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Coordination Dynamics in the Sensorimotor Loop

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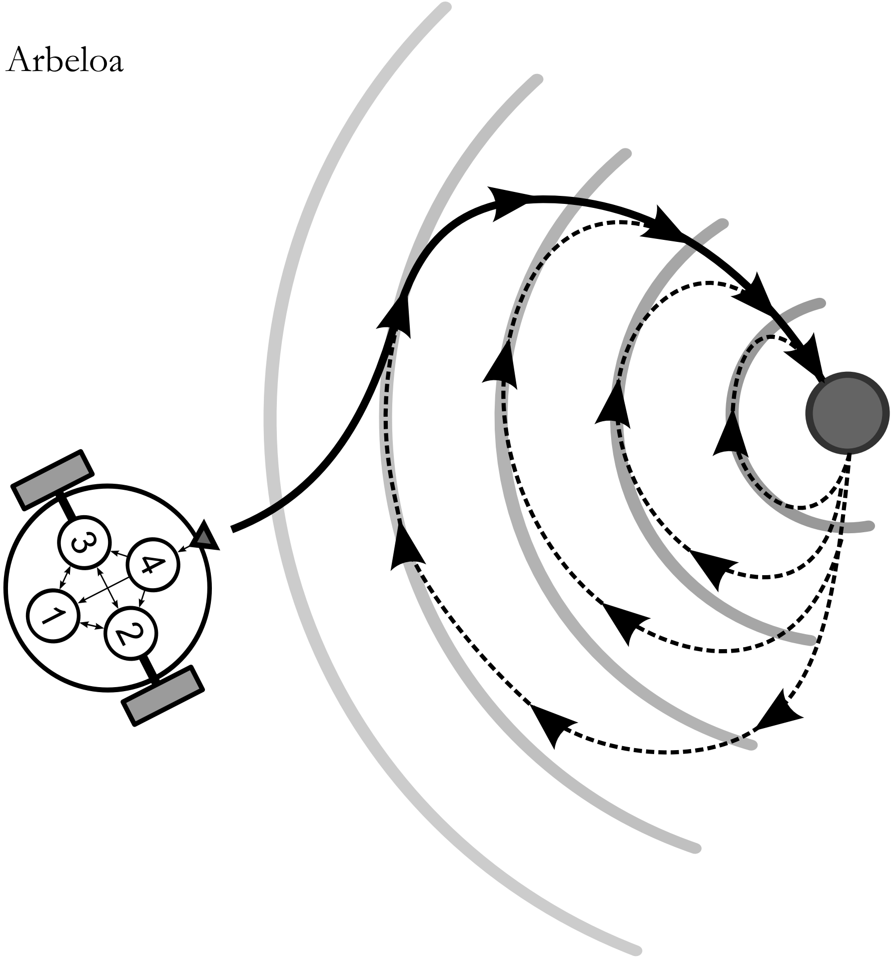

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Abstract

The last two decades have witnessed radical changes of perspective about the nature of intelligence and cognition, leaving behind some of the assumptions of computational functionalism. From the myriad of approaches seeking to substitute the old rule-based symbolic perception of mind, we are especially interested in two of them.

The first is Embodied and Situated Cognition, where the advances in modeling complex adaptive systems through computer simulations have reconfigured the way in which mechanistic, embodied and interactive explanations can conceptualize the mind. We are particularly interested in the concept of sensorimotor loop, which brings a new perspective about what is needed for a meaningful interaction with the environment, emphasizing the role of the coordination of effector and sensor activities while performing a concrete task.

The second one is the framework of Coordination Dynamics, which has been developed as a result of the increasing focus of neuroscience on self-organized oscillatory brain dynamics. It provides formal tools to study the mechanisms through which complex biological systems stabilize coordination states under conditions in which they would otherwise become unstable.

We will merge both approaches and define coordination in the sensorimotor loop as the main phenomena behind the emergence of cognitive behavior. At the same time, we will provide methodological tools and concepts to address this hypothesis. Finally, we will present two case studies based on the proposed approach:

1. We will study the phenomenon known as "intermittent behavior", which is observed in organisms at different levels (from microorganisms to higher animals). We will propose a model that understands intermittent behavior as a general strategy of biological organization when an organism has to adapt to complex changing environments, and would allow to establish effective sensorimotor loops even in situations of instable engagement with the world.

2. We will perform a simulation of a phonotaxis task performed by an agent with an oscillator network as neural controller. The objective will be to characterize robust adaptive coupling between perceptive activity and the environmental dynamics just through phase information processing. We will observe how the robustness of the coupling crucially depends of how the sensorimotor loop structures and constrains both the emergent neural and behavioral patterns. We will hypothesize that this structuration of the sensorimotor space, in which only meaningful behavioral patterns can be stabilized, is a key ingredient for the emergence of higher cognitive abilities.

Resumen

Durante las dos últimas décadas hemos sido testigos de cambios radicales de perspectiva acerca de la naturaleza de la inteligencia y la cognición, dejando atrás algunas de las asunciones del funcionalismo computacional. Del gran número de propuestas candidatas a sustituir el viejo paradigma basado en una percepción de la mente construida sobre la manipulación simbólica de representationes abstractas, estamos especialmente interesados en dos de ellas.

La primera es la de la Cognición Situada y Corporeizada, donde los avances en el modelado de sistemas adaptativos complejos mediante simulaciones por ordenador han reconfigurado la forma en la que explicaciones mecanicistas, corporeizadas e interactivas conceptualizan la mente. Estamos particularmente interesados en el concepto de bucle sensorimotor, que ofrece una nueva perspectiva sobre qué es necesario para una interacción significativa con el entorno, enfatizando el papel de la coordinación entre actividades sensorimotoras al desarrollar una tarea concreta.

La segunda es el marco de la Coordinación Dinámica, el cual ha sido desarrollado como resultado del creciente interés en neurociencia por la auto-organización de las dinámicas oscilatorias en el cerebro. Este marco proporciona herramientas formales para estudiar los mecanismos a través de los cuales sistemas biológicos concretos pueden estabilizar estados coordinados en situaciones en las que de otro modo se volverían inestables.

En este trabajo, uniremos ambas perspectivas para definir la coordinación en el bucle sensorimotor como el fenómeno principal que subyace la emergencia del comportamiento cognitivo. Al mismo tiempo, presentaremos herramientas y conceptos metodológicos para enfrentarnos al problema planteado. Finalmente, presentaremos dos casos de estudios basados en las propuestas anteriores.:

1. Estudiaremos el fenómeno conocido como “comportamiento intermitente”, que se puede observar en organismos a diferentes niveles (desde microorganismos hasta animales superiores). Desarrollaremos un modelo que entiende el comportamiento intermitente como una estrategia general de organización biológica frente a situaciones en las que un organismo tiene que adaptarse a entornos cambiantes complejos, que al mismo tiempo permitiría establecer bucles sensorimotores efectivos incluso en situaciones de interacción inestable con el mundo.

2. Llevaremos a cabo una simulación de una tarea de fonotaxis realizada por un agente controlado por una red de osciladores como controlador neuronal. El objetivo será caracterizar el acoplamiento robusto y adaptativo entre la actividad perceptiva y la dinámica del entorno tan sólo a través del procesamiento de información de fase. Observaremos como la robustez del acoplamiento dependerá de cómo el bucle sensorimotor estructura y limita los patrones emergentes tanto a nivel neuronal como del comportamiento del agente. Plantearemos que esta estructuración del espacio sensorimotor, en la que sólo son estabilizados patrones de comportamiento significativos, es un elemento clave para la emergencia de habilidades cognitivas de nivel superior.

