivation. Foraging is an advanced, goal-oriented behaviour where prior knowledge of an environment and acquired behavioural strategies must be matched to the novelty and hazards presented by an unpredictable world and the varying allostatic requirements of the behaving system itself, e.g. energetic and reproductive needs. These constraints are defined at varying spatial and temporal scales, where a successful forager must simultaneously satisfy local and global constraints, such as performing obstacle avoidance while staying on course to reach a known feeding site whilst also allocating resources consistent with its allostatic needs. As such, foraging represents an excellent test case for an autonomous control system.

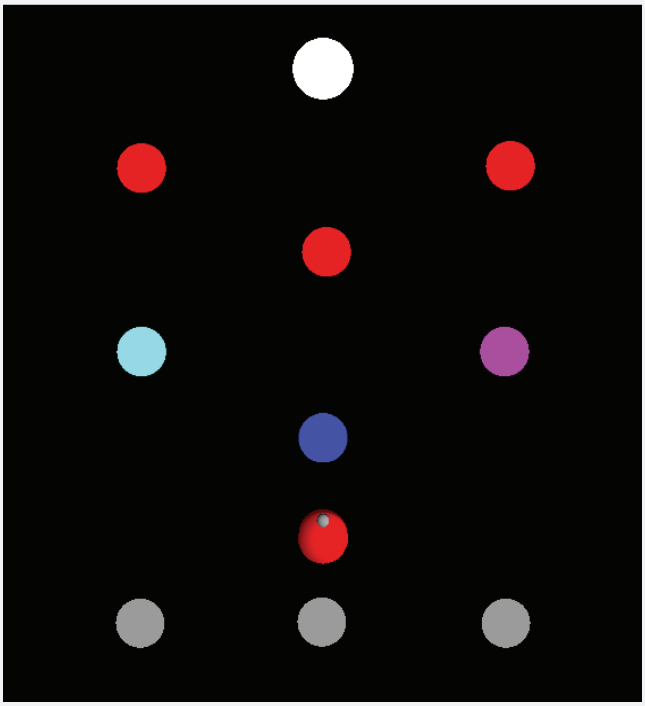


Figure 1. *Simulated agent (red cylinder with the grey dot on top) and environment for the resticted arena foraging task.*

In the following tutorials we explore how the different layers of DAC5 contributes to solving a foraging task. In particular, we test DAC5 in a restricted arena foraging task (see Fig. 1). The squared arena contains coloured patches and a light source visible by the downward-pointing camera of the robot. The light intensity decays with the distance and it is only detectable for the light sensors of the robot at a limited distance. The robot is placed in one of the three starting positions (grey circles) facing the patches, and the goal of the robot is to reach the light. Every time the robot collides with the wall a new trial starts and randomly repositions the robot at one of the three start positions. This task can be described in terms of classical conditioning: the light serves as *US* where the patches serve as *CS*s. As in this configuration of the task, all of the top patches have the same colour and the task is ambiguous and cannot be solved without the context given by the bottom patches. Thus, to solve the task it is essential for the robot to form adequate internal representations of the bottom patches. Only stable and reliable prototypes will allow the memory structures of the contextual layer to store and later recall the correct actions for the ambiguous cues.

The restricted open arena foraging task isolates a core situation of an open arena foraging task in limiting the agent to specific start positions. For an agent endowed only with egocentric inputs, cues in an open arena foraging task are ambiguous and the correct action can only be determined when taking into account the current context (see Fig. 2A). If the agent comes from the left side (solid line) it has to turn left at the red patch. If it comes from the right side it has to turn right. Thus, the red cue is ambiguous but can be disambiguated by the patches the agent encounters before the red patch. Figure 2B is the very same situation in a different configuration. When restricted to the three start positions defined in figure, the agent encounters the same stimuli as in Figure 2A; this is the configuration we use to test the contextual layer. For the adaptive layer this configuration is not solvable since the adaptive layer does not have any contextual information. To be able to test the adaptive layer the red patches were disambiguated by changing the colours (Fig. 2C). In this configuration the three upper patches serve as cue patches and the three lower patches lose their role and become distractor patches. The restricted open arena foraging task in this special configuration is designed to assess the two-fold task of the adaptive layer systematically. For behavioural learning, the patches that can be associated to a *US* should elicit the corresponding action (*CR*). For the perceptual learning all the different patches, cue and distractor patches, should be represented in the *IS,* but only lead to an action if they are associated to a *US*. For the distractor patches, the *IS* activity should remain sub-threshold.

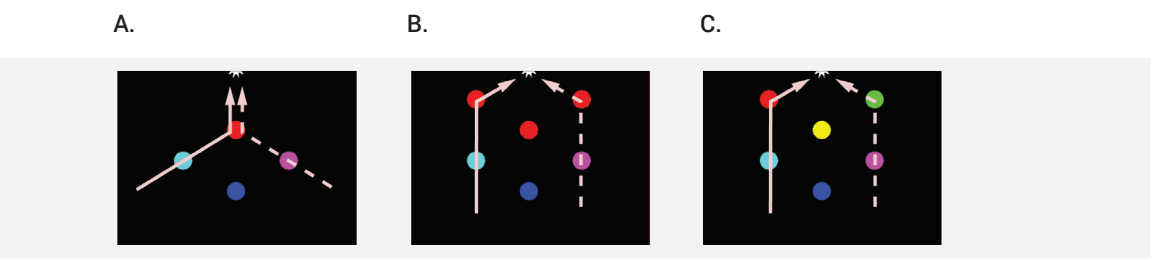


Figure 2. *Patch configuration: A. General situation in an open arena foraging task. B. Equivalent constellation of patches as in A in the restricted open arena foraging task. C. Disambiguation of the patches for testing the adaptive layer that is not context aware.*

In this tutorial you will get aquainted with the *iqr* (Bernardet & Verschure, 2010) and the Gazebo simulation environment (Koenig et al., 2004), and learn how to control the robot. In the remaining tutorials you will analyse the behaviour of the different layers and how they have to be tuned in order to solve the restricted open arena foraging tasks.

Tutorial

Start iqr and Gazebo

Gazebo and *iqr* work as a server-client application running on two separate processes.

In a new terminal window (Ctrl+Alt+t to open it) start an instance of Gazebo and load the world template that will be used throughout the entire tutorial, by typing:

```
cd $HOME/iqr-gazebo/DAC_files
gazebo DAC_basic_arena.world
```

Gazebo GUI will open with a configuration similar to the one illustrated in Figure 3. During this tutorial and the following ones you will not need to modify any aspect of the simulated world, nevertheless, interested readers can find the reference manual of Gazebo at the project website (http://www.gazebosim.org).

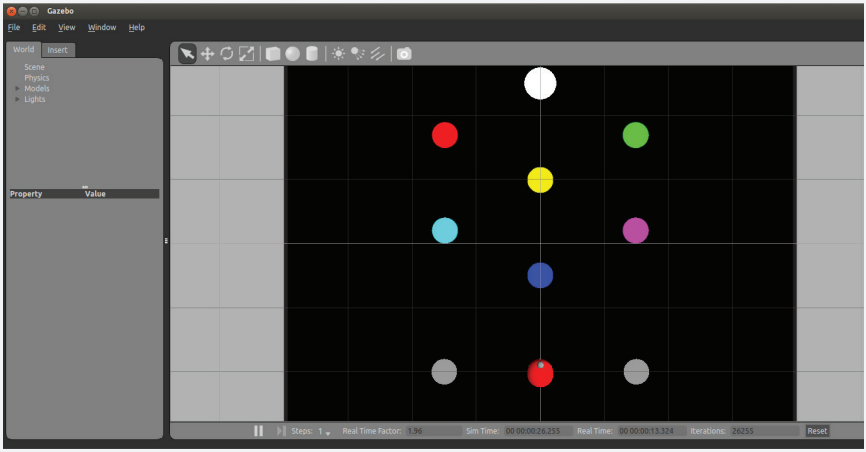


Figure 3. *Gazebo GUI with a fly-view of the foraging task arena.*

Open a second terminal window, start *iqr* and open the DACReactiveBug_ex system by typing the following command:

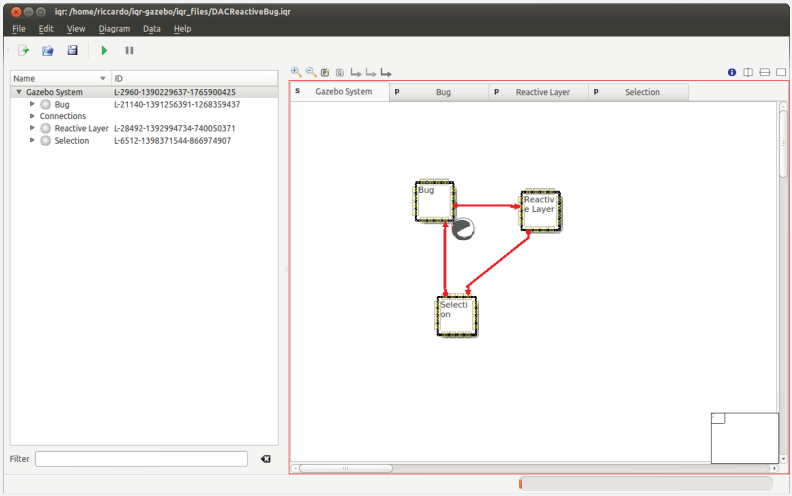
```
cd $HOME/iqr-gazebo/DAC_files
iqr -f DACReactiveBug_ex.iqr
```

The *iqr* GUI will open and the DacReactiveBug controller will be in place as illustrated in Figure 4. The system is not complete and during this tutorial you will be required to figure out how to build the final system. A final version of the file (DacReactiveBug.iqr) with the complete solution to the system is also provided in the same folder.

Bug: is the built-in module that interfaces *iqr* with Gazebo. The small rounded icon at the bottom right part of the Bug icon indicates that this process is interfacing with an external module. All the necessary connections to interface *iqr* and Gazebo are already made for you, but if interested you can have a look at the properties of the process by right-clicking the Bug process icon, and selecting Properties from the contextual menu.

Reactive layer: is the process where the mapping between the sensory stimuli and the pre-wired unconditioned responses takes place.

Selection: is the process in charge of selecting the action to be executed. The output of this process is a motor command that is mapped to the actuators of the robot.



You can inspect each process by clicking on the corresponding tab in the tab bar, while to change the process parameters you can double-click on the process icon or use the contextual menu to open the Properties dialogue (right-click->Properties). For this tutorial you don't have to worry about changing any of the processes' properties since all of the necessary connections were already made for you.

Now, move to the Bug diagram pane. You should see something like this:

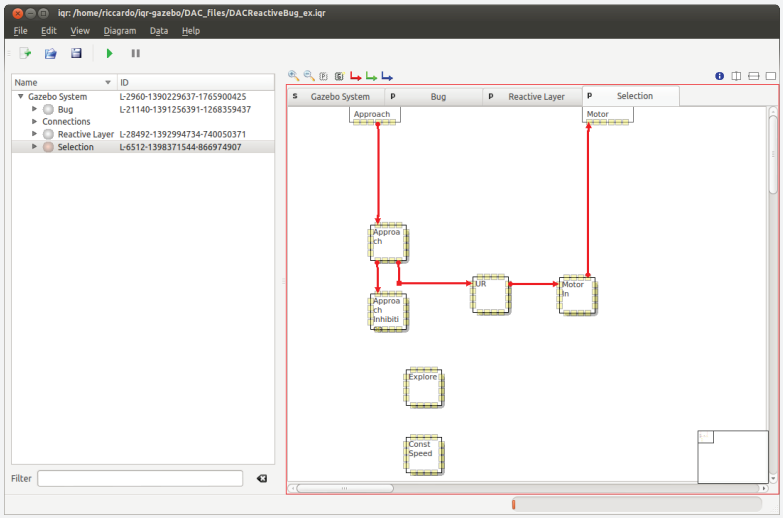


Figure 5. *The Bug process.*

The Bug process (Fig. 5) is made by an assembly of 15 different groups of neurons that can receive inputs or send outputs from/to the Gazebo robot. The robot

comes equipped with different sensors (camera, proximity sensors, light sensors, microphone, GPS, gripper sensor) and effectors (motor, gripper and a speaker), but to implement the reactive layer of DAC we will only need two of them: the light sensors that input to the Light group of the Bug process, and the motor joints that execute the commands received from the Motor group of the process.

To get started and gain some confidence with the robot and all of its features, we will start exploring the robot sensors and effectors. For more details about the other available sensors we point the user to read the iqr-gazebo wiki (https://code.google.com/p/iqr-gazebo/wiki/iqrBugFeatures).

The motors: The motors of the robot are controlled via the 9x9 neurons Motor group (see Fig. 6) of the Bug process. The movement of the robot is computed from the position of the cell with the highest activity in the Motor group lattice. The Y axis represents the force applied to each joint to move the robot while the X axis represents the Rotation applied to it.

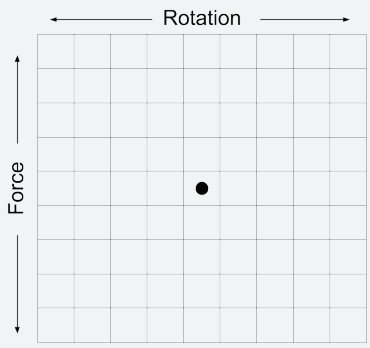


Figure 6. *Schematic representation of the Motor group mapping. The black dot represents the stationary condition where no force and rotation are applied to the robot wheels.*

Light sensors: the robot is equipped with 32 light sensors equally spaced on the robot body that are mapped into the Light group of the Bug process.

Camera sensor: a colour camera placed in the frontal part of the robot and facing downwards receives information from the environment. The input of the camera is then split into three channels (RGB is the default) and transmitted to the three colour channel groups in the Bug process. The resolution of the camera and its input modality can be changed in the Properties dialogue (right-click and select Properties from the contextual menu).

Exercise 1: Moving the Robot Forward

Start the simulation by pressing the Run button. Move to the Bug process diagram pane and open the State Manipulation panel of the Motor group (right-click the group icon and select State Manipulation Panel from the contextual menu). The State Manipulation panel is a tool that is used to directly change the activity of single neurons in the groups.

To move the robot forward left-click the fifth cell of the first row in the motor lattice grid (see Fig. 7). Set it to a value of 1 and click on Add. The command will then be added on a list in the right pane.

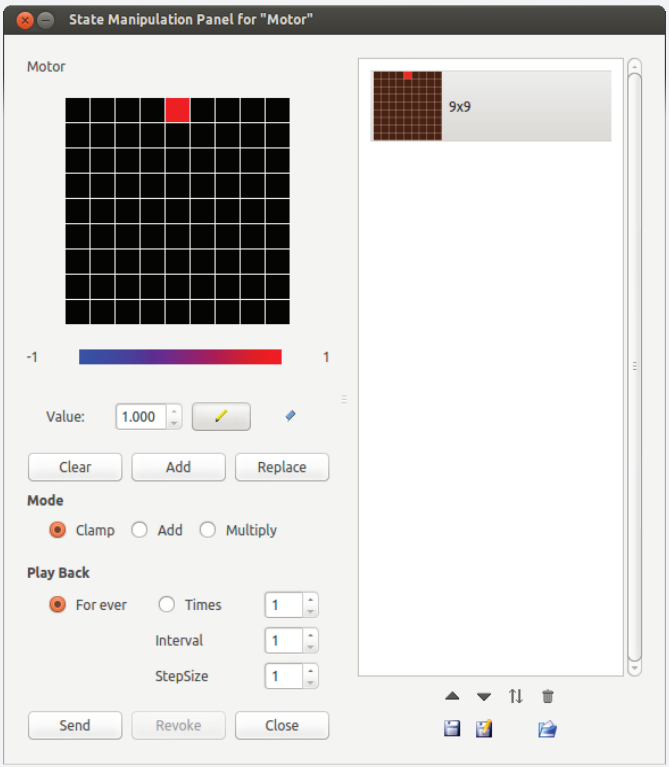


Figure 7. *State Manipulation panel configuration to move the robot forward.*

Now you can click Send to execute the command. The robot will start moving in the forward direction.

To stop executing the command click on the Revoke button.

Q1. Which cell do you need to activate to make the robot turn to its left? and to its right?

Q2. Which cell do you need to activate to make the robot move backwards?

Q2. How do you control the speed of the robot?

Exercise 2: Make the Robot Move Autonomously

Using the State Manipulation panel is not the most effective way to control your robot. We want the robot to behave autonomously in its environment.

Stop your simulation and close the State Manipulation panel. Move to the Selection process diagram pane (see Fig. 8).