Publications

During the development of this thesis, the author has contributed to the following related publications:

Conference Publications

- Aguilera, M., Bedia, M. G., Barandiaran X. E. and Serón, F. (2011). The adjustment-deployment dilemma in organism's behaviour: theoretical characterization and minimal model. Proceedings of the IEEE Symposium on Artificial Life, pp. 116-123. Paris, April 11-15, 2011.
- Castillo, L. F., Bedia, M. G. , Aguilera, M. and Uribe, A. L. (2011). A proposal for improving retrieval processes in case-based reasoning systems able to act in dynamic environments. Proceedings of the International Symposium on Distributed Computing and Artificial Intelligence, **1**(1), 1-4. Salamanca, April 6-8, 2011.
- Castillo, L. F., Bedia, M. G., Aguilera, M., Uribe A. L., Manrique, M. and Isaza, G. (2011). Case-based reasoning and real-time systems: exploiting successfully poorer solutions. Proceedings of the 6th Colombian Computing Congress.

Posters

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Introduction

During the last years we have seen how some of the principles of artificial intelligence have been questioned. Concretely, different approaches have rejected the "computer metaphor", which compares the activity of the human mind with the symbolic information processing carried out by computers. The complaint was that this comparison would have mislead some of the research trying to understand the nature of intelligence. In the actual stage of artificial intelligence, we can easily design a computer capable of beating the best human player in a game of chess, but it is arduous challenge to build a robot able to play ball with a kid showing a human-like performance at the task. This puzzling example lead us to think that we need something else to really understand what intelligence is about.

Letting aside the metaphors comparing human intelligence and rule-based symbolic systems, different research lines have proposed the interactive, embodied and dynamical nature of the cognitive process as a hallmark for understanding intelligence. Now, the focus is not that much designing programs able to develop high level cognitive activities (as playing chess), but systems that are able to adapt themselves to new situations by continuous interactions with the world (like playing ball). Mental processes are not the result of a programmer design but the emergence product of these interactions over time.

We are going to take this conflict about the nature of intelligence and cognition between classical cognitivist approaches and these new emerging perspectives as our starting point for this thesis. This is going to allow us to challenge some of the assumptions about intelligent systems in favor of new ones that open a wide research field for exploration.

The first part of this thesis aims to present some ideas in order to sketch a post-cognitivist framework integrating ideas from different engineering and neuroscientific approaches. Concretely, we bring the ideas of Embodied and Situated Robotics, where agents adapt to their environment not with symbolic manipulation, but by trial-and-error manipulations of their own bodies interacting with the world. From neuroscience, we are interested in Coordination Dynamics, which aspire to describe the different processes going on in the brain in terms of the emergent coordination between its different parts, not because the role of a special coordinating central unit, but rather as a result of the system's ability to organize itself when intentionally coupled to its environment.

In a first place, we identify the importance of sensorimotor loops, i.e., the coupling between neural, bodily and environmental dynamics, as one of the most interesting conceptual tools introduced in artificial intelligence from the research in embodied and situated robotics. The concept of sensorimotor loop is opposed to the perceive-think-act cycle proposed by classical approaches, in which cognition was an abstract process disconnected from the world. Chapter 1 is going to introduce the concept of sensorimotor loop in a context of a dynamical, embodied and situated approach to cognitive science, and it will keep coming back to this idea during the rest of this thesis.

Nevertheless, understanding the emergence of coupled sensorimotor loops, built upon a myriad of processes interacting in nonlinear ways, is going to be an arduous task. Luckily, during the last years the idea of making use of a dynamical systems approach for understanding cognition has not been only limited to the artificial intelligence community. Neuroscientific models have exploited dynamical properties like auto-criticality or metastability for finding the mechanisms that allow brains to coordinate huge numbers of cells into coherent cognitive functions. In chapter 2 we are going to introduce the mathematical framework of coordination dynamics and how it applies to the brain operations. Stressing the role of mechanisms of synchronization and metastability leading to the emergence of cognitive behavior. Also, chapter 3 will review some of the tools that are presented as candidates to provide new understanding about the emergence of cognition in this dynamical framework.

In the second part of the thesis, chapters 4 and 5 will present two case studies that explore some of the implications of the ideas presented in the previous part, as well we try to give some insights about how dynamical processes describing low-level biological mechanisms can be connected to higher level cognitive phenomenon, making a link between neural dynamics and the concept of sensorimotor loop. Concretely, the first model will study the phenomenon known as "intermittent behavior", which is observed at different biological levels (from animals to microorganisms and neurons), trying to find a model that captures the universality and robustness of this mechanism of adaptation to uncertain environments. The second model will implement an agent solving a phonotaxis task using a network of coupled oscillators as a neural controller. There we will analyze how phase information allows robust adaptive couplings between perceptive activity and environmental dynamics; allowing the emergence of the described phenomena of synchronization and metastability within the sensorimotor loop.

Finally, chapter 6 will integrate the conclusions of the different parts of the thesis, trying to build a conceptual and methodological framework that takes the emergence of dynamically coordinated sensorimotor loops as the cornerstone of cognition.

It is worth to note that this work pretends to be a first approach towards a more ambitious research work. So, during its composition we have looked for an equilibrium between the gathering of information about the issues we are interested in and exploration and experimentation within this issues. The separation between these two complementary activities corresponds to parts I and II of the thesis respectively.

Part I

Disentangling Sensorimotor Coupling

Chapter 1

Cognition and the Sensorimotor Loop

Since its foundation, artificial intelligence (AI) has been composed by two overlapping and complementary strands. The first one is the engineering approach to AI, which mainly aims to produce new kinds of intelligent systems, understanding intelligence as the ability of a system to perceive its environment and take actions that maximize its chances of success (Russell & Norvig, 2003). However, many key ideas of artificial intelligence have been developed from a different perspective. This is the scientific approach to AI, which is mainly concerned with understanding what is and isn't possible in natural and artificial intelligent systems. Thanks to this interest in the understanding of what constitutes intelligent behavior and how can it be generated, the major technical and conceptual advances in cognitive science have always been connected directly or indirectly to artificial intelligence.

However, the engineering approach have traditionally ruled over the vast majority of the AI community, frequently dismissing or ignoring some of the critiques related not with particular solutions for specific problems but the very foundations of the research program in AI. These critiques point to what has been called an *ontological blindness* in AI (Sloman & Chrisley, 2005). With this term, it is referred to the fact that the preconceptions about a particular approach to a problem can prevent (e.g., a group of researchers) to identify what kind of entities, properties, relations, and processes need to be explained or modeled; and therefore constraining possible research directions that could point to possible alternative solutions for the problem.

This chapter tries to explain what is our position about the classical approach to AI, presenting some critiques concerned with the nature of intelligent behavior. Also, we introduce what we consider as a powerful conceptual tool for overcoming some of the "blindnesses" that affect the study of intelligence and is the cornerstone of some alternative approaches to cognitive science: the sensorimotor loop.

1.1 Fleeing from Cognitivism. The Dynamical Approach to Cognitive Science

Since the times of the development of formal logic, the theory of computation and the expansion of computers led to the consolidation of the *"computer metaphor of mind"* for explaining intelligence. The central intuition about this metaphor is that intelligence (including human intelligence) is similar to a computer, thus cognition can be defined as the computation of symbolic representations according to some set of rules. According to this view, a cognitive system would act correctly as long as the symbolic representations it processes are actually an accurate representation of the real world; and the processing of such information leads to a successful solution of the problem the system is facing.

This approach to understand intelligence, named the *computationalism* or *cognitivism*, has been the base for traditional artificial intelligence. This approach takes as its starting point the concepts of representation and computation, boiling down cognitive processing to the computational manipulation of representational inner states. The brain is considered to be a piece of biological hardware, and the mind is the software running on top. Cognition consist in rule-governed manipulation of symbols, which can be performed in a Turing machine (Newell & Simon, 1972). The only necessary condition to reproduce any kind of intelligence would be to have a rich enough repertoire of symbols and a detailed enough collection of rules for manipulating these symbols.