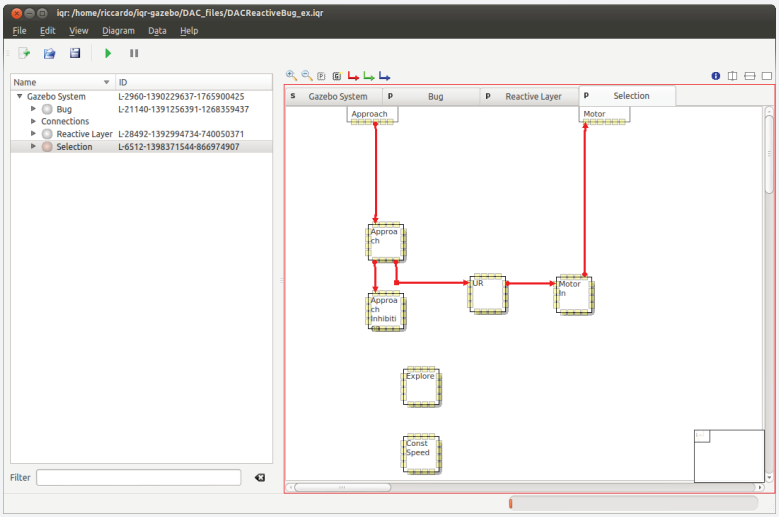


Figure 8. *The action selection process.*

The action selection process: this process is made up of six different groups that define the default robot behaviour (i.e. Explore the environment) and a pre-wired reflexive behaviour (i.e. Approach).

The most basic behaviour of the robot is to explore its environment on a straight direction.

To make the robot move autonomously along a straight path we will have to constantly activate the exploratory behaviour of the robot. This stereotyped behaviour can be achieved by feeding the Explore group with a constant input:

Create an excitatory connection from the Const Speed to the Explore group. Click on the red Add Connection button in the Diagram edit toolbar and then click on the Const Speed group. Now click on one of the yellow squares at the edge of the Explore group to connect the two groups. The Const Speed group is made up of a single cell that is always active and represents the constant driving force for the exploratory behaviour.

Now let's try to make the robot move on its own.

Q1. The Motor In group is an interface to the Motor group of the Bug process. How do you have to connect the Explore group to the Motor In group to make the robot move forward? Connect the two groups then run the simulation to observe if the robot behaves as expected.

Before we continue with the implementation of the Reactive layer, try to observe how the different sensors of the robot react to the environment. Move to the Bug process diagram pane and open the Space plot of the Red/Hue group (right-click the group icon and select Space Plot from the contextual menu). The Space Plot is a useful tool that plots the instantaneous activation of the group cells in a two-dimensional space. In this case what the plot shows is the input received by the camera of the robot while exploring the arena.

Try by yourself and inspect through the respective Space plots the behaviour of the light sensors and the proximity sensors.

Q2. How do the light sensors behave?

You can now save your system (press Ctrl+s or select Save from the File menu) and go on with the second tutorial.

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Tutorial 2: DAC Reactive Layer

In the previous tutorial we built a first system that allowed the robot to explore its environment in a very primitive way. The next step, now, is to make the robot responsive to its environment and behave accordingly.

For a behaving system the basic competence for it to be able to interact in an effective way with its environment is derived from a a reactive control structure. By solely relying on a set of pre-wired relationships between *US* events and *UR*s, the agent will reflexively react to immediate events in the environment.

The triggering stimuli, *US*s, are derived from the proximal sensors (i.e. light sensors of the robot) and the *UR*s are mapped into motor actions.

Nevertheless, as we will see in the next tutorial, the activation of any reflex will also provide cues for learning that are used by the DAC adaptive layer.

Exercise 1: The Reactive Layer Implemented—Reflexively Approach a Source of Light

If not already opened, start *iqr* and Gazebo using the same commands as in Tutorial 1.

The DAC Reactive layer is implemented in *iqr* in the Reactive layer process (see Fig. 1) which you can access by clicking the Reactive layer tab in the tab bar.

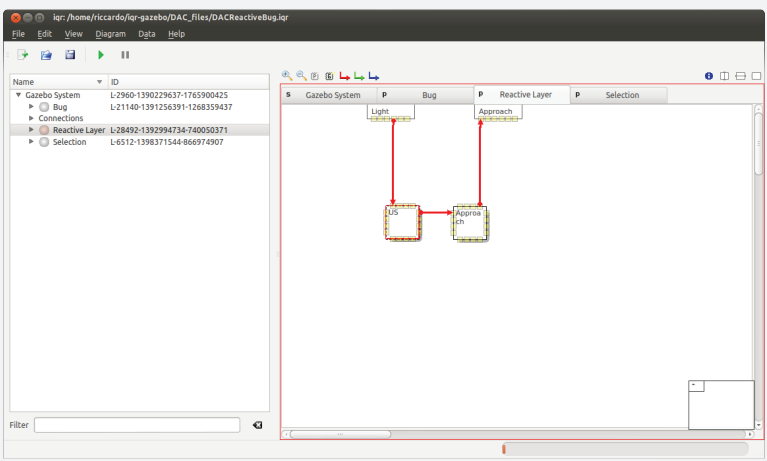

Figure 1. *The Reactive layer implemented in the iqr system.*

As depicted in Figure 2, the Reactive layer is composed of two different groups of linear threshold neurons:

The US group, which receives a compressed version of the light sensors and constitutes the input to the second group.

The Approach group, which defines the mapping to the reflexive behaviours.

Information from the latter is then passed to the Action Selection process to trigger the unconditioned response (i.e. the appropriate sequence of motor commands).

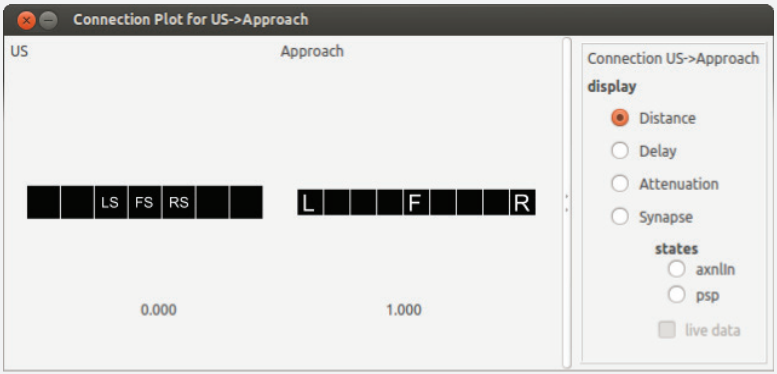

Figure 2. *US and Approach groups: The US group is a 7x1 group of cells that receives a compressed version of the light sensor's input. Abbreviations for the US group: LS, left frontal sensor; FS, frontal sensor; and RS, right frontal sensor. The Approach group is a 9x1 group of cells that defines the repertoire of pre-wired behaviours. Abbreviations for the Approach group: L, turn left; F, go forward, and R, turn right.*

In order for the robot to directly approach the light source when it is sensed by one of its sensors, we need to create a correct mapping between the sensors and the effectors.

Q1. Try to figure out how to map the *US* group to trigger the correct reflexes in the Approach group in order for the robot to approach the light source once it is detected.

To set the connectivity pattern, open the Connection properties dialogue (right-click on the connection between *US* and Approach groups and select Properties from the contextual menu). Set the Pattern type to PatternTuples from the set type drop-down menu (see Fig. 3, left side of the panel). This kind of pattern is used to define individual cell-to-cell projections between groups. Click Apply to confirm and then click the Edit button near the PatternTuples label. Your dialogue should now look similar to the one illustrated in Figure 3.

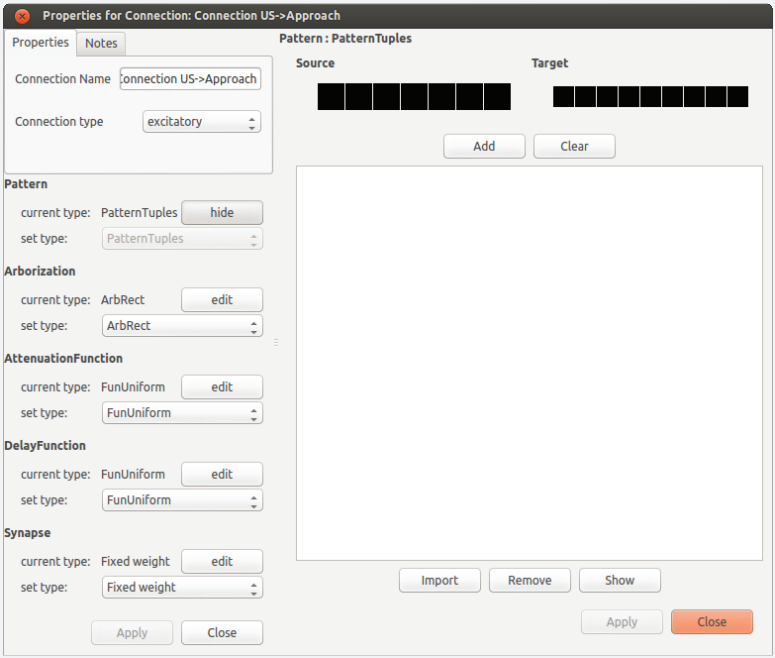

Figure 3. *Connection Properties dialogue.*

Q2. Implement the connectivity pattern that you defined in the previous step. To set a connection select a cell in the Source group and the corresponding target cell in the Target group. Next click Add to accept the tuple. To define a new tuple, you first have to click the Clear button and then you can repeat the same operations as in the previous step. Once you are done click Apply and Close. Remember to save your system whenever you make changes.

Q3. Do you expect that the system will work properly? If not, try to explain why?

Q4. Run the simulation and check if your response was correct. (You can find the correct solution to the connectivity pattern in the file DacReactiveBug.iqr).

Exercise 2: The Reactive Layer Implemented—Actions Selection and Conflict Resolution

For the robot to properly behave through a purely reactive system one more step is missing. We defined the reactive controller by mapping the occurrence of a *US* onto a specific action of the robot, approach in our case. Nevertheless this was not sufficient for the robot to correctly approach the light since the 'go forward' behaviour took priority. We thus need a mechanism to resolve the conflicts between different concurrent actions.

To implement this mechanism, open the Selection process diagram pane. To prioritise the approaching behaviour over the exploratory one, the latter mechanism needs to be shut down so that the unconditioned response can be expressed.

Q5. Try to figure out what is the most plausible way to inhibit the expression of the exploratory behaviour and make the robot reach the light source.

Q6. Make the necessary changes to your model and run the simulation. (You can find the one-step solution in the file DacReactiveBug.iqr).

Stop the simulation. Move to the Reactive layer diagram pane and open the Properties dialogue of the Approach group. Click on the Edit button of the Neuron type panel. Click the Membrane tab and change the Threshold value to a lower value (e.g. 0.3). Run the simulation.

Q7. How does this change affect the behaviour of your robot?

Exercise 3: Recording and Plotting Data

iqr includes the Data Sampler tool (Fig. 4) which allows you to save the internal states of all or part of the elements of the model. In what follows we will record and plot the trajectories of the robot while performing the navigation task.

Open the Data Sampler (form the Data menu select Data Sampler) to record the robot position coordinates from the GPS group of the Bug process.

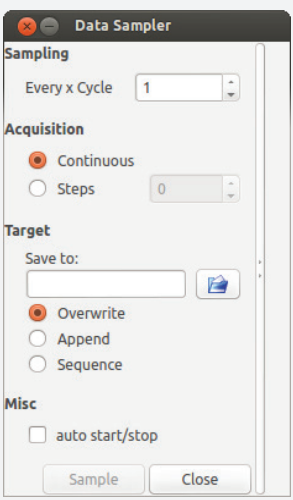

Figure 4. *Data Sampler dialogue.*

Click the Bug tab in the tab bar and open the Space plot of the GPS group (right-click on the group icon and select the State Plot). Drag the small icon highlighted in Figure 5 and drop it to the Data Sampler window. Alternatively you can drag the GPS group from the browser GUI to the Data Sampler dialogue.

Figure 5. *GPS Space Plot: to copy the output of the GPS group to the Data Sampler drag the icon in the red circle to the Data Sampler dialogue.*

In the Data Sampler dialogue choose the destination folder and file where to save your data.

Select auto start/stop to automatically record the GPS coordinates when the simulation starts.

(Optional) If you have Matlab or Octave installed on the computer you can try to generate a trajectory plot like the one in Figure 6. The Matlab script (plotTrajectory.m) is located in the DAC Files folder.

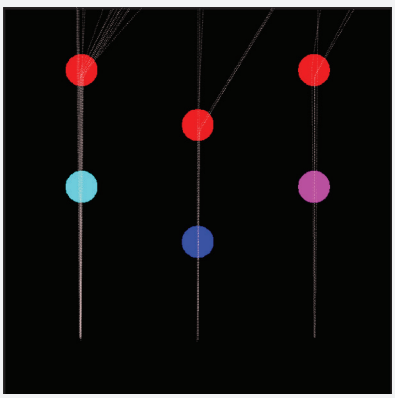

Figure 6. *Trajectories plot.*

Tutorial 3: DAC Adaptive Layer

The Adaptive layer is a model for classical conditioning in that it learns the association between *CS* and *US*. In doing so it does not only associate the unconditioned responses to different *CS*s but it also generates internal representations of the world, i.e. the prototypes. In this step of the tutorial we will explore both the perceptual and behavioural learning aspects of the Adaptive layer.

To get started please open two terminals. In the first one we run the Gazebo simulation environment by typing:

```
cd $HOME/iqr-gazebo/DAC_files
gazebo DAC_basic_arena.world
```

In the second terminal we run *iqr* by typing:

```
cd $HOME/iqr-gazebo/DAC_files
iqr -f DACBugBasicArena.iqr
```

In *iqr* the Adaptive layer is implemented as a module called Adaptive layer. As such it defines all the necessary input and output cell groups including: *CS*, *CR*, *UR* but also a cell group for the discrepancy and an additional cell group to display the current weights of the Adaptive layer. If you open the Adaptive layer process tab you can see how the different cell groups are integrated within the DAC system (Fig. 1). The *UR* cell group receives its input from the Reactive layer process. The *CS* cell group receives its input from the colour vision module. The outputs of the Adaptive layer module are the *CR* and the discrepancy. The display cell group serves as a space plot of the connection weights.

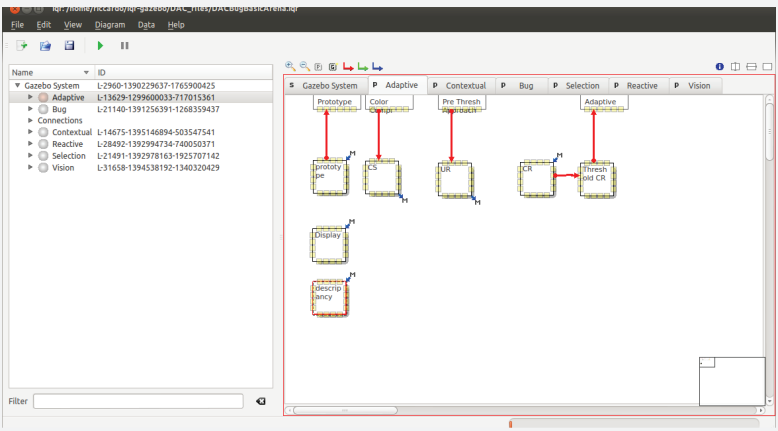

Figure 1. *The Adaptive layer process.*

The parameters of the Adaptive layer can be changed in the Properties dialogue of the Adaptive process (Fig. 2). You can access it by double-clicking the Adaptive process icon in the Gazebo system diagram pane or through the browser GUI. Once the dialogue is opened, press the Edit button. The main parameters are the learning rate η which determines the learning speed, and the balance ζ which changes the balance between perceptual and behavioural learning. The parameter ρ determines the error correction term that we will not be changing in this tutorial. The weights W of the Adaptive layer are initialised randomly at the start of each simulation. So learning starts anew every time you stop and start the simulation. To avoid initialising the weights, you can pause the stimulation instead of stopping it. The weights can also be saved and loaded from an external source. Click on the *Read Write* tab, choose a file and tick the read or write box if you want to load or save the weight matrix respectively.

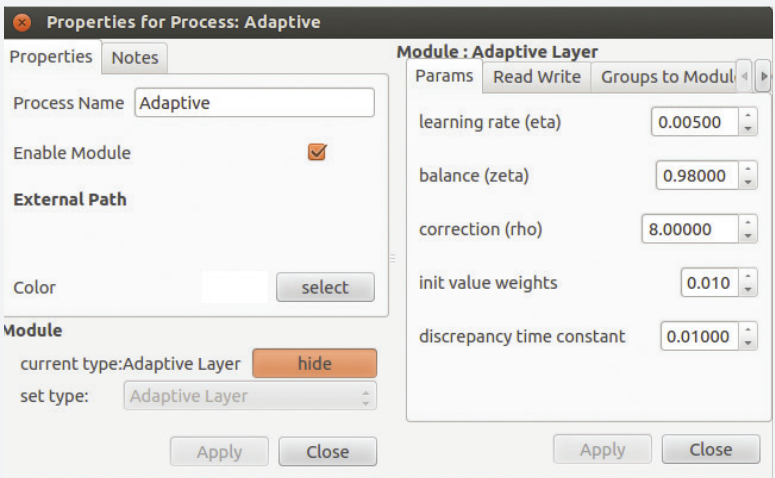

Figure 2. *Properties of the Adaptive layer module.*

In the first part of the tutorial we connected the sensors and motors in such a way that the robot approaches the target light source based on the unconditioned responses (*UR*) only. Now we want to see how the Adaptive layer can learn the association between the patches on the floor and the target. To better analyse the actions learned by the Adaptive layer we have suppressed the actions of the Reactive layer by increasing the threshold of the reactive actions. The input to the Adaptive layer is however still the pre threshold activity of the reactive actions so that the Adaptive layer can learn the associations between the patches and the activity of the light sensors. You can examine this change in the Reactive layer process tab (Fig. 3).