However, as the attempts of classical AI for reproducing a somehow human-like intelligence showed its limitations, the computationalist approach started to be questioned. Concretely, the first critiques started in the '80s with the resurgence of connectionism (Rumelhart *et al.* , 1986), which criticized the idea of a linear processing of symbols according to rules and proposed in turn models inspired in the distributed structure of neural networks. The new connectionist approach emphasized the advantages of distributed systems with massive parallel processing of information, allowing to reproduce cognitive phenomena which have been ignored or let aside before, as pattern recognition, associative memory, preservation of global effectiveness despite of local structural damage, etc.

Even when the connectionist approach solved some of the problems of the computationalist models, it still had some inherited limitations from the old computationalist perspective. In this way, connectionism has been defined as an "unfinished revolution" (Clark, 1997), since it stills maintains the core ideas of computationalism: i.e., cognition is fundamentally a computational and representational process disembodied and dissociated from its biological roots. If classical computationalism reduced cognition to some form of symbol crunching according to algebraic rules, connectionism attempts to explain cognition in terms of the computational manipulation of subsymbols, according to statistical rules. That is, if classical cognitivism assigns symbolic content to the sort of physical entities that get stored in von Neumann architectures, connectionist cognitivism assigns subsymbolic content to the sort of physical entities that are fully distributed and superposed on the neural network's weight matrix. Independently if we consider the mind as a sequential (computationalism) or distributed (connectionism) machine, intelligence is still being defined in terms of abstract manipulation of symbols with sematic value (Gomila & Calvo, 2008).

1.1.1 The dynamical systems approach and post-cognitivism

Despite the limitations of connectionism, it brought a change of perspective with deep implications artificial intelligence. Particularly, the introduction of *recurrent* connectionist models allowed the emergence of a new approach: the Dynamical Hypothesis (van Gelder, 1995). With the slogan "cognitive agents are dynamical systems", this view represents an important extension of the connectionist approach. Recovering ideas brought by the first cybernetists like the recurrent, dynamical nature of the brain (Ashby, 1952), the importance of feedback and stability in complex evolving systems (Wiener, 1948) or the study of systems completely embodied and embedded in the real world (Walter, 1950), the Dynamical Hypothesis insists on *the importance of analyzing the evolution of internal patterns of activations over time* (French & Thomas, 2001).

Dinamicism is not necessarily a complete refutation of cognitivism, but provides a methodological turn that questions some of its basic assumptions. Its breaking point is that it attacks the principal postulate of the computational approach. With the emphasis on the fact that cognition is a phenomenon that evolves over time, symbols and rules are no longer sufficient to explain cognition. Where computationalist said that the underlying mechanisms that gave rise to symbols and rules manipulating them were not important, dynamicists stress the importance of the "subcognitive" mechanisms underlaying the cognitive phenomena. While computationalists were explicitly uninterested in linking the neural level to the higher symbolic level, dynamicists seek to understand how higher levels of cognitive behavior might arise from sequences of lower level actions.

After leaving behind the discussion about cognition being a centralized or distributed process, different post-cognitive views arose, stressing the importance of viewing cognition not as abstract computation but as interactive, embodied an embedded. The difference between both approaches was quite graphically described by Hurley (1998) when she warns against the "cognitive sandwich" metaphor represented by cognitivist approaches. According to them, cognition might fill the space in between a perception-action *bun*. In this view, either in computationalist or connectionist approaches, cognition would play the same role between a perception and an action layer.

In contrast, post-cognitivist approaches conceive cognition and behavior in terms of the dynamical interaction (coupling) of an embodied system that is embedded into its surrounding environment. Thus, it is necessary not understand just the brain/mind in itself, but the whole coupled system, not leaving apart the interaction of perceptual and motor apparatus with their environment.

In the last decades, different scientific programs have explored different approaches to a post-cognitive study of mind. However, in this work, we are going to center our interest in two conceptual issues that we consider to be central for understanding cognitive systems:

- **Sensorimotor coupling:** cognitive systems cannot be understood without the context or environment in which it moves, evolves, develops. Interactivism and dynamicism explain how robust but flexible coupling with the environment emerges, breaking apart the "cognitive sandwich". This dynamic interaction brings sensorimotor aspects to the center of the study of cognition. Also bringing both the importance of the body, as the way to ground behavior in the environment, and active perception, whose role is *guiding action* rather that *constructing representations* of the world.

- **Coordination dynamics:** the mind is a complex, distributed and fluid adaptive process. The real-time interaction of neural, bodily and environmental factors engaged in sensorimotor loops depends crucially on the time course of this process. Neural activity and bodily interactions show non-linear, time dependent and continuous behavior, so dynamical systems theory seems an appropriate framework for studying it. In addition, cognition is an emergent, self-organizing phenomenon, arising out of the local activity of distributed units, with no single location in the system acting as a central controller. Coordination dynamics are fundamental to understand how cognition arises built upon the versatile and flexible mechanisms within the brain.

We will dedicate the rest of this chapter for introducing sensorimotor coupling, while coordination dynamics will be address in chapter 2.

1.2 The Sensorimotor Loop

Cognitive processes emerge from the dynamical interplay between the neural system of an agent, its body, and the environment, creating what we call a sensorimotor loop. The coupled nature of that interaction makes quite difficult, if not impossible, to separate and understand the components of a cognitive system in isolation from the rest of the system. Sensorimotor loops merge both actions and dispositions into a dynamical structure that cuts across the brain-body-environment continuum. As a result, sensorimotor loops stand in a privileged theoretical position to study the relationships between concrete neural mechanisms and behavior. They do not privilege either perception or action, or any other modularist assumption, and cover a wide range of behavior, from simple reflexes to different scales of learning and development.

The concept of sensorimotor loop arises from the ideas brought by different approaches to cognitive science that stressed the role played by the body and the agent's coupling with the environment. These approaches can be synthesized in the concepts of situatedness and embodiment, and understanding these terms would be the first step towards understanding the nature of sensorimotor loops.

1.2.1 Situated Cognition

The idea of situatedness means that the agent is embedded in a world, in opposition to classical AI models that are just given some information to solve a problem in an uncoupled way, not participating in the world as would agents in the usual sense. When agents are situated, their whole interaction with the environment is controlled by the agent itself. Information is perceived through sensors (e.g. photodetectors, microphones, collision sensors) and behavior of the agent has to be deployed by means of its own actuators (e.g. legs, wheels, arms). Thus, agents do not deal with abstract descriptions of the world, but they use its own perception of the world, the here and now, to generate its behavior. In this sense, being situated in an environment is going to give sense to the agent's actions.

We could synthesize the role of situatedness in the following ideas (Beer, in press), which have been traditionally neglected in AI and cognitive science:

1. Concrete action. Taking action in the world is more fundamental than making abstract descriptions of it. While conscious deliberation clearly has its role, the ultimate job of an intelligent agent is to do something, to take some concrete action with external consequences.

2. Situatedness. An agent's immediate environment plays a central role in its behavior. This environment is not only a rich source of constraints and opportunities for the agent, but also a context that gives meaning to the agent's actions.

3. Interactionism. An agent's relationship with its environment is one of ongoing interaction. The environment does not serve merely as a source of isolated problems for the agent to solve, but rather a partner with which the agent is fully engaged in moment-to-moment improvisation.

A classic example of situated cognition are Braitenberg vehicles, which develop complex behavior based in quite simple mechanism that allow different degrees of coupling with the environment, generating complex and unpredictable behaviors (Braitenberg, 1984). For example, a vehicle with two light sensors directly connected to a pair of motors is able to perform a phototaxis task (figure 1.1). We can see how the agent does not perform any kind of computation, but the problem is solved through a continuous interaction with the environment and a sensorimotor coupling between the motor actions and the sensory signals. Even when the robot is very simple, it can perform an interesting behavior. And, when the complexity of the vehicles is slightly increased, the behaviors shown by them are surprisingly interesting.

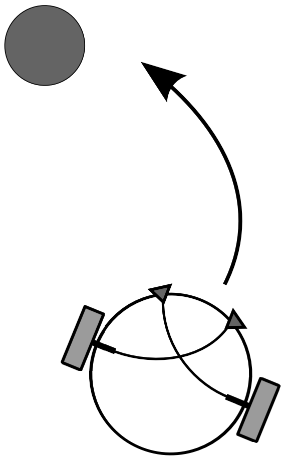


Figure 1.1: Braitenberg phototactic vehicle. The agent approaches a light source with just two connections between the right sensor and the left motor and viceversa. Situated interaction with the environment allows simple control systems to display complex behaviors. Figure adapted from Braitenberg (1984).

1.2.2 Embodied Cognition

As we have explained, one of the greatest potentialities of the dynamicist approach is its capability to take account of how abstract cognitive abilities emerge from mechanisms at the biological level. This fact leads directly to the notion of embodied cognition, which claims that it is impossible to understand cognition without the bodies in which cognitive processes take place. According to this view, the body allows an agent to experience the world directly, since its actions are dynamically engaged with the world and have an immediate feedback on the agent's own sensations.

Embodiment constitutes a physical grounding of the agent, which is forced to face the kind real-world issues organisms have to deal with. As result, material properties and morphology of the body often play a key role in the generation of behavior. Thus, the body not only imposes constraints in the behavior of an agent, but it is going to allow an agent to exploit the world by sensorimotor coupling with the environment.

According to Beer (in press), there are at least three distinct ways in which embodiment affect cognition:

1. Physical embodiment. Physical aspects of an agent's body are crucial to its behavior, including its material properties, the capabilities for action provided by the layout and characteristics of its degrees of freedom and actuators, the unique perspective provided by the particular layout and characteristics of its sensors, and the modes of sensorimotor interaction that the sensors and actuators collectively support.

2. Biological embodiment. Not only are the physical characteristics of bodies important, but the specifically biological facts of an organism's existence must also be taken into account, including the relevant neuroscience, physiology, development and evolution.

3. Conceptual embodiment. Even when engaged in pure ratiocination, our most ab-

stract concepts are still ultimately grounded in our bodily experiences and body-oriented metaphors.

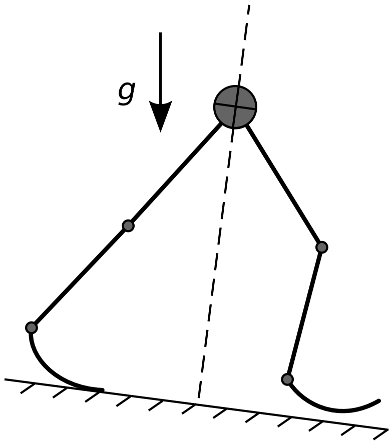


Figure 1.2: Passive dynamic walkers exploit its morphology to walk down a slight incline without external power. Figure adapted from McGeer (1990).

A good example of how embodiment can be exploited for generating behavior are passive dynamic walkers (McGeer, 1990, figure 1.2), which are capable of walking down a ramp without any sensing, actuation, or control. Nonetheless, the behavior of the robot emerges from the exploitation of its own dynamics - i.e., how gravity, friction, and the forces generated by the swinging of the legs and arms act on it. As a result their walking behavior is very energy efficient and looks surprisingly natural. This presents a big contrast compared with classical AI walking robots, which normally are hard to design and show clumsy and unnatural movements. In dynamic walkers, the processing normally required for controlling walking is taken over by the proper morphology and the right materials, as well as the coupling of the legs movements with gravity in a pendulum-like way. As well, animals also exploit this embodied dynamical mechanisms for walking, exploiting the complexity of a system constituted by our bones, joints, tendons and so on.

1.2.3 Brain-Body-Environment Systems

So far we have explained how the dynamical approach to cognitive sciences emphasizes the temporal dimension of behavior, while situatedness concerns the role played by the ongoing interactions of an agent with its immediate environment and embodiment stress the role of the physical properties of the agent's body in its behavior. Even when all these ideas have been historically developed in different contexts, they work much better when they are understood as a unit. The combination of the three of them leads to the notion of a brain-body-environment system, composed of an agent's nervous system, its body, and its environment; conceptualizing all of them as coupled dynamical systems which are in continuous interaction (Beer, 1995a, figure 1.3). The idea of a brain-body-environment system has fundamental implications in cognitive and brain sciences and raises many empirical and theoretical challenges. A review of the accomplishments of the research in this direction was developed by Beer (2008).

The traditional view in Artificial Intelligence and Cognitive Science decomposes the sensorimotor loop into an open perceive-think-act loop, understanding that the purpose of perception is to create an internal model of the environment to decide what is the right action to perform. This view assumes the existence of a central stage, between sensing and acting, where the contents of the environment are represented. On the other hand, the brain-body-environment system approach remarks that the role of perception is not reconstructing the environment, but *transform* the sensory signal to produce some motor output.

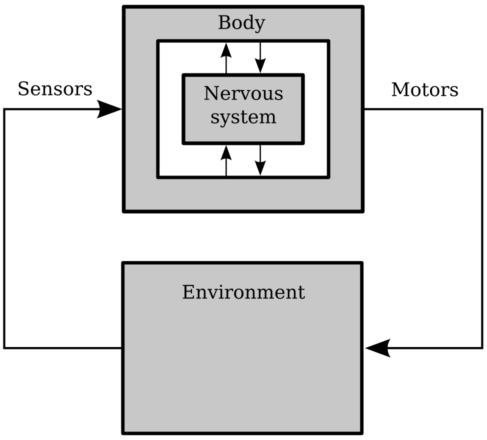


Figure 1.3: An agent and its environment as coupled dynamical systems in a sensorimotor loop. The agent is composed of coupled nervous systems and body dynamical systems.

A deeper critique to the traditional perceive-think-act view points its tendency to ignore the closed-loop nature of the perceptual process (Pfeifer & Scheier, 1999). According to the brain-body-environment perspective, behavior can be only understood when the sensorimotor loop is considered as a whole, and we cannot understand it by studying its parts in isolation. Indeed, the very nature of the problem to be solved can change when the sensorimotor loop is established. This is the case for active vision, where gaze control simplify the processing of visual perception (Ballard, 1991), auditory perception of distance, which is improved when movement is involved (Rosenblum, 1993) or tactile perception, where object recognition is greatly enhanced with active manipulation (Lederman & Klatzky, 1996). This view suggests that perception is an ongoing activity of exploration rather than an abstraction of perceptual experience into a final interpreted percept.

1.3 Redrawing the cognitive phenomenon

The approach presented here, which considers the sensorimotor loops to be at the center of the emergence of cognition, can be summarized in the three 'radical embodiment' propositions presented by Clark (1999):

1. Understanding the complex interplay of brain, body and environment requires the tools and methods of dynamical systems theory.
2. Traditional notions of internal representation and computation are inadequate and unnecessary.
3. The typical decomposition of the cognitive system into a variety of functional subsystems or modules is often misleading, and blinds us to the possibility of alternative, and more explanatory decompositions into dynamical systems that cut across the traditional brain-body-environment divisions.

Within this framework, the power of dynamical tools is to model the embodied agent-environment interactions and the biological mechanisms that do not stand for any specific representational or cognitive function but, in turn, are able to produce a cognitive behavior. From this perspective, the focus is not anymore the manipulation of various symbols in the head, but the low-level mechanisms that actually produce transitions from one representation to another, being the states of the system something that is not predetermined by a designer but emerges from the dynamics of the system itself. This is a property of self-organized systems, in which there is no need for a central control like in traditional AI systems, and is crucial for understanding life and cognition.