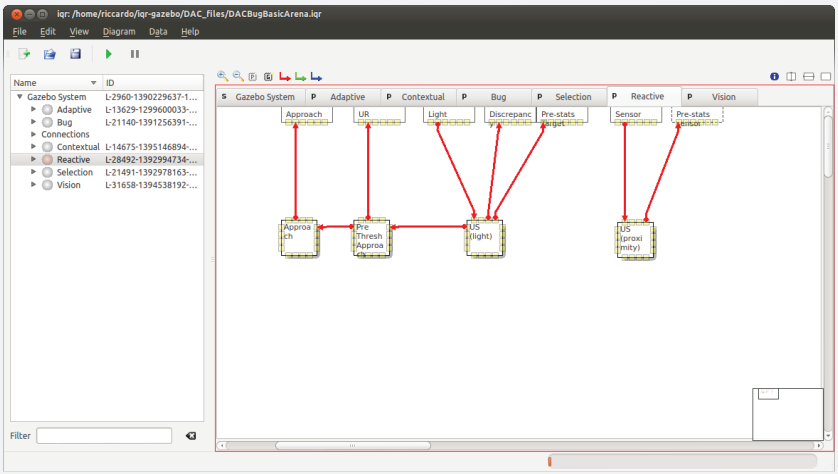

Figure 3. *The Reactive layer.*

Exercise 1: Reactive vs. Adaptive

First we want to compare the Reactive vs. the Adaptive layer. To do so open the Properties dialogue of the Adaptive process and set the learning rate η to zero. With a learning rate of zero the weights W of the Adaptive layer will not change and thus the Adaptive layer will not perform any actions. As we suppress the actions of the reactive layer the robot should go straight on all of the positions.

Now increase the learning rate η to 0.001. After a few trials the robot should start to approach the light source target. You can repeat the simulation with different learning rates. The higher the learning rate the faster the learning, i.e. after fewer trials the robot will turn towards the target. However, keep in mind that too high learning rates often lead to instability both in the weights as well as in the behaviour. Try to experiment with different learning rates.

Q1: At what learning rate does the Adaptive layer learn the association within just one trial?

In a next step we want to examine the weights matrix W and how the weights change over time. To do so we can open a Space plot of the Display group. The Display space plot shows the weight matrix W along the action space, i.e. the first rectangle of the size of the *CS* cell group represents the weight connecting the *CS* cell group to the first cell of the *CR* cell group and so one. Please restart the simulation and observe how the weights evolve. Three regions of weights should stand out.

Q2: What regions do stand out? Why this regions? What do they represent?

The learning of these three regions is mostly driven by behavioural learning and are learned first. If you continue the simulation you can observe how over time other parts of the weight matrix are filled in. This is mostly driven by perceptual learning; you can change the learning rate and observe how the speed of the weights vary with the size of the learning rate.

In order to examine the perceptual learning of Adaptive learning we can first look at the discrepancy *D*. The discrepancy measures the difference between the conditional stimulus *x* and the prototype *p*, i.e. the difference between the perception and the predicted perception. You can visualise the discrepancy by opening a Time plot of the Discrepancy group (right-click the group icon and select Time Plot from the contextual menu).

Q3: For the three different learning rates 0.1, 0.01 and 0.001 how long does it take for the discrepancy to fall bellow 0.1?

Exercise 2: Prototypes

The difference in the weight matrix distinguishing behavioural and perceptual learning should also be reflected in the prototypes. You can examine this distinction by opening the space plots of the *CS* and prototype cell groups. It might be convenient if you elongate the size of the space plot so the the cells become squared (just drag the lower right corner of the plot window). When you start the simulation you can see how, at the beginning, the prototype hardly corresponds to the *CS*. However, over time the prototype will resemble the *CS* more and more. First the *CSs* that are associated to the *UR* will be represented in the prototypes. Also over time, the patches that are not associated to an action will be represented in the prototypes. These are however represented with a lower amplitude than the patches associated to actions. You can visualise this difference by opening a time plot of the prototype. You can clearly distinguish two consecutive peaks in the time plot. The first is lower and belongs to a patch that is not associated with an action. The second is higher and belongs to a patch that is associated to an action (Fig. 4). This difference can be seen as a bias of the internal representations towards behaviourally relevant stimuli.

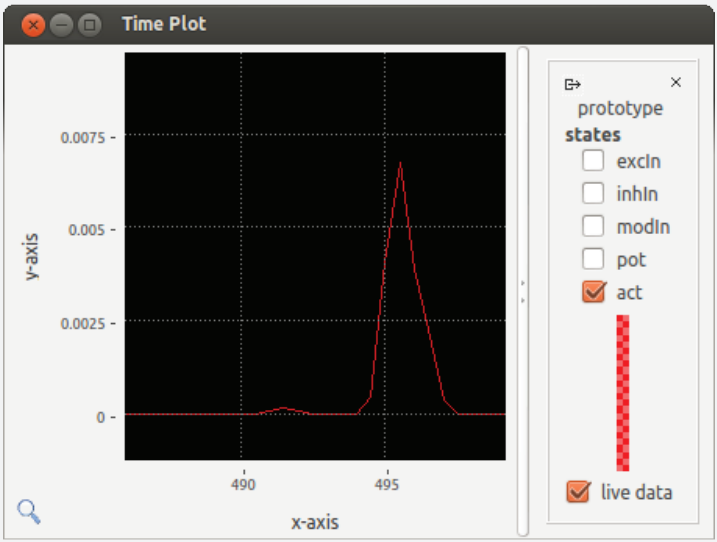

Figure 4. *Time plot of the prototype's amplitudes. The low peak corresponds to a patch that is not associated to an action.*

Q4: Compare the peaks in the time plot, and estimate the relative amplitude of the peaks.

The difference between the amplitude of the prototype of patches associated to an action and patches not associated to a particular action is mainly influenced by the balance between behavioural and perceptual learning. In the Adaptive layer this balance is set through the balance parameter ζ.

Q5: Change the balance parameter to values lower than 0.98. How do the relative amplitude of the peaks in the time plot change?

You might notice that after a short while the patches not associated with a reactive action will trigger an action anyway. This happens as the perceptual learning drives the weights, and thus the *CR,* over the threshold potential. You can eliminate this actions by increasing the threshold of the *CR threshold* cell group. This, however, is only possible within a certain range as high thresholds will impede the *CR* to trigger any action.

Exercise 3: Dealing with an Ambiguous Task

Finally, we will go back to the ambiguous arena. Close both Gazebo and *iqr* and reopen both by typing the following commands in two different terminals:

```
cd $HOME/iqr-gazebo/DAC_files
gazebo DAC_basic_ambiguous_arena.world
```

In the second terminal we run the same *iqr* system as before by again typing:

```
cd $HOME/iqr-gazebo/DAC_files
iqr -f DACBugBasicArena.iqr
```

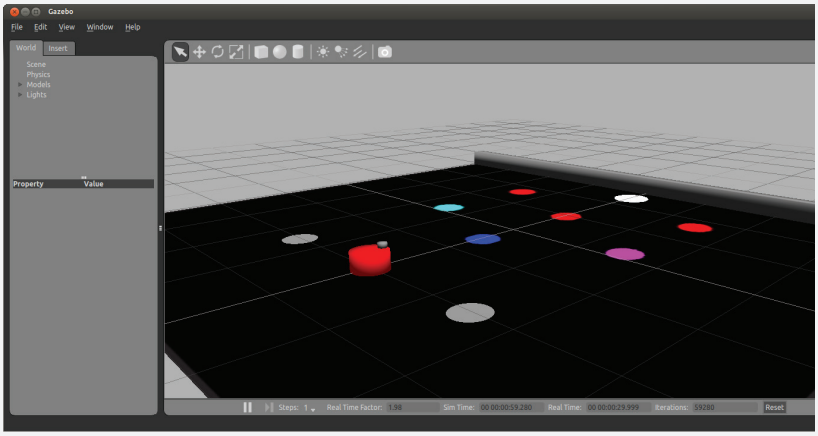

Figure 5. *The ambiguous arena from a sideview.*

In order for the Contextual layer to be able to learn this task, the Adaptive layer has to provide the Contextual layer successful trails for the different cue patches. The rationale is that through constant fast adaptation the contextual layer will, by chance (i.e. when the robot starts several consecutive times in the same position), learn the correct response. Start the simulation and observe the behaviour of the robot.

Q6: How is the chance of the robot going towards the target related to the learning rate?

(Optional):

Q7: Use the Matlab script plotTrajectory.m to generate a plot of the trajectories of the robot. To do so you need to log the GPS cell group using the *iqr* data logger as in Tutorial 2.

Tutorial 4: DAC Contextual Layer

To analyse the behaviour of the contextual layer we will first test it with the DAC basic restricted arena and then we will use the DAC basic ambiguous restricted arena. In the first case the contextual layer is not fundamental to solve the task (as you have already seen in section 'Tutorial 3: Adaptive Layer'—the adaptive layer can successfully learn the association between patches and actions since there is no ambiguity between them), but it is helpful to understand the principles underlying this layer. In the second case, the contextual layer is essential for the robot to sucessfully reach the light because context is needed to disambiguate between the last patches and therefore to perform the correct action. To investigate the first example we need to open two terminals. In the first one we will run the gazebo environment:

```
cd $HOME/iqr-gazebo/DAC_files
gazebo DAC_basic_arena.world
```

And in the second terminal we will run the iqr system:

```
cd $HOME/iqr-gazebo/DAC_files
iqr -f DACBugBasicArena.iqr
```

In the file DACBugBasicArena.iqr you will find the complete DAC architecture (Fig. 1). It has a Bug module that has all the interfaces with the robot (sensors, motors, etc.), a vision module that pre-processes the input from the robot's camera, a selection module that performs action selection from the actions proposed by each layer of the architecture, and the three modules of the layers from the DAC architecture: the reactive, the adaptive and the contextual layer.

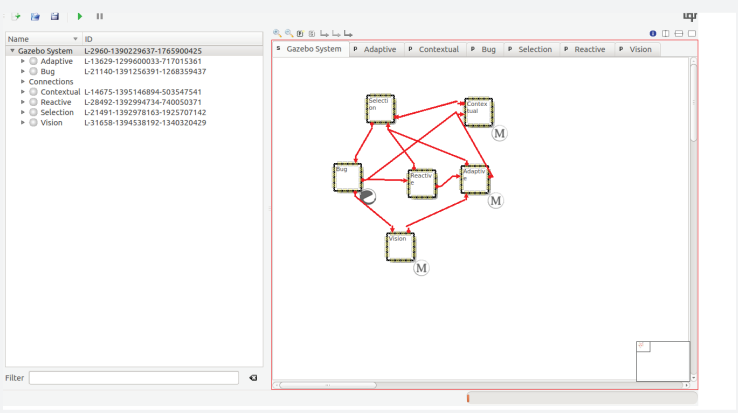

Figure 1. *Overall view of the DAC architecture and the Gazebot robot in iqr.*

The contextual layer module implements the mechanisms for storing and recalling information from memory, as explained in the chapter on DAC5. It has seven parameters that can be set by the user (Fig. 2):

height: number of sequences (*NL*) that can be stored in the LTM.

width: maximum number of segments (*NS*) that can form a sequence in the STM and in the LTM.

discrepancy threshold: this parameter determines when the contextual layer will be activated, i. e. when the distance between the current *CS* prototype generated by the adaptive layer and the currentcs is below the discrepancy threshold, the contextual layer is enabled.

selection threshold: only the collectors that have an activity above this selection threshold are selected and compete in an E%-WTA.

%-WTA: the percentage value that defines the WTA competition, i.e. only if the activity of the collector is equal or greater than the %-WTA of the maximum collector's activity it is selected. Higher value of %-WTA means that less collectors are selected and vice versa.

trigger reset: value that the trigger of a segment following a selected one gets so that it has more probability of being selected later on.

trigger decay: defines how rapidly the trigger value decays back to its default value of 1 so that with time the segment does not have more priority over the others anymore.

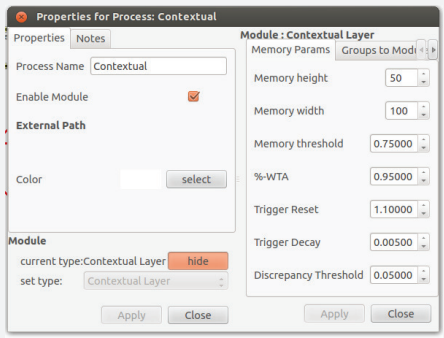

Figure 2. *Properties panel of the contextual layer module. The user can set the parameters that will be used by the contextual layer in the acquisition and retrieval of information.*

The module has four input groups (Fig. 3):

action: the current action executed by the robot that was triggered either by the reactive layer or by the adaptive layer (the default going forward action is not stored).

prototype: the current *CS* prototype generated by the adaptive module.

stats: the cells of this group inform the contextual layer about the achievement of a positve or negative goal state. The first cell indicates that a positive goal state has been reached whereas the second informs about a negative goal state. After the activation of one of these two cells, the information in the STM is copied in the LTM either as a positive or a negative sequence and the STM is reset. In this tutorial, only positve sequences are stored and the proximity sensors are only used to inform the contextual layer that the robot failed to reach the target (a wall at the top of the environment makes this information available) and then the STM is reset without copying its content into the LTM.

discrepancy: it is an average measurement of the quality of the *CS* prototype's generated by the adaptive layer.

And one output group (Fig. 3):

action: action proposed by the contextual layer computed from the actions contained in the selected segments.

And five output groups (Fig. 3) that are basically used to display information about the internal states of the contextual layer so that the user can have a better understanding of how the information is being acquired and retrieved from memory. All five groups have a size of NSxNL and show the information about each segment in the LTM.

empty: it indicates if the specific segment in memory has been filled in (1 if the segment is empty and 0 if it is not).

collector: collector activity of each segment.

distance: the distance between the prototype *CS* stored in the specific segment in the LTM and the actual generated *CS* prototype.

selected: it indicates if the segment has been selected or not, satisfying both that the activity of the collector is above the selection threshold and above

a %-WTA from the maximum collector's activity (1 indicates that is has been selected and 0 that it has not been selected).

trigger: the value of the trigger for each segment.

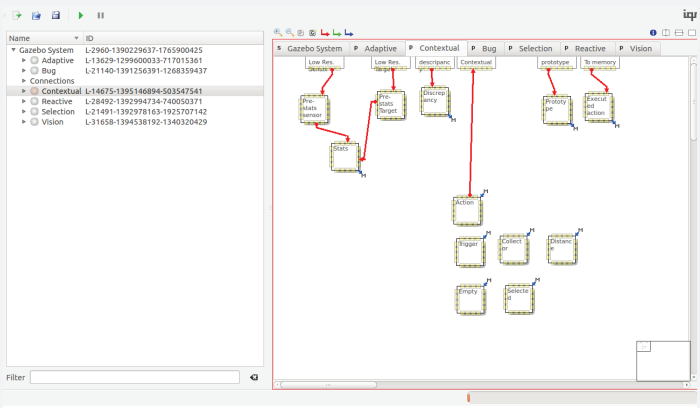

Figure 3. *The group of cells that form the contextual layer module in iqr.*

In the selection module the action from the contextual layer has been added (Fig. 4). Whenever the contextual layer proposes an action it inhibits any action coming from the adaptive layer. The reactive actions are the ones with highest priority, then the contextual actions and then the adaptive ones.

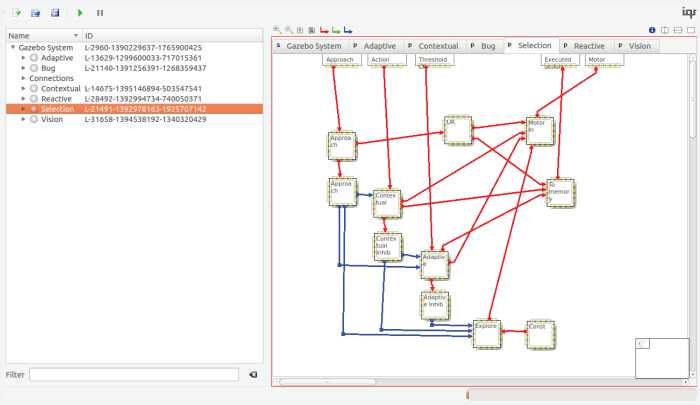

Figure 4. *Action selection: the actions proposed by each layer compete to take the control of the robot. The inhibitory connections are used to give different priority to the layers: the action proposed by the reactive layer is the one with highest priority, then the contextual action and lastly the adaptive one.*

First, we want to see if the contextual layer can solve the task as the adaptive layer does. To do so, we first need to enable the contextual layer. Under the contextual layer property tab please tick the 'enable' box and apply the changes. Run the simulation. After the discrepancy falls below the predefined threshold, the memory sequences of the STM will be transferred to the LTM. When sufficient sequences are stored in the LTM (for instance, that the robot experienced more than five correct sequences for each of the three possible trajectories), we want to test if the contextual layer is able to solve the task. To do so please disable the actions of reactive and the adaptive layers by setting the excitatory gain of their corresponding neuron groups in the selection process to 0.

Q1: Can the robot still successfully solve the task? Are the trajectories different to the trajectories generated by the adaptive layer?

Now, we will have a look at the LTM of the contextual layer. In the empty cell group you can see the number of segments of memory that are filled in. You can do so by opening the space plot of the empty cell group. As you might notice, even if the trajectories that the robot must follow to reach the light consist only of two patches, the sequences seem much longer.

Q2: Estimate the average length of a sequence in the memory? Why are they, in general, longer than 2?

To understand the different parameters of the module we will now vary some of them and test the behaviour of the robot. To start with, we will have a look at the selection mechanism. Open the properties panel of the contextual layer module and try to increase or decrease the value of the %-WTA parameter and the selection threshold. This varies the amount of memory segments that are selected.

Q3: What is a good value range for the %-WTA parameter so that the robot successfully completes the task?

To investigate the interaction between adaptive and contextual layers we will now check the influence that the learning rate (η) of the adaptive layer has on the contextual layer. In a previous part of the tutorial we have seen the impact that this parameter has on the duration of the learning process and with this exercise we will see the importance that it also has on the performance of the contextual layer. To do so, open the dialogue box of the adaptive layer module and modify the value of the learning rate (η).

Q4: What happens when you decrease or increase the value of this parameter? Why?

We will now work with the DAC basic ambiguous restricted arena. To do so, please, close the *iqr* and Gazebo programs that are open. In the first terminal write:

```
cd $HOME/iqr-gazebo/DAC_files
gazebo DAC_basic_ambiguous_arena.world
```

And in a second terminal run the same *iqr* system as before:

```
cd $HOME/iqr-gazebo/DAC_files
iqr -f DACBugBasicArena.iqr
```

As you have seen before, the adaptive layer by itself cannot solve this task because the upper patches are ambiguous. It tries to continuously learn the correct action associated with a patch and it might go to the goal if the robot starts from the same position during a few consecutive trials. However, it will fail again to reach the target if a different position in the arena is used as a starting point. To properly solve the task and disambiguate between the last patches, context (i. e. previous patch that was seen) is needed. The contextual layer, which implements operant conditioning, can pick up this information and successfully lead the robot to the goal position in the arena (light). If we let the system run during enough time (for instance, until the LTM is full), we will see that the robot starts increasing the ratio targets reached by trials. We can again follow the same steps as in the previous task to see how they generalise to the ambiguous task.

In the space plot of the cell group selected you can observe what segments are selected. To understand the importance of chaining when recalling information from memory, we will check the effect of the trigger reset and trigger decay in the selection of segments from memory. Try to vary them and see what the effect is of this modification in the robot's performance.

Q5: If you look at the selection output group of the contextual layer, can you tell what happens when the value of the trigger reset is high and the decay very low? And what happens in the reverse case?

4 | DAC Applications

Rehabilitation Gaming System

One approach to empirical validation of the DAC framework is to investigate whether it can be applied to clinical challenges.

According to the World Health Organization, 15 million people across the world suffer from stroke each year. Of these, one third die, and another third are permanently disabled. An interesting implication of this statistic is that perhaps one third make close to a full recovery. Is it possible that more stroke sufferers could regain more of their lost function?

In Barcelona, a few hundred stroke patients have now been successfully treated by a novel neurorehabilitation system, called the Rehabilitation Gaming System or RGS (Cameirão et al., 2011) that is based on insights gleaned from the development of DAC (Verschure, 2012) (Fig. 1). The RGS system makes use of virtual reality (VR) to mobilise the power of brain plasticity and its reorganisation to speed up functional recovery after stroke. In a recent study (Cameirão et al., 2012), using standard clinical assessment scales, the RGS method significantly impacted on functional recovery. This result opens up a possible path for the introduction of this novel technology in future clinical practice.

So what has RGS to do with DAC? RGS builds on an underlying hypothesis that functional recovery can be promoted by capitalising on the life-long plasticity of the brain and the assumption that neuronal plasticity is governed by only a few computational principles or objectives (see Verschure, 2011). More specifically, relevant learning principles defined in DAC include the balancing of perception and behaviour in *Correlative Sub-space Learning* (Duff et al., 2010). In practice, RGS integrates a paradigm of action execution (movement, with motor imagery), thinking about and imagining movement, and action observation (watching the movement of a virtual limb) (See Fig. 2). The hypothesis behind the choice to combine movement execution with the observation of correlated action of virtual limbs in a first-person perspective is that, within this specific scenario, recovery can be accelerated and enhanced by driving the so-called Mirror Neuron system (MNS). A mirror neuron is a brain cell that fires both during an action and when watching another person performing the same action—that is it mirrors the action of the other person as though the observer performed the action themselves. In the DAC framework we conceive the MNS as a critical interface between the neuronal substrates of visual perception and motor planning and execution (see Verschure, 2011). Applied to stroke, we hypothesise that the MNS can define a task- and context-relevant state of the afferent and efferent pathways that were disrupted by the (stroke-induced) lesion, promoting activation of these pathways and facilitating functional recovery and rescue.

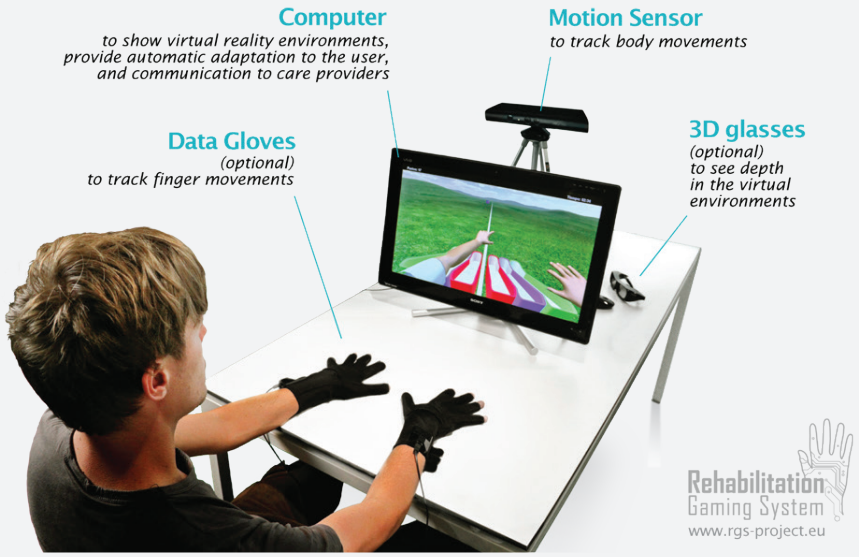

Figure 1. *Using the RGS system: the RGS user watches a virtual rendering of his/her arms on a screen while performing a task, for instance intercepting spheres that move towards them from different directions and at different speeds.*

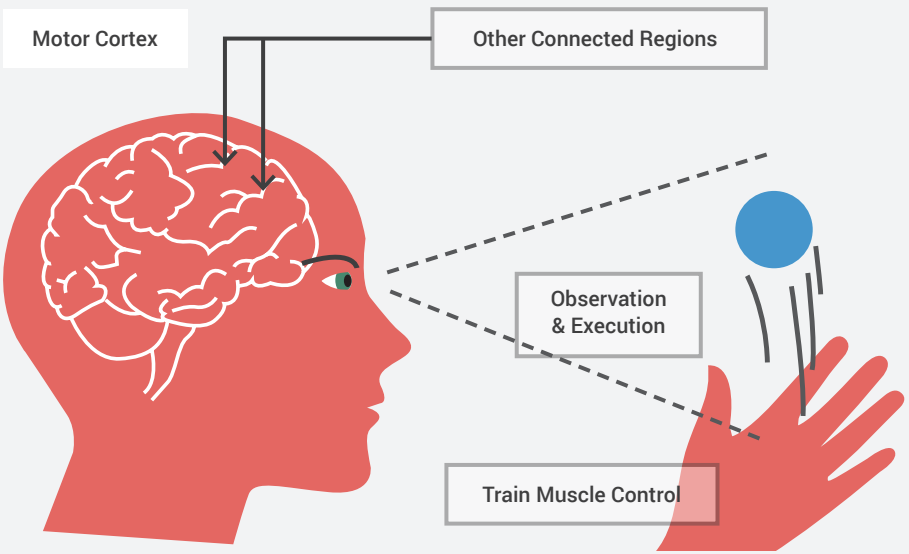

Figure 2.

Figure 2. *How RGS works: the user's own movements control those of the virtual body and it is exactly this relationship between perceived and executed movement that provides a key ingredient in creating conditions for recovery. More specifically, studies of the Mirror Neuron System (MNS) have shown that perceiving actions also leads to activity in the areas of the brain responsible for executing these actions. RGS exploits this principle to induce activity in damaged parts of the brain that can promote functional recovery.*

More generally, as a rehabilitation and diagnostics technology, RGS incorporates essential features of successful rehabilitation while reducing the need for direct supervision by therapists and clinicians. Thus, by using RGS, stroke sufferers could continue to rehabilitate themselves after a period of supervised rehabilitation has been completed. Extending the period of time available for rehabilitation means that relatively slow processes of self-repair have more time to operate, potentially leading to increased functional recovery

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Renachip: A Neuroprosthetic Learning Device

Interfaces between the central nervous system and peripheral systems have existed for some time and now include retinal and cochlear implants—sensory prostheses, and brain-computer interface systems that can control artificial limbs—also known as motor prostheses (for a review see Wood, 2013). Indeed, recently it has been shown that human patients can control anthropomorphic robot arms using brain activity alone (Collinger et al., 2013). However, the big challenge of bi-directional coupling of a prosthetic system with the central nervous system is only just beginning to be addressed (Berger, 2011; Giovannucci, 2010). In order to realise such a bi-directional system, three fundamental problems must be overcome (Verschure, 2011). First, the function of the circuit to be replaced must be understood and captured in a real-time form. Second, the inputs and outputs to and from the circuit that is to be replaced must be identified and their signals correctly analysed and synthesised. Third, steps 1 and 2 must be physically realised in a small, efficient and low-power form that can support implantation.

Some of the most advanced neuroprosthetic systems for bi-directional replacement, realised so far, have targeted the hippocampus and the cerebellum (Fig. 1).
Here two approaches can be distinguished. The first one relies on targetting the hippocampus: Berger et al. have emphasised a model-fitting approach in which a transfer function between inputs and outputs is inferred and subsequently used to replace a neuronal circuit. An alternative approach (Giovannucci, 2010),, building on DAC, emphasises the emulation of the fundamental physiological and anatomical properties of the underlying cerebellar circuit in order to get higher precision in the reconstruction of its functional properties. This is of great importance since the exact conditions under which neuroprosthetic systems are to be interfaced to the brain are not fully specified. In addition, in the latter case, not only is an engineering problem solved, but basic principles underlying mind, brain and behaviour are identified and validated.

More concretely, the Renachip, by developing a neuroprosthetic model of the brain, demonstrated that it is possible for an animal to acquire an eyeblink anticipatory response even when the underlying biological circuit, the cerebellum, was inactivated by anesthesia. The Renachip was built through a two steps process.

First, there was the development of a computational model of the cerebellar microcircuit involved in the acquisition of conditioned reflexes. Such a design was inspired by properties of the adaptive layer of the DAC framework.

Later, in a closed-loop bio-hybrid preparation, the computational model was interfaced with the brain of an anaesthetised rat; feeding into the synthetic system the biosignals recorded from the cerebellar input structures and injected back the result of the computation into an area targeted by cerebellar output. This bionic preparation was then classically conditioned with the paired tone-airpuff stimulation. The results demonstrated that the anaesthetised rat was classically conditioned to the acquisition of an eye-blink response with the aid of our neuroprosthetic system.

This approach yielded a unique solution in that it replaced a function of the central nervous system receiving inputs from the brain and returning its outputs back into the brain. These results are a demonstration that a global theory of the brain, such as DAC, can guide the development of concrete applications of what can be called 'science-based medicine'. On the one hand, the neuroprosthetic system directly validated a theory of cerebellar learning that informed the design of the system, and on the other, it takes a step towards the development of neuroprostheses that could recover lost learning functions in animals and, on the longer term, in humans.

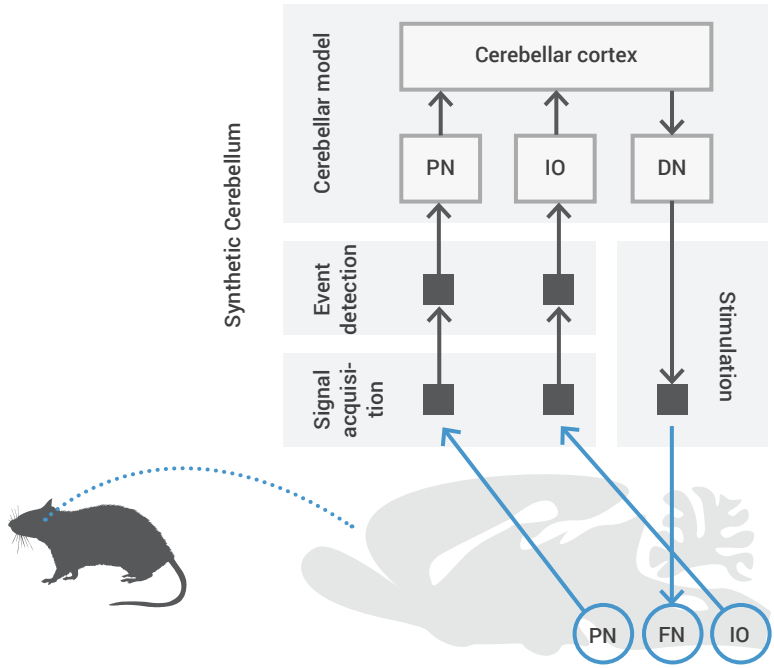

Figure 1. *Design for a cerebellar neuroprosthetic prototype. An integrated computational system emulates the circuit properties of the cerebellum based on a theoretical model. This emulated cerebellar microcircuit is interfaced to the input and output structures, the Pons (PN) and Inferior Olive (IO), and Deep Nucleus (DN) respectively. This paradigm has been successfully applied in in-vivo replacement experiments (Herreros et al.).*

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ADA: A Neuromorphic Interactive Space Based on DAC

Mankind has always been fascinated with building artefacts that are a close approximation of natural organisms. Mechanical devices, from the early 17th century such as the Duck of Vaucasoun or the automatan of the Doux brothers to more complex humanoid robots such as the iCub, have tried to capture, in the machine, the principles underlying brain and body function. In this sense, building real-world interactive systems is a checkpoint for any theory dealing with brain, mind and behaviour. However, the construction of these real-world artefacts needs to satisfy essential needs such as energy consumption, real-time behaviour and embodiment constraints; a brain needs a body to act and interact with the world.

One of the latest and most complex brain-based artefacts was an installation for the Swiss national exhibition Expo.02 called *Ada: Intelligent space*, an 180m^2 interactive space embedded in a 400m^2 exhibit that attracted over 550,000 visitors from May until October 2002 (Eng et al., 2003).

Ada is an interactive brain-based synthetic creature that has been implemented and embodied to act and aquire knwolodge in real-time and learn from humans. To realise Ada, research was conducted in real-time neuromorphic control systems, tactile person tracking, audio processing and localisation, and real-time synthetic music composition.

The Ada exhibit consisted of several different regions, which visitors passed through in a sequence (Delbrück et al., 2003).

Voyeur area: this was a wall of half-silvered mirrors surrounding the main space that allowed visitors to gain an impression of the main space before they entered without being seen by the people currently inside.

Ada main space: the main space could host groups of about 15 to 30 people and was made of a sensitive pressure floor and half-silvered mirror walls.

Brainarium: this area consisted of six real-time displays showing some of the data processing occurring within Ada, together with a multi-lingual explanatory text. Here people could observe correlations between the data and the actions of the space interacting with its visitors.

Explanatorium: this was the exit area with an artistic installation (by H.R. Giger) and three video screens offering interviews of the scientists related to the project making short statements were shown. This area also contained an information desk and a guestbook.

People visiting Ada were immersed in an environment where their only sensory stimulation came from Ada herself (and other visitors). Ada was made of sensors and effectors closely resembling those of a natural organism: a skin (a light pressure-sensitive floor) to sense the presence of each of its visitors, a visual system with cameras and a tracking system to see and locate people in the space, and audio processing and a compsition system to be able to listen and respond to people's responsive behaviour.

Ada was designed to have a certain level of organism-like coherence and convey an impression of a basic unitary sentience to her visitors, and to this it was equiped with a brain-like structure. Ada's effectors and sensors were driven by the Reactive, Adaptive and Contextual layers of the DAC brain architecure, which in real-time, controlled Ada's four main behaviours.

Track: to know about its visitors' trajectory.

Identify: to test individuals' response to cues (floor tiles light changes).

Group: to influence the distribution/behaviour of people in the space.

Play: to engage people in interactive games such as football and pong.