However, even if we study cognition from a dynamical systems approach, there is still problems we should try to avoid (French & Thomas, 2001):

- First, dynamical approaches often lie in the characterization of attractors based on huge amounts of data (and calculations), not taking care if brains can actually process this kind of intensive information. The understanding of how nature avoids this problem with emergent structures showing self-organized criticality is going to be a key point about the organization of dynamical systems performing complex behaviors.

- In second place, when we are in the process of analyzing cognitive dynamics loops it is important not losing the sight of cognition itself. Just describing the dynamics underlying a cognitive process do not mean that we understand it. Understanding the dynamics of neural networks or body movements is not sufficient to understand cognition if we are not able to explain how these dynamics are related to cognition itself. Here, it is fundamental not to leave apart the idea of the sensorimotor loop as a process that cut across the brain-body-environment system, stressing the importance of the role played by the ongoing interactions between the agent and its immediate environment, grounding the agent's activity in an cognitive task.

The first of these two problems is explicitly addressed in the rest of the first part of the thesis. We analyze the biological mechanisms that give rise to the kind of versatile and flexible behavior observed in the brain, as well as the formal mathematical tools that could allow us to understand how coordination dynamics operate in the brain. Also, our objective is trying to grasp the general abstract mechanisms that lie on brain functioning, trying to understand the emergence of intelligent behavior. In that sense, we will present a methodology for studying intelligence, based in the modeling of artificial agents in order to understand how cognitive behavior arises from dynamical interactions.

The second problem addresses the issue of how abstract intelligence could emerge from self-organized brain-body-environment interactions. The resolution of that problem presents great theoretical and experimental difficulties. Even when the resolution of the problem is away from the scope of this work, we are interested in it, and our purpose is to explore some threads that could lead to a research program that explicitly addresses the issue of how structured sensorimotor loops could constitute the base of cognitive operations and allow the emergence of abstract intelligence. In that sense, the second part of this thesis will present two case studies trying to advance towards the definition of a framework of analysis that includes these ideas.

Chapter 2

Synchronization and Metastability in the Brain

The human brain is a device of huge complexity that intensively integrates flows of information from several sources, while interacting with the world through different sensorimotor loops at different temporal and spatial scales. Cognition is a process which is deployed in time, through the nonlinear interaction of a great number of elements that leads to the emergence of patterns that constitute cognitive behavior. This approach, presented in the previous chapters as the Dynamical Hypothesis, is certainly promising, but many problems remain. One of this problems is how could brains handle all the intensive information needed for the creation of dynamical processes that engage in the adequate sensorimotor couplings.

In this chapter we will present what it is known about the organization of the brain, trying to put together the features that allow it to deploy an incredibly complex and adaptive behavior. Also, we will present Coordination Dynamics, a mathematical framework to describe the emergence of coordinated behavior governing the coupling of environmental stimuli to the agent's effectors. Finally, we introduce some examples of how coordination mechanisms could allow the emergence of different cognitive functions, as well as we hypothesize how coordination dynamics could go beyond the neural substrate to give birth to a web of interacting sensorimotor loops.

2.1 Self-Organization: Simple Rules for Complex Behavior

In contrast to the computationalist view, the brain is not just an information processing device. Instead, most of the brain's activity is generated endogenously (Buzsáki, 2006), i.e., it is *self-organized.* "Representation" of external reality is just the effect of outside influences in the brain's self-generated patterns. Accordingly, control of brain activity is not going to start with their sensory inputs but their motor outputs. Action is going to be the goal of cognition.

How does the organization of the brain emerge from within? Self-organized systems consist on large numbers of elements interacting in non-linear and selective ways, spontaneously creating different kinds of patterns. Many types of physical, chemical, biological or social systems show self-organizing properties. In these complex systems emergent properties cannot be attributed to specific or well-distinguishable parts, since the "observable" (macroscopic) behavior of the system cannot be, in practice, derived from the simple principles of the component-level (microscopic) interactions. This makes impossible to apply classical decomposition methods to the study of complex living or cognitive systems.

Complex systems, despite their variety, share some generic properties. They all are situated in a critical region far from equilibrium, i.e. near nonequilibrium phase transitions, in a situation where only a few degrees of freedom contribute to characterize the emerging patterns of the system. Those relevant degrees of freedom are called the **order parameters** of the system. It is important to understand that even when complex systems emerge from low level bottom-up interaction of its components, what constitutes them is the action of high level emerging patterns modifying or channeling low level interactions. The order parameters emerge from the coordination between the components of the system, but also constrain and limits their behavior in a recurrent feedback loop. This phenomenon is called circular causality (figure 2.1).

Besides order parameters, we can identify parameters that modify the system but do not depend on the patterns that are emerging from the system. We call them **control parameters** of the system. Control parameters may have no direct relation with the pattern changes they induce (in the sense that they do not prescribe them in any way), and they lead the system to dynamic instabilities required for complex behavior to emerge. Finally, **fluctuations** are the forces that allow the system to create o switch between different patterns.

The effect of both fluctuations and changes in the control parameters is going to change the situation of the system. Furthermore, as result of the high non-linearities presented by complex systems, we often are going to find situations where the patterns of the system change in a dramatic way after a critical point is crossed. This phenomenon is referred to as a **phase transition** of the system, and its occurrence is going to be reflected in the order parameter of the system.

In complex systems, mapping between structure and function is highly problematic because the conspicuous lack of a one-to-one relationship between self-organized coordination patterns and the structures that realize them. Rather, many-to-many relationships are the rule in complex systems.

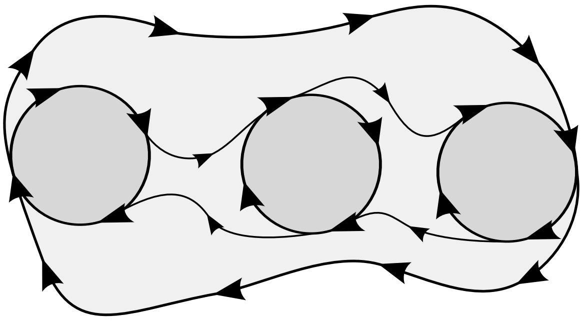


Figure 2.1: Circular causality. We see how three processes generate a high-level processes (order or coordination parameters), which in turn channel the activity of the low-level processes.

A lot of physical and chemical systems are self-organized, constituting complex systems. However, biological and cognitive systems show a much wider variety of interacting components and non-linear interactions modes. More precisely, they show an intricate and rich functional diversity within a modular and hierarchical dynamical organization. This organization is endowed with global collective properties, like highly robust self-maintenance, and shows singular patterns of behavior in their environments, like agency, multiscale adaptive flexibility, etc.

Biological and cognitive systems hide not only more complexity than physical systems, but rather different forms of it. Their much richer internal structure and functional diversity constitutes second-order forms of complexity (Moreno *et al.* , 2010). Everywhere in biology and cognitive science systems are made of parts with different functionalities behaving in a selective and harmonized way, coordinating themselves at different timescales, interacting hierarchically in local and global networks. The organization of living systems consist in different, and interconnected levels which, being somewhat self-organized in their local dynamics, depend globally one upon the others.

2.2 Criticality in the Brain

We have claimed that biological and cognitive systems self-organize themselves in hierarchical levels interacting at different timescales. The question here is what properties might have a self-organized system to allow the emergence of such kind of organization in biological systems. Bak *et al.* (1987) developed a theory of Self-Organized Criticality designates the properties of dynamical systems that have a critical point as an attractor. In consequence, system displaying self-organized criticality exhibit non-equilibrium phase transitions only dependent on their intrinsic dynamics. In this kind of systems, it is not necessary to tune the value of the control parameters by external influences to generate a phase transition, i.e., phase transitions are self-generated.

Systems of this kind evolve spontaneously to a critical state where its responses to fluctuations have a drastically reduced number of degrees of freedom and present temporal and spatial scale invariance (i.e., the system does not have any characteristic scale of length nor time). The later property is characteristic of $1/f$ noise, where the power distribution between frequency bands is inversely proportional to frequency (f), being somewhat in between the disordered and high information content of white noise (flat frequency content) and the predictable and low information content of brown noise ($1/f^2$ frequency content). The different oscillations existing in the brain have the same scale free $1/f$ statistics, as result of oscillatory interactions at several temporal and spatial scales (Freeman *et al.* , 2000). So, the brain shows self-organized criticality, displaying, interactions in which slow rhythms modulate the activity of the faster ones.

Also, as it has been observed in EEG measures, the relationship among neighboring waveform frequencies in the brain are correlated on a logarithmic scale rather than a linear scale (Penttonen & Buzsáki, 2003), i.e. the relation between different frequency bands is an irrational number. Since the frequency bands ratios are not rational numbers, they cannot just lock-step to achieve stable phase synchronization. Instead, phase transitions are linked according to their ability to couple with adjacent phase shifts in a constant state of transition between unstable and stable phase synchronization. This is going to characterize the behavior of the brain as a state of perpetual fluctuation between unstable and transient stable phase synchrony, with multiple coupled oscillators perpetually engaging and disengaging each other. This state has been defined as **metastability** in the brain.

Anyway, even when the presence of $1/f$ dynamics determine a high lability of neuronal states, avalanches (characteristic of chaotic $1/f$ systems) are going to be prevented by **coordination dynamics** between oscillatory patterns. Where scale-free dynamics generated complexity, oscillations allow for temporal predictions. According to Buzsáki (2006), the most crucial characteristic of the brain would be its ability to constantly shift from the complex to the predictable, that is, shifting from a state of complex $1/f$ dynamics to a highly predictable oscillatory state. Brain dynamics are in between of two worlds, order and complexity, and brains take advantage of that obtaining the best from both. Rapidly switching from a metastable highly complex state, in which the brain is able to respond to weak and unpredictable environmental perturbations; to a predictable oscillatory state with linear variables, giving rise to the emergence of mechanisms as “anticipation”, “prediction” or “expectation”. This switching behavior is the most efficient way for the brain to detect changes in the body and the environment while maintaining its autonomous internal organization.

2.3 The Function of Oscillations in the Brain

During the last two decades, the study of brain oscillations has allowed considerable progress in the understanding of a variety of cognitive phenomena. The self-organization, emergent patterns, phase-synchrony and oscillatory rhythms are now common issues in the study of brain dynamics, the challenge is to find the mechanisms that allow complicated things to happen in a coordinated way in the brain (Buzsáki, 2006).

Coordination happens at different levels of neural activity. Neurons show cyclic alteration of its membrane potential, following different dynamical regimes depending on the cell properties (Izhikevich, 2000). At higher levels, groups of neural cells generate global oscillations in a synchronized collective manner. Synchronization happens either because of the action of pacemaker cells or as a result of recurrent neural network activity with inhibitory-excitatory connections. The different kinds of oscillations generate electric and magnetic fields which can be measured by Electroencephalography (EEG) and Magnetoencephalography (MEG). Hints about the dynamic properties of brain functioning can be obtained by the study of these signals, relating them to sensorimotor activity and cognitive phenomena. This section tries to extract the insights that have been gained by different neurophysiological studies and may be useful in the context of the dynamical systems approach to cognitive science.

2.3.1 Sleep Patterns and Alpha Rhythms: Perturbation of Default Self-Organized Patterns

Buzsáki (2006) considers the complex patterns of the different sleep stages, as well as oscillation associated with resting, as the best examples with self-organized operations in the brain. Characterizing sleep as a *default* state of the brain, its main function would be to isolate the brain from the body. In this way, neural sleep patterns like the K-complexes and sleep spindles have been related with disengagement of the cortex from the sensor input.

Sleep drastically isolates the brain from its inputs, but we can also selectively eliminate some of them when we are awake. Alpha oscillations have been characterized as an indication of the cortical disengagement from inputs of the body and the environment, being attenuated by a diverse range of specific and nonspecific stimuli and behaviors. In this way, different alpha oscillations can be blocked by eye-opening, eye movement, mobility of skeletal muscles, acoustic stimulation or even mental activity, such as arithmetic calculations (Buzsáki, 2006).

Anyway, disconnection from some (or all) aspects of the environment do not means a decreased brain performance. Experience-induced neuronal patterns during sleep have real-life implications in memory consolidation (Eichenbaum, 2002) or catalyzation of the creative process (Wagner *et al.* , 2004), and alpha oscillations are believed to be not just a result of sensory disengagement but may reflect internal mental processing. In various cognitive tasks, alpha power increases with task difficulty.

Nevertheless, isolating some inputs do not necessarily mean that the information already obtained from them is going to be lost. Instead, sleep is going to temporarily stabilize the dynamics of the brain, inducing a strongly synchronous neuronal activity. This highly synchronized state is going to be suitable for storing information about the previous walking brain activity. In other words, when harmonic oscillations take place, i.e., the system is highly predictable, it is easy to predict future system behavior from current observations. Buzsáki speculates about daily experiences perturbing the internal dynamics of sleep patterns leaving their marks in them.

Another hint about the function of self-organized patterns in sleep and resting states can be found in the similarities between some sleep and alpha oscillations patterns and rhythms found in newborn animal pups or preterm human babies. Concretely, sleep spindles and μ oscillations (a type of alpha oscillations) have been related to baby and pup spindles, which are linked to activities like baby kicks in the late stages of pregnancy and spontaneous motor patterns in pups like muscle twitches, limb jerks and body startles. Buzsáki affirms that these spindle-induced movements to the organization of movement coordination and representation of the body metrics.

Despite the huge difficulty of organizing all the possible combinations of the hundreds of muscles in the body, only a limited fraction of these combinations is ever realized due to the physical constrains of the body and limbs. So, behavior is going to arise on top of spontaneous spindle-related movements, creating this way the real-world metric space that is going to be necessary later in life for sensorimotor coordination. Other phenomena as song learning in songbirds or babbling in human babies reflect the same kind of self-organized intrinsic dynamics. In Buzsáki's words, *"perturbation of the default self-organized patterns of the brain is a more effective mechanism of pattern formation than the de novo, tabula rasa approach because the former can exploit the existing dynamics of the maturing brain networks"* (Buzsáki, 2006, p. 227).

How could sleep and rest patterns have something in common with the self-organization of pattern formation? Buzsáki's explanation is that processes similar to the self-generated pup movements are necessary in adulthood. As the body shape and size changes during the whole life, sleep spindles or μ oscillations may assist the somatosensory system to the preservation of body representation. Some examples of this would be the crucial role in visual perception played by active exploration of the visual field by eye movements (Leopold & Logothetis, 1999) and the role of the motor system in perception learning (Held & Hein, 1963). The idea is that no explicit experience can emerge without the brain's output. The brain's sensory representations acquire real-world metrics in early development, and muscle activity sensations, which begin during late intrauterine life, are a key mechanism for that. Similarly, other perceptual skills, such as vision and spatial orientation would need these kinds of self-organized rhythms for pattern formation mechanisms to develop properly.

2.3.2 Gamma Rhythms: Binding by Synchrony

Gamma oscillations are ubiquitous throughout the brain, and phase coupling of gamma oscillations allows synchronization among different areas of the brain. Also, since their period fits the best conditions for synaptic strengthening and weakening in neurons, they are a key component for timing/selection mechanisms in neuronal communication.