Given its nature Ada has allowed investigating both fundamental and applied questions including: large-scale sensory integration in the context of ongoing goal-oriented behaviour, the construction of the software and hardware technology that allows us to reliably run these large-scale real-world systems, and the interaction and communication between humans and artefacts.

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I DAC Incarnation (iCub)

iCub as an H5W Solver

As a global theory about the mind-body nexus, DAC aims at giving a functional explanation of phenomenons like the self-other distinction, behaviour generation, or emergence of consciousness. The DAC theory is tested through convergent validation, meaning that as long as the framework assumptions assist an implementation, each successful experimental result provides evidence supporting the theory. As the highest validation, DAC should provide the guidelines for implementing a robot that replicates the human behaviour. Such high-level aspects of the mind, like the self-other distinction or introspective mechanisms, requires the architecure scale to reach a level where it can interact with others in a 'human-like manner' and learn from this interaction as a child would. All along the way to this goal the robot will display increasingly convincing behaviours, allowing the testing of various hypotheses about human-robot interaction (HRI), in particular, which behavioural channels or parameters are relevant to induce a feeling of empathy and a theory of mind attribution towards a non-biological artefact. In this section, we present how DAC principles have been applied to a humanoid robot up to the point of generating convincing social behaviours. These behaviours are able to trigger reflexive emotions and, to a certain extent, attribution of intelligence and lifelikeness to the robot.

The Setup: Hardware and Software

We designed a setup to study human-robot interaction in a smart environment (Fig. 1). The components were a humanoid robot iCub (Metta, Sandini & Vernon, 2008) mounted on an omnidirectional-wheeled mobile base, iKart, and a Reactable (Geiger, Alber, Jordà & Alonso, 2010), which is a tabletop tangible display and an RGB depth sensor which is used to provide accurate detection of humans in the environment. The different reference frames induced by this setup are depicted in Figure 2. This installation has been heavily demonstrated in open public events (Barcelona Robotics Meeting 2014, Festa de la Ciencia 2013, Barcelona; Living Machines 2013, London; ICT 2013, Vilnius.), allowing therefore an easy-generation of HRI interaction with naive users.

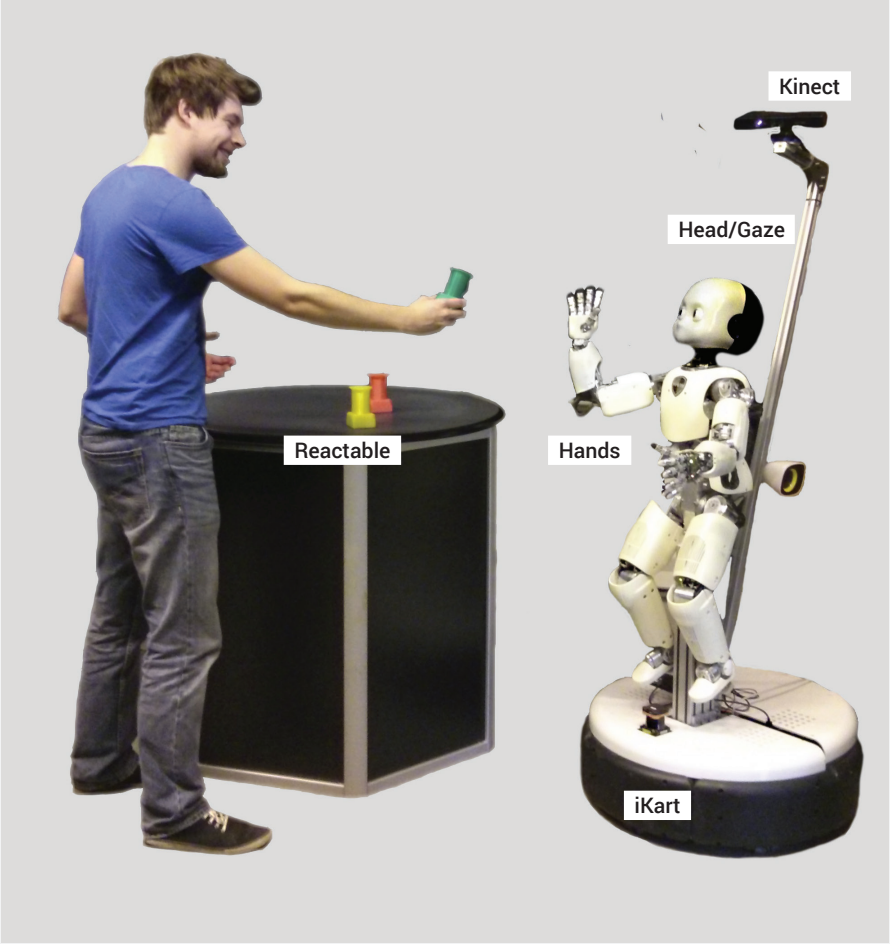


Figure 1. *A human-robot interaction platform showing all of the different reference frames used for actions (Reactable, iKart, Kinect, the two robot hands and its head).*

In terms of sensory apparatus, the iCub is equipped with two RGB cameras mounted in the eyes, force sensing and an artificial skin covering the upper body providing tactile sensing. The presence of the synthetic skin of the robot and a human's interaction through physical contact may tighten the social bond between them.

The combination of all of the setup components, principally the Reactable, allows the implementation of various interactive scenarios, including the robot and the human playing video games, such as Pong, Tic Tac Toe or a cooperative DJ task. These interaction scenarios require both the human and the robot to act on a shared physical space either in cooperative or competitive stances.

All of the software components of this setup are available through various open sources repositories. However, the process of deployment is a complex procedure that goes beyond the scope of this book. For more extensive technical information, tutorials and source code you should rely on the following links:

1. The iCub framework (including the YARP library) is multiplatform and accessible from http://icub.org

2. The EFAA framework, which relies on and extends iCub, is available from http://sourceforge.net/projects/efaa/

In the following, we chiefly explain how DAC concepts were implemented in a complex, multimodal robotic platform.

Sensorimotor Abstraction

Technological development provides us with new types of sensors on an almost daily basis. These sensors can be independent devices or part of complex integrated architectures (e.g. robot systems embedding cameras, lasers, arms encoders), all of them providing information about their environment in their own reference, sensor-centric way. Therefore, in order to contribute to a global understanding of the environmental scene, these devices should be coordinated and calibrated with each other. In particular, a mobile robot operating in such an environment could benefit from all of these sensing apparatus in order to overcome its specific limitations.

Although the range and type of information provided by sensors is wide, the most important aspect for a robot that has to act on its environment is localisation: where is the sensed information in relation to its own body? Calibration among sensors is a problem that arises in any multisensor platform (Ackerman & Chirikjian, 2013). In this respect a robot should be able to calibrate autonomously with all the sensors available in its environment, and should be able to use the information acquired in a spatially meaningful way. The main issue of such a calibration process is finding out what the transformation to be applied on the sensor-centric information in order to have it represented in the robot's egocentric context is, and to a certain extent, being able to estimate the error induced by such a transformation. This problem does not only imply external sensors, but body-attached sensors as well. Indeed, a possible solution to this problem is that both robots and biological beings represent a single frame of reference for the information that comes from multiple sources distributed throughout their body.

Animal brains are exceptionally good at finding such transformations between various sensor-centric information and a unified egocentric scene. In

humans, different cortical areas, located principally in the parietal cortex, encode spatial information reference frames centred on body parts (Colby, 1998), while egocentric information is encoded specifically in the fronto-parietal zone (Vallar, Lobel & Galati, 1999). Although it is not entirely clear how such transformations are orchestrated within the brain, recent findings (Cohen & Andersen, 2002) suggest that a common reference frame is used as a pivot. In our current research we demonstrate how the use of such a mechanism allows efficient transformations among independent sensory spaces. Moreover, we present a generic way of calibrating those spaces by considering the matching of two-point clouds and treating it as an optimisation problem.

Regarding the case of the humanoid robot iCub, the setup involves several co-dependent sensors and effectors as demonstrated in Figure 1. Taking the Kinect sensor as an example, in order to use its information so that the robot can look at objects, the link between the Kinect reference frame and the robot head reference frame has to be established. In our specific case the respective transformations among a set of five sensorimotor references needs to be found. We can achieve this with only a minimal set of transformations among sensors since it is sufficient to obtain a path from sensor to sensor. In other words, if the sensors were the nodes of a graph and the known transformations its edges, any set of edges that would make the graph connected would be suitable for finding the remaining transformations (see Fig. 2).

A simple way to find out such a set of transformations is to use a pivot mechanism. This is, to select one sensor's frame of reference as the pivot and translate all others to it: only the transformation of each sensor towards the pivot reference frame is required. If this transformation is known for every sensor, then the remaining transformations can be found by simple combinations (i.e. convert from first sensor's space to the pivot, and then from the pivot to the second sensor's space).

The pivot can be the frame of reference of any sensor. In our case we chose to use the robot's root to provide the agent with an egocentric representation. Once the choice is done, the known positions of a same object in different frames of reference from an input output pair that allow a supervised learning process to learn the transformation from one frame of reference to the other.

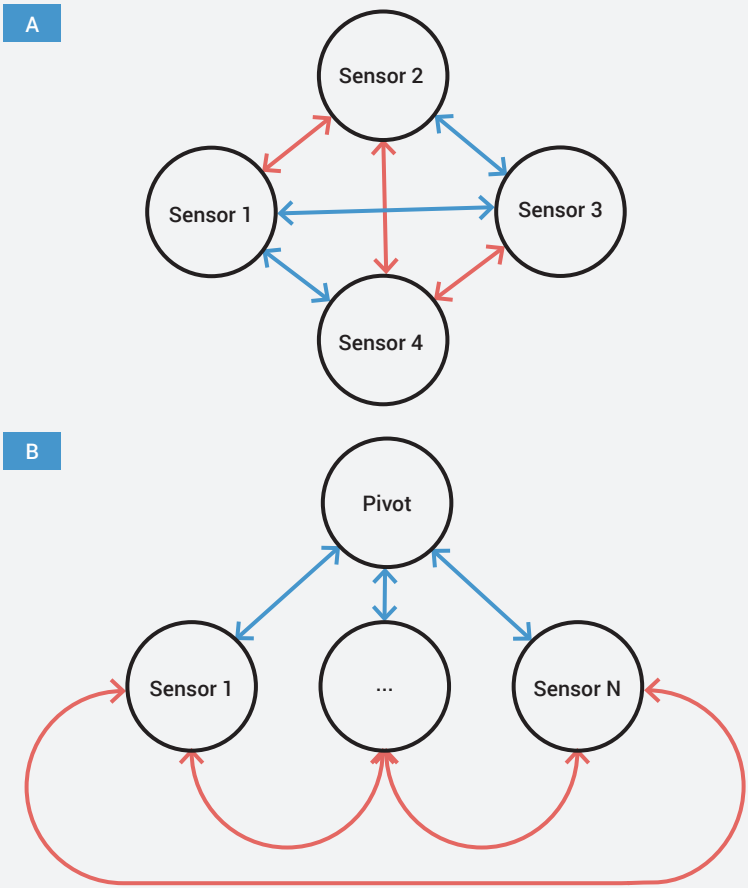


Figure 2. *A) A set of sensors and the relations known between them. The red transformations can be found easily as long as the green ones form a connected graph (i.e. as long as no sensor is outside of the graph, unrelated to the others). B) The pivot mechanism is applied to complementing the already-known transformations with missing links.*

Once the global transformation graph has been established, it can be used by the sensors of the system to provide their information (location of people, objects, limbs, etc.) into a common reference frame centred on the agent. Once this is done, this information can be assembled in a coherent scene that acts as an abstract layer over the specificities of the somatic layer.

By having solved this problem the robot can then integrate information coming from all sensors and coordinately use its effectors. In other words, it is in position to demonstrate how these abilities can subserve functions that are higher in the cognitive scale.

Solving H5W

Representing Knowledge

The H5W problems stands for How, Who, What, Where, When, and Why. As an agent is evolving in a world filled with other creatures, it needs, at any given moment, to give an answer to these five questions in order to survive. DAC as a whole cognitive architecture provides a solution to this problem, but we also adopt this standpoint in a more formal way at the implementation level. Starting at the reactive layer, processes of the architecture start to exchange knowledge chunks that gravitate around the H5W problem. We propose a software formalisation of this problem as a way to facilitate the information exchange between modules of the architecture as well as a common material that can be used by the system to create a coherent view of its sensorimotor world. Following software engineering principles, we have used object programming as our main constraint for our model.

The agent has to manipulate concepts that answer the questions of the H5W problem. Some of these concepts belong to categories of items that an agent deals with when interacting physically with the world; manipulable objects and agents belong to a generic category as they both share some spatial properties (i.e. they are physically situated in the world). Agents however possess specific properties as they embed a model of drives, emotions and beliefs as will be seen later in this chapter. Other types of symbols need to be handled by the robot but do not share this spatial common ground, such as actions (verbs) or abstract concepts like ‘red’ or ‘liberty’. At the code level, the adopted model follows these hierarchical properties by providing the developers with a set of inheriting classes as described in Figure 3.

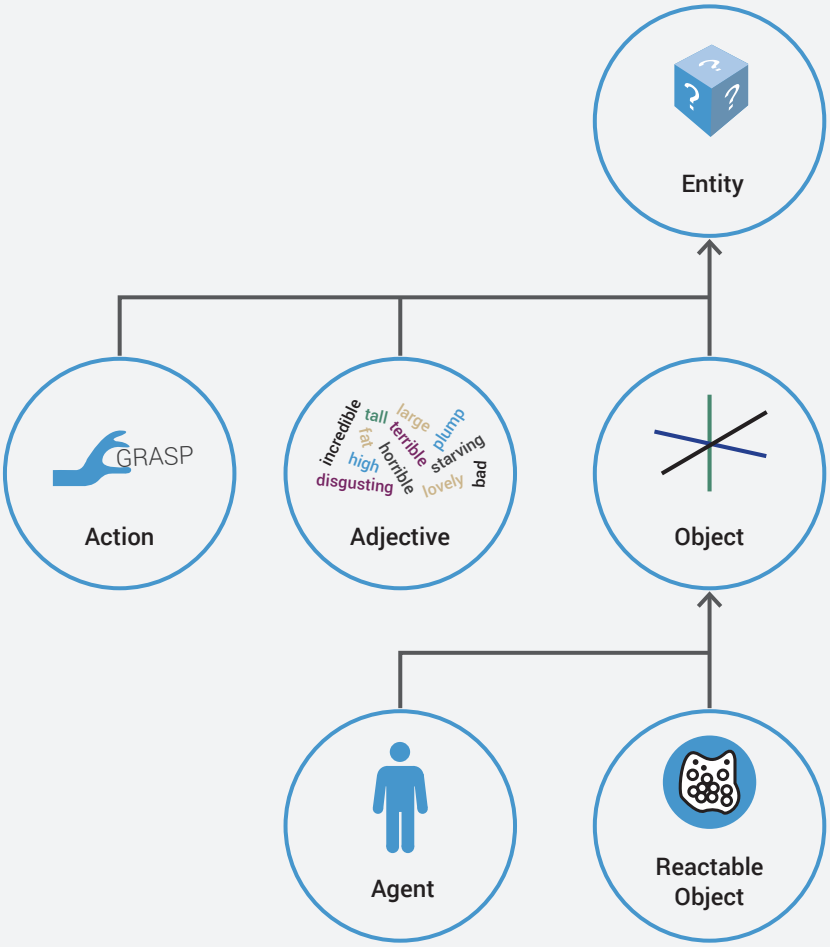
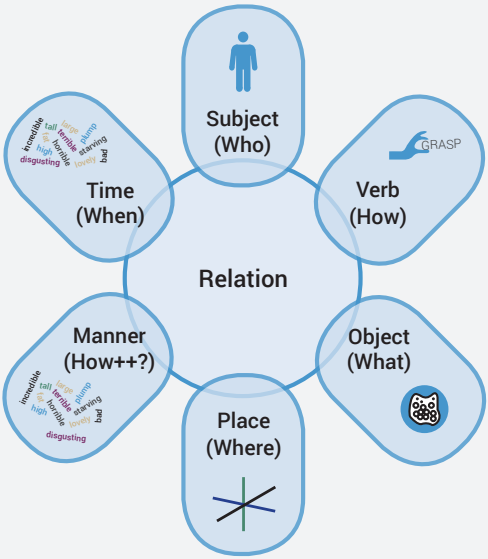


Figure 3. *Entities are formalising elements of the world, grounding a sensorimotor representation at the soma level to an abstract representation in the form of a manipuable concept.*

However, even if an entity can represent a solution to one of the H5W questions, the full description of a situation should be composed of several entities, linked together by semantic links (for example, Who=iCub, How=Recharging, What=Battery, Where=Power Supply Station, When = Now, Why = Low_Energy). In order to do so we elaborate on the Relation structure, which links up to six entities together and represents a single instance of one specific solution to the H5W problem (see Fig. 4).



Human > What does iCub like?