One of the most important functions attributed to gamma oscillations is to be a key component to solve the century-old "binding problem" in perception (Revonsuo & Newman, 1999). This problem raises questions about how, in a highly distributed system as the brain, the different attributes of objects (color, texture, position, distance, smell) are bound together to give rise to a coherent representation. That is, if I see a red square and a yellow circle, being shape and color processed by different parts of my brain, how do I know that red is coupled with the concept of square and yellow with circle? And how do I consciously perceive them as as two independent separated objects?

One of the coordinating mechanisms for solving the binding problem appears to be the synchronization of neuronal activity by phase locking of self-generated network oscillations in the gamma band (Philips & Singer, 1997). This proposal, addressed as the "binding by synchrony" model, differs with previous hierarchical feed-forward models because convergence of connectivity is no longer the main variable of feature extraction; rather, it is the temporal coherence of neurons, representing the various attributes of objects, that matters. The main advantage of this approach, is that it offers an unlimited coding capacity for feature combinations, as well as the possibility of mapping cross-modality representations onto each other without altering the their coding formats.

It has been proposed that this coding may be achieved by means of phase information (Singer, 2007), due to the ability of neurons to code aptitude values into a temporal code of spike timing. Even when binding operation can be accomplished by fixed anatomical connections, binding must be a versatile mechanism since features processed in parallel by different areas of the brain need to be bound selectively and transiently. Such versatility can be obtained by exploiting the temporal dimension as coding space. Here, oscillatory networks offer the option to use phase relations of spike timing for the selection, gating and routing of signals exploiting by adjusting oscillation frequencies, phase relations of oscillations and exploiting a variable spectrum of conduction velocities.

2.3.3 Theta Rhythms: Representation by Phase Information

Hippocampal cells studies in rats discovered the existence of the so called “place cells”, which encode information about the position of a rat in its cage, exhibiting a high firing rate when the animal is in a specific location in an environment corresponding to the “place field” of the cell. It was also discovered that the spike phase of place cells shifted systematically in relation of the ongoing theta oscillations (O’Keefe & Recce, 1993). This phenomenon, called phase precession, is the same hypothesized for phase coding in binding mechanisms. When recording the activity of a place cell when the rat crosses a linear track corresponding with the place field of the cell, the phase of the place cell spikes shifts monotonically as a function of the rat’s position. The relationship between position and spike phase is independent of the firing rate or the speed of the animal, and depends only on the size of the place field. Ideally, the slope is a line between the beginning and the end of the place field, spanning 360 degrees, so that information about successive metric distances is reflected in the precise temporal sequences within cycles.

Furthermore, place fields overlap, and place cells establish stronger associations with cells that are activated near each other in time, tying together sequential places. This allows to link representation of the current positions with representation of the past and the expected future. This way, the temporal compression mechanism of the theta oscillation objectively defines spatiotemporal context.

Coding for ordered locations and distances is analogous to learning an episode of sequentially presented or visited items. The difference lies in the nature of the inputs rather than the nature of hippocampal computations. The same principles used in navigation in a one-dimensional track can be used to explain episodic memory.

The situation changes when we turn to trying to explain navigation in two-dimensional maps and semantic memory. While cells in one-dimensional travel had unidirectional place fields (determined by the position in the track), in two-dimensional environments, exploration leads to crossing the same positions from different directions. Now, place cells are going to be tied to different routes, becoming omnidirectional. Their activation is no longer going to depend on a temporal context. They explicitly define positions. Similarly, multiple episodes involving a common item can free this item from its spatiotemporal context. Neurons which are members of an omnidirectional assembly collectively define or symbolize the semantic “meaning” of an item (Buzsáki, 2006).

2.4 Coordination Dynamics

Observations of brain modes of behavior can be fascinating and give us important insights about self-organization in the brain. However, it is hard to achieve a deeper understanding of brain activity if we cannot build models representing how they work. A promising formal counterpart for the previous observations can be found in the framework of Coordination Dynamics, which describe the mathematical formulae and paradigms governing the coupling of environmental stimuli to their effectors. Kelso (1995) proposed coordination as a fundamental feature of life, allowing neurons, brain and mind to give rise to complex patterns of behavior. The proposed mechanisms for achieving coordination are self-organized interactions, leading to the spontaneous formation of patterns and pattern change in open non-equilibrium systems. According to this, mental activity would not constitute a programmable, static, timeless entity outside the brain, but would be sustained by a constantly shifting dynamic system of pattern formation.

Coordination dynamics has presented some surprisingly simple and elegant models as the Haken-Kelso-Bunz (HKB) model, which describes the dynamic of the relative phase between two non-linearly coupled oscillators (Haken *et al.* , 1985); Also, this approach introduces a important difference with other dynamical systems approaches: *"in contrast to classical dynamics that deals with fundamental quantities such as mass, length, and time and their relation, coordination dynamics deals with informational quantities of a relational kind"* (Kelso, 1995, p. 95). The proposed relational quantities are the relative phases of different non-linearly coupled oscillators, which characterize the relation among different parts of the system, independently of the nature of interactions. In this way, relative phases would constitute the order parameter of neural systems.

Coordination Dynamics is based on nonlinear coupling of the components of the system, constituting an emergent coordinative (higher) level of description of the system behavior. The nonlinearity of the coupling is a fundamental characteristic allowing the coupling to be nonspecific with respect to the patterns of coordination that emerge. That is, different coupling functions can give rise to the same coordination patterns, and changes in coordination can be brought about in a variety of ways. These *invariance of function* and *multifunctionality* are intrinsic properties of the coordination dynamics approach, hypothesized to be one fundamental characteristic of living organisms. Being the lack of a one-to-one relationship between self-organized coordination patterns a basic property of life.

2.4.1 The HKB Model

The HKB model is the driving example for Coordination Dynamics, describing the behavior of two non-linearly coupled oscillators. Initially, the model described the relative phase dynamics of bimannual coordination, but the model has been proved to represent the coordination dynamics of different behavioral (Kelso, 1995), neural (Jirsa *et al.* , 1998) and social (Kelso *et al.* , 2009) phenomena.

In the basic version of the HKB model, the relative phase derivative between the two oscillators follows the equation:

$$\dot{\phi} = \delta\omega - a \cdot \ sin(\phi) - 2b \cdot sin(2\phi) + \sqrt{Q} \cdot \varepsilon \tag{2.1}$$

where ϕ is the relative phase between the two interacting oscillators; a and b are the coupling coefficients; $\delta\omega$ is the difference between the intrinsic frequencies of the pair of oscillators; and ε represents the presence of noise fluctuations of strength Q. In (Kelso, 1995) it is found a more detailed description of this equation.

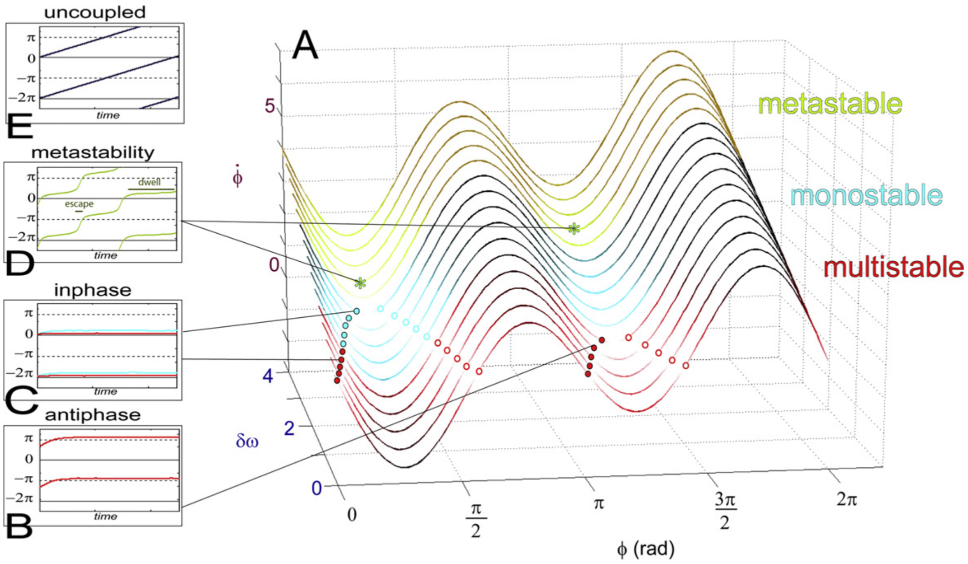


Figure 2.2: A simple theoretical model of brain coordination dynamics exhibits multistability, adaptive phase shifts, critical phase transitions and metastability. Taken from Tognoli & Kelso (2009)

We can consider the HKB model as a self-organized system, where ϕ is the order parameter, and a, b and $\delta\omega$ are control parameters. For fixed values of a and b, and shifting the value of $\delta\omega$ (although a different selection of control parameters could show the same results), we found three different possible situations for the model (figure 2.2):

1. When $\delta\omega \in (0, 1)$, there is a situation of *multistabiliy*, where there coexist two attractors at $\phi = 0$ y $\phi = \pi$ (i.e., the two oscillators being synchronized in-phase and anti-phase).