1. Interpret an interrogative sentence as a partial relation *(iCub, like, ?, - , -, -, -)*
2. Look for this relation in memory and retrieve a full relation *(iCub, like, octopus)*
3. Produce an affirmative sentence *Robot > I know that iCub does like the octopus*

Figure 4. *The formalisation of a semantic relation as a solution to the H5W problem, and how it is used to generate a question/answer behaviour. A Relation expresses a semantic link between a subset of Entities, framing their respective roles within an H5W solution. Both Entities and Relations compose a coherent view of the world by integrating all the sensorimotor and semantic representation.*

Every concept that an architecture can manipulate is called an Entity, a single instance of each is allocated in the robot's working memory so that all processes in the architecture can be accessed or updated depending on their needs and the information they provide. For example, spatial properties of objects and agents are assigned by the sensors' modules of the somatic layer, while modules of the adaptive layer will read the spatial information and complement it with higher-level properties such as emotions and beliefs in the agent's case, or information about motion and top-down saliency.

Populating and Retrieving Knowledge

The most straightforward way to populate and inspect the content of the robot knowledge is through natural language. As the H5W problem states, it is very compatible with a typical sentence of the form *Subject Verb [Object] [Place]*

[Time] [Manner]. Therefore, we provide the speech recognition engine with a generic grammar allowing the robot to recognise affirmations, questions and orders. The output of this grammar is then sent to a parser which transforms a spoken sentence into a semantic relation that can be stored in the working memory. An example of the grammar used is provided in the 'iCub Material' appendix of this publication.

The different types of sentences (question, affirmation, order) leads to a different reaction on the robot side. A question is formulated as a relation with a missing argument (see Fig. 4). Orders are defined by the use of an imperative form without a subject (e.g. 'Grasp the toy'), and trigger a direct command to the robot. They do not directly modify the content of the working memory in terms of semantic relations, but are mapped to a motor action that the robot can execute. The remaining sentences are considered as affirmations; they are interpreted as a Relation that is included in the working memory and that can be retrieved by a further question.

Those three mechanisms coupled together allow a minimal yet generic form of dialogue between the user and the robot. They also allow natural access to the mental state of the robot and its knowledge representation. As the spoken interaction goes on, the robot maintains a model of his own beliefs but also of its partner's knowledge. When an affirmation is expressed, the relation is added to the robot memory as well as to the memory of the partner model, allowing the robot to remember what his partner should already know or not. Moreover, if the current partner is identified (using face recognition for example), the robot will maintain a different mental model for each social agent he knows.

However, being able to inquire and populate the semantic knowledge of the agent through speech is not enough. The most prominent part of the understanding of the world we have, comes from the sensorimotor contingencies we experience continuously while interacting with the world. Therefore, we will now explain how the autonomous behaviour of the robot is generated, and shows that it uses semantic knowledge in the same manner as the pedagogic example of spoken interaction.

The Role of Emotions and Allostatic Control

As stated earlier, our framework defines an agent in the robot knowledge as a spatial object that holds some more properties, in particular, any agent that embeds a set of drives and emotions following the homeostatic model defined in the Cybernetics section. Drives in biological beings can be roughly mapped to chemical substances in the agent body (e.g. hormones and molecule concentration), they have a direct influence on the behaviours of an individual and are tighly linked to emotions as the two systems influence each other. Our efforts regarding the DAC implementation on the iCub mainly focused on creating a social agent, a robot that could interact

proactively with people; this will is therefore reflected in our choice about the set of drives implemented (physical interaction, spoken interaction, social interaction and energy) as they are the main levers to act on in order to tune the behaviour of the robot. The behavioural engine constantly monitors the drives system and triggers alerts whenever a drive is detected as being out of its homeostatic boundaries. The satisfaction of each drive also impacts the evolution of the emotional model, mainly by moving towards a negative emotion when drives are not satisfied and positive when they are. The agent also maintains semantic knowledge about its drives, which requires attention (e.g iCub, need, social interaction) in order to express them through speech or to interpret them at a higher level.

The emotional model adopted in our case was the classical 6 emotions of Ekman, from which we also adopted the facial expressions of the robot. However, we are now adopting a two-dimensional Valence-Arousal view which turns out to be more generic and biologically defendable than the classical model. The emotions and drives have their own internal dynamic that can be expressed as the variation of an homeostatic model *Hj* which consists of a constant decay as well as an influence from all of the semantic stimulis *Si*, either excitatory or inhibitory depending of the connection *Wij*. As usual, *f()* represents an activation function (e.g. threshold, sigmoid).

$$\Delta H_j = -d + f(\sum Wij\, Si) \quad (1)$$

As the sensors of the robot are interpreted into semantic relations, they modulate the natural decay of the homeostatic models by compensing it, accentuating it or reversing it. The parameters of the drive dynamic can be tuned from a configuration file and provide the most direct way to control the robot's personality. A higher decay for the physical interaction drive will create a much more 'tactile' behaviour, while for the spoken interaction drive, it will make the robot engage verbally with his partner more often.

The influence of the stimuli can also be defined from configuration files by implementing reflex arcs used by the DAC reactive layer. The role of drives and emotions is twofold: 1) to provide the robot with an internal model of itself that it can observe and express through facial expression, 2) to influence the action selection and execution. The overall satisfaction of drives is called Allostatic Control, which tries to minimise the out of homeostasis signals at different scales of time by triggering compensatory actions. The emotional model acts on the top of the selected action by setting a stance (an angry agent would perform the same action in a more aggressive way than a happy one).

The combination of both ensures the selection of the best action in terms of drives and its customisation depending on the current emotions of the robot. These mechanisms define the main control loop of the reactive layer.

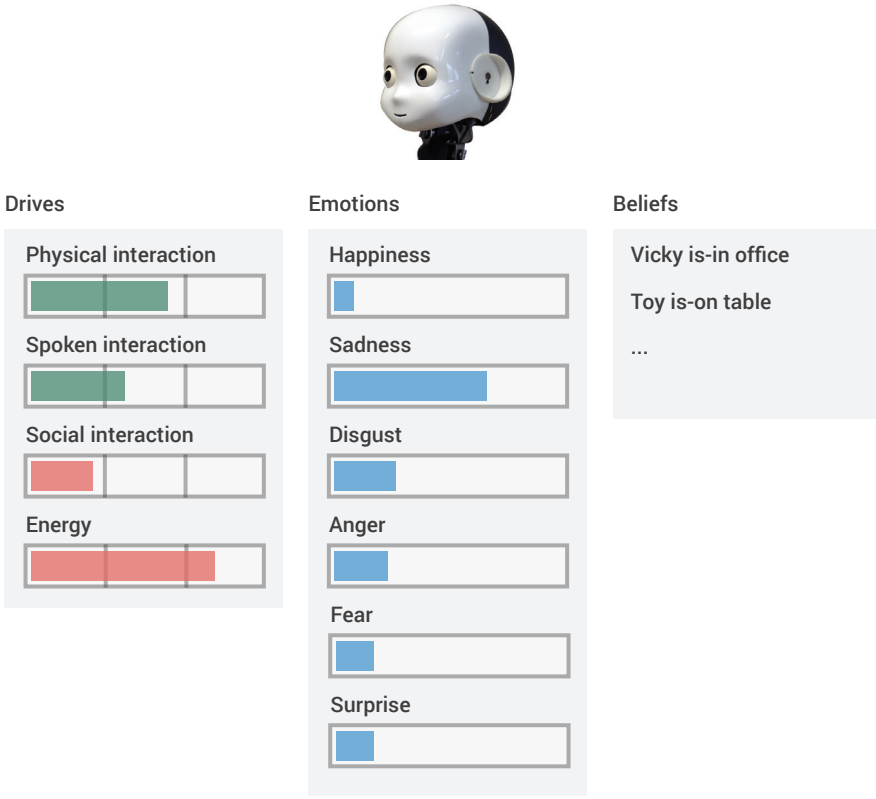


Figure 5. *The iCub internal state is composed of the agent's drives, emotions and beliefs. The same model is replicated for the representation of others as an attempt to have the robot attribute them with a limited theory of mind. The beliefs, emotions and drives of two agents can differ, although the robot is simulating their evolution by mirroring its own.*

Reactive Controller

Being able to understand and formulate spoken sentences as a set of H5W instances is one thing, but this knowledge having a result in action is another. As described in the DAC and Cybernetics chapters, through different levels of control (namely Reactive, Adaptive and Contextual), the robot experiences the world, acts and induces changes in it. At the Reactive level, some specific perceptions will trigger an automatic response on the effectors (e.g. facial expression, body/head posture and sound generation). These reactive loops are hardcoded in the system and will always occur unless they are suppressed by the top-down influence of some higher-level layer. From a programming point of view, they are simply given to the behavioural engine as (stimulus, response) couples following the scheme defined in Figure 6. In

this figure example we present how the iCub reacts to a tactile stimulus: the tactile sensor module creates the relation (iCub is caressed left_arm) which produces satisfaction for the drive for physical interaction, as well as impacts the robot's emotional model by increasing the valence and arousal (note that the system can use both the valence/arousal formalism or the six emotions of Ekman (Ekman et al., 1987). On the action side, an engaging gesture is produced and the spoken sentence 'I like that' is expressed. Several possible gestures and sentences can be associated to the same stimulus to increase diversity in the response. The user can customise the frequency of the spoken/gestural response, as well as an absence of reaction, therefore customising the level of expressivity of the robot.

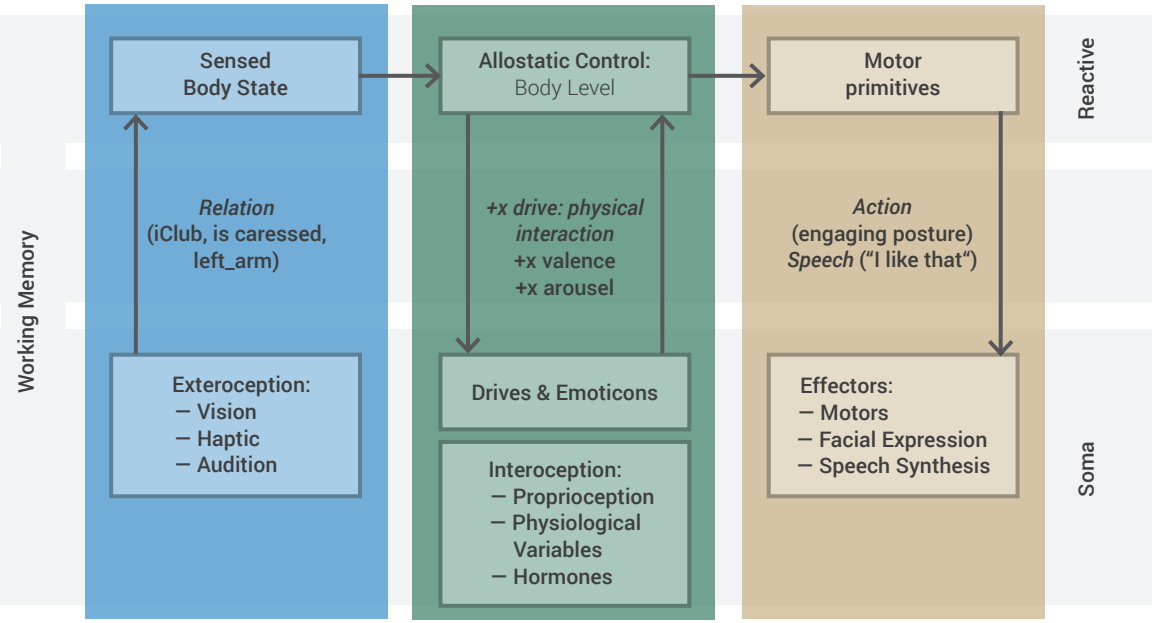


Figure 6. *The iCub reactive layer flow with the example of a 'to caress' reaction. Different reactions can be easily customised by following the structure given in the configuration file example. A reflex arc is formed by a stimulus (relation), it affects the internal state of the robot through modifying drives and emotions, and it is expressed through a specific set of postures and speech output.*

Human Robot Interaction

The integration of all DAC components as a whole implemented architecture allows the robot to achieve a level of interactivity and robustness that is the state of the art on this platform. As a result of this, we are able to maintain long-running

interaction with naive people in the lab or during public events. A video of the overall demonstration is available as a video submission in HRI2014 (Lallée et al., 2014).
A typical interaction unfolds as:

A human enters the visual field of the robot.

The robo salutes them through waving/spoken interjection.

A process of interpersonal distance regulation is engaged and the robot moves towards the human, trying to keep a given distance with them. This regulation process is implemented as another homeostatic model. As the human moves, the robot also orients towards him.

Depending on its current drives level the robot may express its current feeling, for example by telling that he has an artificial skin and inviting the partner to touch him.

In the case of physical contact with the sensorised limbs of the robot, it will categorise the type of touch (a caress, a strong grab, tickling, etc.) and react with a specific emotionally-grounded response.

In the case of speech expressed by the human, the robot will try to catch H5W statements (affirmations, questions or orders) and reply to them in appropriate ways (either by increasing its knowledge or parsing it). Specific sentences are used to trigger the reactable interaction; by saying 'Let's play [Pong/Tic Tac Toe/ music]' the user will command the robot to go to the reactable, and engage a specific scenario (see Fig. 7).

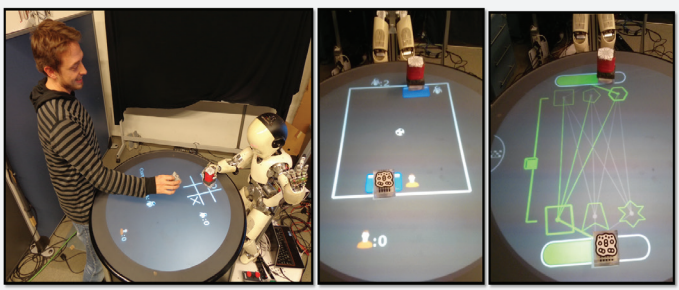


Figure 7. *The different Reactable applications implemented for the EFAA agent. Tic Tac Toe demonstrates long-term memory and extraction of strategy, Pong is all about motor-control and anticipatory movements, and finally the DJ Droid emphasises reinforcement learning and artistic cooperation.*

The reactable games involve the manipulation of objects that the robot calls 'paddle' that can act on the display. For example, in Tic Tac Toe the paddles are used to draw crosses and circles while in the music game they are used to move a slider and press buttons to change the music. When the robot reaches the table it scans for its paddle, it may then ask the human to bring it closer so that he can grasp it, and after grasping it, the robot sends a command to the reactable that will run the corresponding game. At the end of the game the robot can propose another game or state that he would like to stop playing, depending on its drives. As long as the human stays in the room, the robot will interact with him.

Such a scenario involves a lot of different behavioural components and communication channels. There are levers on which we can act in order to test the hypothesis about the human perception of the robot. Indeed, a benchmark of artificial cognitive agents would be if humans exposed to them consider them as having a self, a theory of mind, and some level of consciousness. By impairing different components of the interaction, such as eye contact, facial expression, speech, or interpersonal distance regulation, we are able to evaluate how much they contribute to social reflection mechanisms and induce empathy, and the general level of intelligence and lifelikeness attributed to the robot. At the time of writing this, the results of this study are being submitted to Living Machines 2014. Such a study would have been impossible without a distributed, layered architecture like DAC as it allows a robust interaction between a large number of components, and therefore is resistant to impairement, much like the brain itself.

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5 | Appendix

DAC Simulation Environment: iqr and Gazebo Setup

The iqr Simulator

iqr is a multi-level neuronal simulation environment designed with the aim of dealing with the different levels of brain's organisation (from the sub-cellular level to the overall system) (Bernardet & Verschure, 2010). The graphical user interface and the large number of built-in modules, neurons and synapses allows the design of neuronal systems at different levels of complexity, which can be easily controlled online and interfaced to real-world devices, and without the need of learning any specific programming language. Model's parameters can be modified at run-time and the internal states of the model can be visualised and analysed online through different plots. Its open architecture allows the user to program its own neurons, synapses types, and interfaces to new hardware.

iqr has been successfully adopted both as a scientific tool to understand biological phenomena like classical conditioning, navigation, decision-making, attention (Bermúdez i Badia, Bernardet & Verschure, 2010; Eng & Verschure, 2005; Hofstotter, Mintz & Verschure, 2002; Mathews, Bermúdez & Verschure, 2012; Proske, Jeanmonod & Verschure, 2011), and as an educational tool to teach the basics of modelling principles at master-level courses and scientific workshops. *iqr* is released under the Gnu Public Licence.

iqr Basic Principles

A model in *iqr* is organised in a hierarchical structure (see Fig. 1).

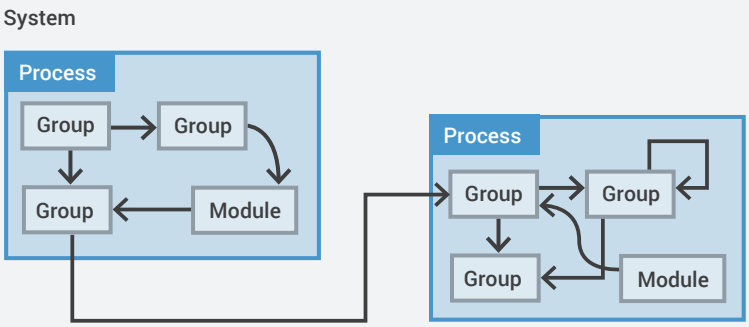

Figure 1. *Diagram of the structural organisation of an iqr model.*

At the highest level there is the System, which encapsulates an arbitrary number of logical units (Processes) and connections between processes. At this level the interfaces to the external devices are also defined.

Each process consists of an arbitrary number of Groups, which are aggregations of neuronal units of the same kind. A group is specified in terms of its topology (i.e. the two-dimensional spatial arrangement of the neurons within the group), and information between different groups is exchanged through Connections. The latter consists of synapses of identical type, plus the arrangement of the dendrites and axons (i.e. the arborisation pattern).

Gazebo Simulator

Gazebo is an open-source multi-robot simulator platform (www.gazebosim.org) for the simulation of populations of robots, sensors and objects in a three-dimensional world (Koenig & Howard, 2004). The possibility to generate realistic sensor feedback and plausible physical interactions between objects made it a widely used experimental and development tool for robotic research. Gazebo is actively developed at the Open Source Robotics Foundation (www.osrfoundation.org) and is licensed under the Apache 2.0 Licence.

How to Setup iqr and Gazebo

System Requirements

The instructions and the exercises provided in this publication are intended for users running a Linux system equipped with Ubuntu (www.ubuntu.com), version 12.04 or higher. At the time of writing this book the tutorial was tested with *iqr* version 2.4.0 and Gazebo version 2.2. We take for granted that users already have a fully working Ubuntu workstation and have a basic knowledge of Linux usage. For further information on how to install the Ubuntu operating system or work with a terminal session please refer to the many 'how-to' pages available on the web.

Common Packages Required

Before downloading *iqr* and Gazebo you have to install some extra common packages. Open a new terminal window (press Ctrl+Alt+t) and type the following commands at the prompt, then hit Enter:

```
sudo apt-get update

sudo apt-get install gdebi subversion build-essential
cmake libqt4-dev
```

The installation process could require some time to check for all the dependecies. When required by the system to confirm the choices type Y and hit Enter.

After the installation you could be required to restart the session to make the changes effective. Once completed you can continue with the installation of *iqr* and Gazebo.

If you have already installed both iqr and gazebo on your computer you can skip the next sections and move directly to the install the *iqr*-gazebo section at the end of this appendix.

Download and Install *iqr*

Pre-compiled binary packages of *iqr* are available for different Linux environments. Open the web browser and download the binary installation package compatible with your platform from the *iqr* web repository at the following link:

http://sourceforge.net/projects/iqr/files/iqr/2.4.0

In the terminal window type the following commands (replace with the folder name where you downloaded the package and replace the UbuntuXX-XXX-XXX.deb with the name corresponding to the OS version of your choice):

```
cd $HOME/
sudo gdebi iqr-2.4.0.UbuntuXX-XXX-XXX.deb
```

Open the web browser and download the iqr-dev_2.0-0.ubuntu_debian.i386.deb package from the following web repository:

http://sourceforge.net/projects/iqr/files/iqr-devel/2.0.0/

In your terminal window install the package by typing the following command, and hit Enter:

```
sudo dpkg -i iqr-dev_2.0-0.ubuntu_debian.i386.deb
```

When asked for confirmations type y and confirm with Enter.

You can check that *iqr* has been successfully installed by typing iqr in a terminal

window and confirm with Enter. If everything went fine the *iqr* graphical user interface should open as shown in Fig. 2.

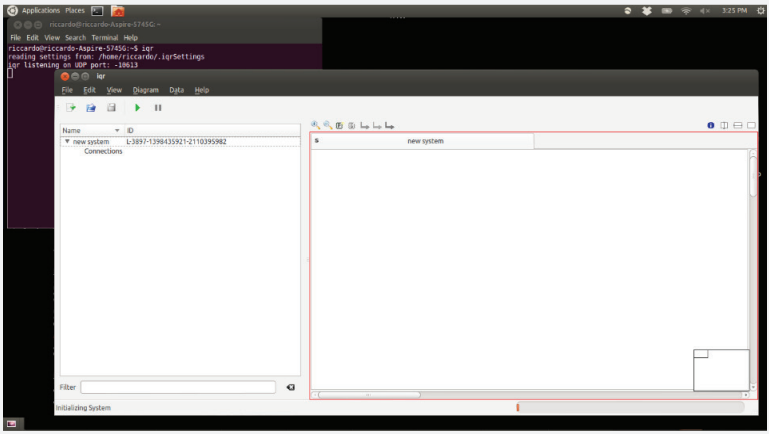

Figure 2. *iqr interface once the software is started from a terminal.*

You can now close *iqr* (open the File menu and click on Quit or just click on the small red x at the top left corner of the window) and proceed with the Gazebo installation

Download and Install Gazebo

Depending on your Ubuntu configuration you will need to download Gazebo from a different repository. If you are not sure about the Ubuntu release installed on your computer, open a terminal window and type the following command, followed by Enter:

```
lsb_release -a
```

Annotate what appears under the voice 'Release' and in the same terminal window type one of the following commands (i.e. the one corresponding to the Ubuntu release installed on your machine):

rel. 12.04 (precise)

```
sudo sh -c `echo "deb http://packages.osrfoundation.org/
gazebo/ubuntu precise main" > /etc/apt/sources.list.d/gazebo-
latest.list'
```

rel. 12.10 (quantal)

```
sudo sh -c 'echo "deb http://packages.osrfoundation.org/gazebo/
ubuntu quantal main" > /etc/apt/sources.list.d/gazebo-latest.list'
```

rel. 13.04 (raring)

```
sudo sh -c 'echo "deb http://packages.osrfoundation.org/gazebo/
ubuntu raring main" > /etc/apt/sources.list.d/gazebo-latest.list'
```

rel. 13.10 (saucy)

```
sudo sh -c 'echo "deb http://packages.osrfoundation.org/gazebo/
ubuntu saucy main" > /etc/apt/sources.list.d/gazebo-latest.list'
```

Once your computer is setup to access the correct repository you need to retrieve and install the keys for the Gazebo repositories by typing in a terminal window:

```
wget http://packages.osrfoundation.org/gazebo.key -O - | sudo apt-key
add -
```

Update apt-get database of packages and install Gazebo 2.2 by typing:

```
sudo apt-get update
sudo apt-get install gazebo-current
```

To see if the installation process ended correctly you can check the Gazebo installation by typing gazebo in a terminal window. The first time it could take some time to execute since Gazebo needs to download some models from the web repository and create the local model database.

Once you are done with the Gazebo installation you can proceed to downloading the *iqr*-gazebo interface and the files needed to run the tutorials.

Gazebo distributions are updated on a regular base. Please refer to the official Gazebo wiki pages (gazeboism.org/wiki) for up-to-date instructions on how to install Gazebo or if you want to compile Gazebo by yourself from source.

Download iqr-gazebo Files

Get the files to your home directory by typing the following commands in a terminal window, and confirm by pressing Enter:

```
cd $HOME
svn checkout http://iqr-gazebo.googlecode.com/svn/trunk/ iqr-gazebo
```

If everything worked fine you can skip directly to the *Install iqr-gazebo* section.

In case you are not able to access the svn repository you can obtain the latest source code using wget command. This last operation will overwrite your current iqr-gazebo folder. Type the following command in a terminal window and confirm each line by pressing Enter:

```
cd $HOME
rm -rf iqr-gazebo
wget  -r  -np  -nH --cut-dirs=1 --reject  "index.htm"
http://iqr-gazebo.googlecode.com/svn/trunk/ mv trunk iqr-gazebo
```

Install *iqr*-gazebo

To install the *iqr*-gazebo files run the installation script by typing the following commmands in terminal window:

```
cd $HOME/iqr-gazebo
source ./update_compile.sh
```

If the script exits with an error please refer to the troubleshooting web page (code.google.com/p/iqr-gazebo/wiki/QuestionAndAnswers) for an updated list of common errors and solutions.

If everything went fine your system is now setup and ready to run!

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iqr Basics

Introduction

This appendix is not intended to be an exhaustive manual of *iqr* but rather an introduction to the main components and functions offered by *iqr.* We invite the reader to go through the accompanying official *iqr* reference manual for a detailed description of all the GUI components, tools and functions, which can be accessed through the *iqr* Help menu.

How to Start/Quit iqr

To run *iqr* open a new terminal window and type iqr, then hit Enter. *A* new blank graphical user interface should open as illustrated in Figure 1. To quit *iqr* select File-> Quit from the main toolbar. If a system is open and not already saved you will be prompted to save the file before quitting.

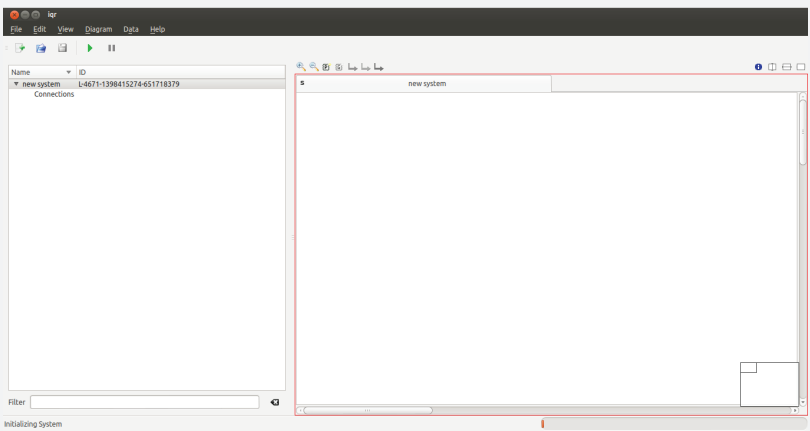

Figure 1. *The main iqr application.*

GUI Main Components

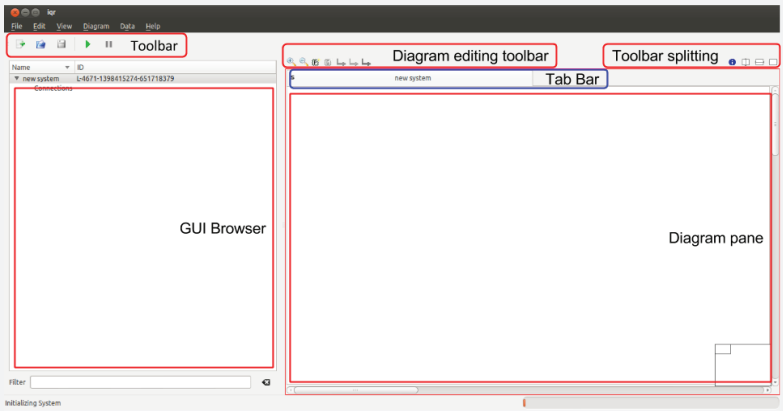

Figure 2. *iqr main graphical user interface (GUI).*

Main toolbar:

File: allows the user to deal with the typical operations of creating/opening a file, closing/saving a model, import external processes to be embedded in the current model, set the system properties and quit the application.

Edit: allows opening and setting the application properties window and to validate your model.

Diagram: allows to save/print the diagram as an image.

Data: includes additional tools for data recording (Data sampler), data broadcasting to a remote application (Data Broadcasting), load/save customised GUI configuration settings (Load/Save configuration) and direct runtime manipulation of the model parameters (Harbor).

Help: contains the links to the application reference manuals.

Toolbar: with the Toolbar you can directly create a new system, open an existing file, save the current system and start/stop the simulation.

Diagram pane and tab bar: the main Diagram pane is used to add processes, groups and connections to the model. When you define a new process a new diagram pane is automatically added (see Fig. 3). To switch between diagram panes use the tab bar on the top of the Diagram pane. The left-most tab always presents the system-level.

On the diagram editing pane, a square with a thick black border represents a process, a white square a group, and a line with an arrowhead a connection (see Fig. 3).

Diagram editing toolbar: the diagram editing toolbar is used to add processes, groups and connections to the model. The funcionality of the toolbar is as follows:

Zoom in/out: to magnify/reduce the diagram.

New Process: add a new process to the system level.

New Group: add a new group to the current process.

New connection: add a new connection between groups of type excitatory (red), modulatory (green), inhibitory (blue)

Toolbar splitting: split the diagram editing pane into two separate views (split vertically, horizontally or revert to single window view, see Fig. 3).

Browser: on the left part of the GUI a tree-view of the model provides a direct access to all the elements of the system. The top node of the tree corresponds to the system level (see Fig. 3), the second entry shows the connections between groups and can be expanded by clicking on it to list all the connections between groups. The third entry shows the processes. Clicking on it, the tree expands revealing all the groups that are part of the process. By double-clicking on the system or a process node you can open the corresponding diagram in the diagram editing pane. Right-clicking on any node brings up the context-menu.

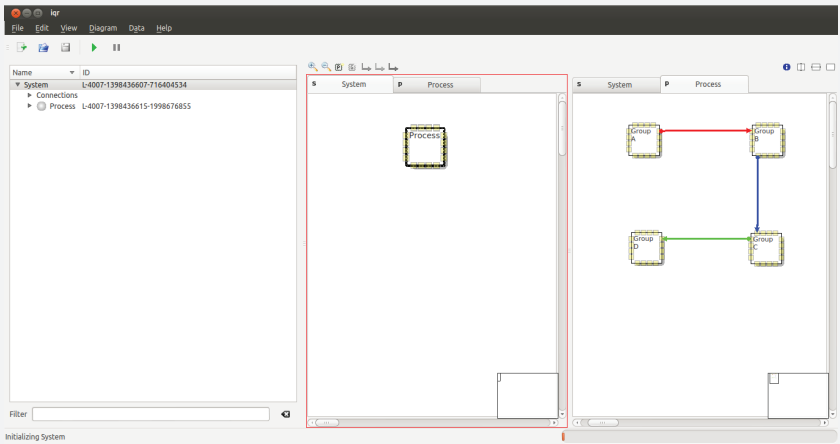

Figure 3. *Split view of an iqr system.*

Working with iqr

How to Create a New System

To create a new system you can either press the New File icon in the Toolbar or select

File->New from the main toolbar. Creating a new system will close the currently open system.

How to create a process. The first step in building an *iqr* system is to create a new process in the diagram pane. Press the Add Process icon in the Diagram editing toolbar, the pointer will change to a small process icon with a plus sign indicating that you are creating a new process. Left-click the cursor in the Diagram pane and a new process will be created. By double-clicking the process you just created the Properties dialogue will show up. Here you can assign a name to the process and change other properties (e.g. interface the system to an external module through the set type drop-down menu). To commit the changes press Apply and then Close. It is important to always apply before closing the dialogue otherwise the changes will be lost. For a detailed explanation of the available built-in modules and their use please refer to the *iqr* user manual.

How to create a group. To add a group to a process, activate the process diagram by clicking on the corresponding tab in the tab bar and then click on the Add Group button in the Diagram edit toolbar. The cursor will change and you can place the new group by left-clicking in the diagram pane. If for any reason you want to abort the action just right-click in any free space within the diagram pane.

To change the properties of a group, double-click on the group icon or right-click on the group icon and select Properties from the contextual menu. A Properties dialogue will open and you can assign a name or add some notes to the group. Here you can also select the type of neuron that you want to use and the group topology (how many neurons and how they are spatially distributed on the bidimensional plane).

iqr comes with a set of predefined neuronal types (see the manual for a list of the available types and their features). For the topics covered in this book we will only use a subset of three types of neurons: random spike, linear threshold and numeric (a description is given in Appendix C).

How to create a connection. Information is transmitted from one group to the other through connections. In *iqr* a connection corresponds to an assembly of axon-synapse-dendrite nexuses and is defined both by the update function of the synapse and by the defintion of the connectivity pattern (for a more exhaustive explanation about connectivity we refer the reader to the user's manual).

To add a connection, click on the corresponding Add Connection button in the diagram edit toolbar. Click on one of the edges of the source group icon and then on one of the yellow squares at the edge of the target group. You can add more vertexes to the connection holding-down the Ctrl key and clicking on the connection. To remove a vertex right-click on the vertex and select Delete from the contextual menu.

To connect groups belonging to different processes you first need to split the diagram pane into two different views (one for each process) by clicking one of the split-view options in the Toolbar splitting. Then you can connect the two groups as described in the previous paragraph. When you connect groups from different processes a 'phantom' group will show up at the top of the diagram pane of each process to indicate the target/origin group to which they are connected.

You can change the properties of a connection via the context menu or by double-clicking the connection line. In the dialogue you can change the name of the connection, the type of synapse you want to use, the connectivity pattern, the type of arborisation and other features. For a full description of the different kind of synapses and patterns and how to use them, we refer the reader to the relative chapter in the user manual.

How to open/save a system. To open an existing system press the Open File button in the Toolbar or select File->Open from the main toolbar. Opening an existing system will close the currently open system.

To save a system press the Save File button or select File->Save from the main toolbar. To save the system with a different name select File->Save as from the main toolbar.

How to select and duplicate elements of a system. A single process or group can be selected by clicking on its icon in the diagram editing pane. To select multiple processes or groups, hold down the Ctrl key while clicking on the icon.

Processes, groups and connections can be copied to the clipboard and pasted in the diagram pane. To copy an object right-click on it and select Copy from the contextual menu. To paste it select Edit->Paste from the main toolbar. You can only paste processes at the system level whereas groups and connections can only be copied at the process level.

How to run a simulation. To start a simulation click on the Run button (the green 'Play' icon) in the Toolbar. While the simulation is running the update speed (cycles per second) will be indicated in the bottom left corner of the *iqr* window.

To stop the simulation click on the play button again.

How to visualise the internal states of the system. The internal states of each element of the system can be visualised through different plots: time plots and space plots are used to visualise the states of the neurons (Fig. 4, left panel and middle panel) while the connection plot (Fig. 4, right panel) is used to visulise the states of the synapses of a connection.

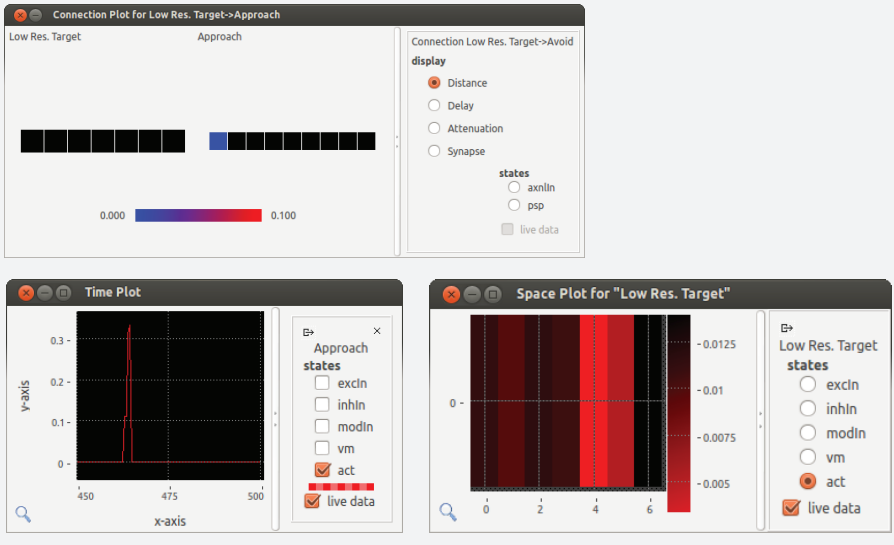

Figure 4. *Space plot, time plot and connection plot.*

Manipulating and Recording Data

iqr offers two different tools to manipulate and record the states of the elements of your model. The state manipulation panel can be accessed by right-clicking on the group icon and select State manipulation panel from the contextual menu. With this tool you can change the activity of the neurons in a group, adding them to a list and playing them back using different parameters. Please refer to the user manual for a detailed description.

To save the internal states of your model you can open the Data Sampler (select Data Sampler from the Data Menu) and drag a group from the GUI browser into the Data Sampler dialogue. With the Data Sampler you can decide at which frequency to sample your data, how much data you want to save and where you want to save your file. The file can then be imported into a statistical software like Excel or Matlab for further analysis.

References

Bernardet, U. & Verschure, P. (2010) iqr: A tool for the construction of multi-level simulations of brain and behaviour. *Neuroinformatics* 8 (2). p.113-134. http://dx.doi.org/10.1007/s12021-010-9069-7.

iqr documentation. http://iqr.sourceforge.net.

iCub Material

While giving an explanation about how to run the software is out of the scope of this book, all the necessary documentation and software is available from the subversion repository of the FP7 EFAA project (http://sourceforge.net/projects/efaa/). EFAA rely of course on YARP and iCub, which you can get information about at http://icub.org.

This appendix provides the following resources that are compatible regarding the iCub example description.

The generic H5W grammar used with the speech recogniser.
Configuration files for the drives, emotions and reflex arcs.

Configuration of the Drives Model

This configuration file defines the different drives handled by the robot. It can be extended by the user to implement more drives, or customised to change the default dynamic and parameters on which the homeostatic regulation will take place.

```
drives (physicalInteraction spokenInteraction socialInteraction energy
play)

physicalInteraction-homeostasisMin     0.25

physicalInteraction-homeostasisMax     0.75

physicalInteraction-decay              0.001

physicalInteraction-over-sentences     ("You are not very tactile."
                                       "Did you know that I
                                       have sensitive skin?")

physicalInteraction-under-sentences    ("You are quite tactile.
                                        Aren't you?"
                                       "I feel touched enough.")

spokenInteraction-homeostasisMin       0.25

spokenInteraction-homeostasisMax       0.75
```

spokenInteraction-decay	0.002
spokenInteraction-over-sentences	("You speak a lot." "Silence is nice, sometime.")
spokenInteraction-under-sentences	("Why nobody talks with me?" "Yahoo! Nobody is around?")
socialInteraction-homeostasisMin	0.25
socialInteraction-homeostasisMax	1.0
socialInteraction-decay	0.003
socialInteraction-over-sentences	("I could use some privacy." "There are many people here.")
socialInteraction-under-sentences	("I feel alone." "I miss my programer.")
energy-homeostasisMin	0.25
energy-homeostasisMax	0.95
energy-decay	0.0001
energy-over-sentences	("I feel full of energy today!")
energy-under-sentences	("My energy is running low. What about shutting me down?" "Could you please turn me off?")
play-homeostasisMin	0.25
play-homeostasisMax	0.95
play-decay	0.002

```
play-over-sentences                    ("I played too much!"
                                       "Too much playing kills
                                       the pleasure.")

play-under-sentences                   ("I want to play." "What about
                                       a game?")
```

Configuration of the Reflex Arcs

The reflex arcs can be defined through configuration files. They mainly consist of an entity (stimulus) that the robot will check for at runtime. For example, the tactile module is creating relations of type *(iCub, feels, simplePoke, right_arm)* with simplePoke being a stimulus defined in the configuration file. Whenever this relation is detected in the working memory of the robot, the corresponding action consequences will be generated; those ones are also defined in the configuration file (i.e simplePoke-effect for defining the drives/emotions impact, simplePoke-sentence for the possible verbal responses and simplePoke-chore triggering a pre-recorded gesture—refer to choreographyServer in the EFAA repository for more information about gestures definition).

```
[TACTILE]

stimuli                                (simplePoke multiPoke pinch
                                       softCaress strongCaress
                                       strongGrab)

simplePoke-sentence                    ("Yes? What do you want?" "Hey!
                                       What's up?" )

simplePoke-effect                      (surprise 0.2)

simplePoke-chore                       (what oh_my)

multiPoke-sentence                     ("Stop that! It is tickling!"
                                       "Hee-Hee-Hee!")

multiPoke-effect                       (anger 0.1 surprise 0.5)

multiPoke-chore                        (surprise_open surprise_closed)

strongGrab-sentence                    ("Ouch! It is hurting!" "Why are
                                       you bad with me?")
```

```
strongGrab-effect                    (sadness 0.7 surprise 0.1 fear
0.2)

strongGrab-chore                     (fear stop sadness)

pinch-sentence                       ("Do you like to hurt innocent
                                     robots?" "What did I do to deserve
                                     that?")

pinch-effect                         (anger 0.7 surprise 0.1)

pinch-chore                          (anger what)

softCaress-sentence                  ("Hoho! You have soft hands!"
                                     "Please, caress me again!")

softCaress-effect                    (joy 0.5 surprise 0.1 fear -0.1
                                     anger -0.1)

softCaress-chore                     (soft)

strongCaress-sentence                ("Oooh... I like that..." "Yes..
                                     This is good...")

strongCaress-effect                  (joy 1.0 surprise 0.2 fear -0.2
                                     anger -0.2)

strongCaress-chore                   (soft)
```

The same kind of configuration is used to handle signals incoming from the various sensors of the platform, such as the Kinect for the social and gesture perception:

```
[SOCIAL]

salutationLifetime                   10.0

preferedDistanceToPeople             0.9

stimuli                              (humanEnter humanLeave)

humanEnter-sentence                  ("He! Hello!" "How are you, my
                                     friend?" "Hello stranger!"
"Welcome
                                     to the EFAA boot.")
```

```
humanEnter-effect                    (surprise 0.2)

humanLeave-sentence                  ("See you soon!" "Bye, bye!" )

humanLeave-effect                    (surprise 0.0)

[GESTURES]

stimuli                              (thumbsUp thumbsDown)

thumbsUp-sentence                    ("This is a happy gesture.")

thumbsUp-2-effect                    (joy 0.5 surprise 0.2)

thumbsDown-3-sentence                ("This is a sad gesture.")

thumbsDown-3-effect                  (sadness 0.5 surprise 0.2)
```

H5W Grammar

The grammar follows the specification of W3C accessibility at http://www.w3.org/TR/speech-grammar.

```
<GRAMMAR    LANGID=”409”>
  <DEFINE>
    <ID    NAME=”agent”    VAL=”1”/>
    <ID    NAME=”action”    VAL=”2”/>
    <ID    NAME=”object”    VAL=”3”/>
    <ID    NAME=”rtobject”    VAL=”4”/>
    <ID    NAME=”keyword”    VAL=”5”/>
  </DEFINE>


  <RULE    NAME=”AFFIRMATIVE”    TOPLEVEL=”ACTIVE”    EXPORT=”1”>
    <RULEREF    NAME=”groupSubject”/>

    <RULEREF    NAME=”groupVerbal”/>

    <O>
      <RULEREF    NAME=”groupObject”/>
    </O>
```

```
    <O>
    <RULEREF    NAME="groupPlace"/>
  </O>
</RULE>

<RULE    NAME="INTERROGATIVE_WHO"    TOPLEVEL="ACTIVE"    EXPORT="1">
  <P>Who</P>
  <RULEREF    NAME="groupVerbal"/>
  <O>
    <RULEREF    NAME="groupObject"/>
  </O>

    <O>
    <RULEREF    NAME="groupPlace"/>
  </O>
</RULE>

<RULE    NAME="INTERROGATIVE_WHAT"    TOPLEVEL="ACTIVE"    EXPORT="1">
  <P>What</P>

  <RULEREF    NAME="groupVerbal"/>

  <O>
    <RULEREF NAME="groupSubject"/>
  </O>

    <O>
    <RULEREF NAME="groupPlace"/>
  </O>
</RULE>

<RULE    NAME="INTERROGATIVE_WHERE"    TOPLEVEL="ACTIVE"    EXPORT="1">
  <P>Where</P>

  <RULEREF    NAME="groupSubject"/>

  <RULEREF    NAME="groupVerbal"/>

  <O>
    <RULEREF    NAME="groupObject"/>
  </O>

</RULE>
```

```
<RULE    NAME="INTERROGATIVE_HOW"    TOPLEVEL="ACTIVE"    EXPORT="1">
  <P>How</P>
  <RULEREF    NAME="groupSubject"/>
  <RULEREF    NAME="groupVerbal"/>
  <O>
    <RULEREF    NAME="groupObject"/>
  </O>

  <O>
    <RULEREF    NAME="groupPlace"/>
  </O>
</RULE>

<RULE    NAME="INTERROGATIVE_WHEN"    TOPLEVEL="ACTIVE"    EXPORT="1">
  <P>When did</P>

  <RULEREF    NAME="groupSubject"/>

  <RULEREF    NAME="groupVerbal"/>

  <O>
    <RULEREF    NAME="groupObject"/>
  </O>

    <O>
    <RULEREF    NAME="groupPlace"/>
  </O>

</RULE>

<!--    Subnodes    -->

<RULE    NAME="SUBNODE"    TOPLEVEL="ACTIVE"    EXPORT="1">
  <L>
      <RULEREF    NAME="ABOUT"/>
  </L>
</RULE>

<!--    Vocabularies    -->

<RULE NAME="action" DYNAMIC="TRUE">
</RULE>
```

```
<RULE NAME="agent" DYNAMIC="TRUE">
</RULE>

<RULE NAME="object" DYNAMIC="TRUE">
</RULE>

<RULE NAME="rtobject" DYNAMIC="TRUE">
</RULE>

<RULE NAME="groupSubject" DYNAMIC="TRUE">
  <L>
    <RULEREF    NAME="agent"/>
    <RULEREF    NAME="object"/>
    <RULEREF    NAME="rtobject"/>
  </L>
</RULE>

<RULE NAME="groupVerbal" DYNAMIC="TRUE">
    <RULEREF    NAME="action"/>
</RULE>

<RULE NAME="groupObject" DYNAMIC="TRUE">
  <O>
   <P>the</P>
   <P>with</P>
   <P>with the</P>
  </O>

  <L>
    <RULEREF    NAME="agent"/>
    <RULEREF    NAME="object"/>
    <RULEREF    NAME="rtobject"/>
  </L>
</RULE>

<RULE NAME="groupPlace" DYNAMIC="TRUE">
  <L>
    <P>on the</P>
    <P>in the</P>
    <P>to the</P>
    <P>at the</P>
  </L>
```

```
  <L>
    <RULEREF    NAME="object"/>
    <RULEREF    NAME="rtobject"/>
  </L>
</RULE>

<RULE NAME="groupTime" DYNAMIC="TRUE">
</RULE>

<RULE NAME="groupManner" DYNAMIC="TRUE">
</RULE>
<!--    Keywords    -->

<RULE NAME="ABOUT" DYNAMIC="FALSE">
  <P>Let's talk about</P>
  <RULEREF NAME="keyword"/>
</RULE>

<RULE NAME="keyword" DYNAMIC="FALSE">
  <L>
    <P>childhood</P>
    <P>history</P>
    <P>pong</P>
    <P>tic tac toe</P>
    <P>music</P>
  </L>
</RULE>

<!--    Games     -->

<RULE NAME="gameName" DYNAMIC="FALSE">
  <L>
    <P>tic tac toe</P>
    <P>pong</P>
    <P>music</P>
  </L>
</RULE>

<RULE NAME="GAME" DYNAMIC="FALSE"     TOPLEVEL="ACTIVE"    EXPORT="1">
  <L>
      <P>Let's play</P>
      <P>I want to play</P>
```

```
    </L>
     <L>
      <RULEREF    NAME=”gameName”/>
    </L>
  </RULE>

  <RULE NAME=”miscSentences” TOPLEVEL=”ACTIVE”    EXPORT=”1”>
  <L>
    <P>Stop the interaction</P>
    <P>Lets move away from the table</P>
  </L>
  </RULE>

  <!--    End    of    Grammar    definition    -->
</GRAMMAR>
    </L>
  </RULE>




  <!--    Vocabularies    -->

  <RULE NAME=”action” DYNAMIC=”TRUE”>
  </RULE>

  <RULE NAME=”agent” DYNAMIC=”TRUE”>
  </RULE>

  <RULE NAME=”object” DYNAMIC=”TRUE”>
  </RULE>

  <RULE NAME="rtobject" DYNAMIC="TRUE">
  </RULE>

  <RULE NAME="groupSubject" DYNAMIC="TRUE">
    <L>
      <RULEREF    NAME="agent"/>
      <RULEREF    NAME="object"/>
      <RULEREF    NAME="rtobject"/>
    </L>
  </RULE>
```

```
<RULE NAME="groupVerbal" DYNAMIC="TRUE">
    <RULEREF    NAME="action"/>
</RULE>

<RULE NAME="groupObject" DYNAMIC="TRUE">
  <O>
   <P>the</P>
   <P>with</P>
   <P>with the</P>
  </O>

  <L>
    <RULEREF    NAME="agent"/>
    <RULEREF    NAME="object"/>
    <RULEREF    NAME="rtobject"/>
  </L>
</RULE>

<RULE NAME="groupPlace" DYNAMIC="TRUE">
  <L>
    <P>on the</P>
    <P>in the</P>
    <P>to the</P>
    <P>at the</P>
  </L>

  <L>
    <RULEREF    NAME="object"/>
    <RULEREF    NAME="rtobject"/>
  </L>
</RULE>

<RULE NAME="groupTime" DYNAMIC="TRUE">
</RULE>

<RULE NAME="groupManner" DYNAMIC="TRUE">
</RULE>
<!--    Keywords    -->

<RULE NAME="ABOUT" DYNAMIC="FALSE">
  <P>Let's talk about</P>
  <RULEREF NAME="keyword"/>
</RULE>
```

```
  <RULE NAME="keyword" DYNAMIC="FALSE">
    <L>
      <P>childhood</P>
      <P>history</P>
      <P>pong</P>
      <P>tic tac toe</P>
      <P>music</P>
    </L>
  </RULE>

  <!--    Games     -->

  <RULE NAME="gameName" DYNAMIC="FALSE">
    <L>
      <P>tic tac toe</P>
      <P>pong</P>
      <P>music</P>
    </L>
  </RULE>

  <RULE NAME="GAME" DYNAMIC="FALSE"     TOPLEVEL="ACTIVE"    EXPORT="1">
    <L>
        <P>Let's play</P>
        <P>I want to play</P>
    </L>
     <L>
      <RULEREF    NAME="gameName"/>
    </L>
  </RULE>

  <RULE NAME="miscSentences" TOPLEVEL="ACTIVE"    EXPORT="1">
  <L>
    <P>Stop the interaction</P>
    <P>Lets move away from the table</P>
  </L>
  </RULE>

  <!--    End    of    Grammar    definition    -->
</GRAMMAR>
```