2. When the control parameter shifts to $\delta\omega \in (1, 2)$, we find a nonequilibrium phase transition. That is, when the control parameter passes through a critical point, a qualitative change in the attractors takes place. In this case we will only have one attractor at $\phi = 0$, and the attractor at $\phi = \pi$ disappears. If we reverse the situation, decreasing $\delta\omega$ again, the system will stay always in the $\phi = 0$ attractor, thereby exhibiting *hysteresis*.

3. When the control parameter approaches a given threshold, the system attractors move and eventually disappear. Over this threshold, when $\delta\omega \in (2, 4)$, the relative phase have no longer fixed points but engages in what Kelso calls a *metastable dynamic*. In this state, relative phase tends to stay near one of the previous attractor points, $\phi = 0$ and $\phi = \pi$, but eventually escapes and falls into the other attractor. It is important to note that, even when the attractors do not exist anymore in the metastable zone, there is still attraction. When the relative phase system is in a point where it used to be an attractor (near , $\phi = 0$ and $\phi = \pi$), the system tends to stay in that point, even when eventually it is going to be forced to leave. Anyway, due to the periodic nature of relative phases, the system is always going to be temporarily trapped again around the metastable quasi-attractor.

This HKB models reflects some important properties of biological dynamics, as multistability, hysteresis and metastability. In a nutshell, coordination dynamics provides two useful mechanisms to understand the behavior of neural dynamics:

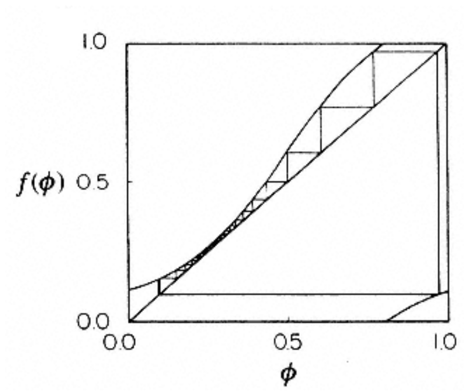


Figure 2.3: Dynamics of a metastable behavior where ϕ is the relative phase of the system at instant t and $f(\phi)$ is the relative phase at instant $t + 1$. It is show how the system is temporally trapped near a quasi-attractor. Taken from Kelso (1995).

- It allows to represent a situation where the system is able to switch between two states qualitatively different in an open nonequilibrium system. Classical Artifitial Intelligence implements switches or regulators to model changes of behavior. In contrast, Coordination Dynamics is able to explain switching without any switches at all.
- In the dynamical approach to cognitive science there are tendencies to model different behaviors just adding attractors to the system (see for example Dynamic Field Theory implementations (e.g., Bicho & Schöner, 1997), or the attractors of an artificial neural network). Coordination Dynamics is able to model attraction without the need of attractors (figure 2.3). This mechanism is hypothesized to allow the brain to rapidly change between behavioral states, preventing either the brain dynamics to get stuck in a fixed point or flying apart due to the lack of attracting forces.

The thesis of Coordination Dynamics is that the human brain would be a device that, rather than compute information, would hop quickly among different metastable states. In the human brain, attraction and repulsion influences coexist in a finely balanced way, allowing the emergence of two key properties: one, the ability to enter and exit coherent spatiotemporal patterns of neural activity; and two, the ability to engage and disengage participating subsystems in a flexible way (Kelso, 1995).

2.5 Metastability and Cognitive Dynamics

Computationalism views the brain as a passive, stimulus driven device, simply reacting to sensory inputs according to 'bottom-up' processing in hierarchically organized neural architectures. However, this view has been challenged by new neurophysiological data indicating that the brain should be regarded as a much more active and adaptive system, in which 'top-down' mechanisms continuously create predictions about forthcoming stimuli and constantly match expectations against signals from the environment (Engel *et al.* , 2001), therefore defining cognition as a fundamentally action-oriented phenomenon.

However, despite the great amount of mathematical and simulation modeling in current large-scale neurodynamics, there is still little systematic exploration of the coupling between brain, body and environmental dynamics. Most approaches focus on how oscillatory coordination carry information within the brain, letting apart ideas about situatedness and embodiment of the cognitive phenomenon (see chapter 1), which assume that cognition does not build on context-invariant models but is subject to constrains imposed by and ever-changing brain-body-environment relations that have to be coped with in an adaptive and context-dependent manner.

This section aims to gather some of the insights that could be useful to integrate recent discoveries in large-scale neuroscience about oscillatory coordination with the emphasis of the traditional dinamicist approach to cognitive science on sensorimotor loop coupling.

2.5.1 Temporal coding mechanisms for building 'top-down' loops

It was proposed by Singer (1999) that internal coordination of spike timing in cortical neural networks was a relevant factor representing context dependent dynamic interactions. As seen in section 2.3.2, dynamic binding strategies would depend on the dynamically adjustable configuration of the response of distributed neurons rather than a hierarchical structure of neurons. Also, temporal cues seem to be exploited for perceptual coupling (Lee & Blacke, 1999). As well, psychophysical and physiological evidence indicates that neural networks are highly sensitive to temporal relations among discharges in input connections, being particularly receptive to synchronous inputs (Singer, 1999).

Thus, coding in neural networks is proposed to be achieved by means of oscillatory modulation (Singer, 2007). Timing of neuronal spikes relative to the phase of the oscillation cycle depends on the strength of the excitatory drive. When the drive is stronger, discharges will take place earlier. In consequence, the amplitude of excitatory drive can be converted into spike timing, being the phase precession of discharges a direct measure of input intensity. This relation makes it possible to convert rate coded amplitude values into a temporal code of spike timing. These neurophysiological observations link directly with the ideas of Kelso about relative phases being the main coordination parameter encoding valuable information in organisms, leading to the emergence of higher system levels channeling individual neuron responses.

In this way, oscillations allow to encode information and to define relations between the activity of spatially distributed neuron groups. When neuronal groups become entrained in synchronous oscillations, they will tend to emit spikes in synchrony and this enhances the impact that these output signals will have on target cells. Synchronization can thus be used to select signals for further joint processing and to accelerate the propagation of the signals across distributed networks.

The above leads to a discussion about the structure of information flows in neural networks (Engel *et al.* , 2001). According to the cognitivist view, the ideas of 'top-down' and 'bottom-up' were referred to the distinction between expectation-driven processing and stimulus-driven processing. In this way, behavior could be controlled largely by a sensory stimulus or dominated by intrinsic factors such as attention, memory or expectation of forthcoming sensory events. On the other hand, complex systems ideas introduce a new view of 'top-down' where the whole is able to determine the perception of the parts. However, coordinated temporal encoding of information lead us to another variant of a 'top-down' approach, in which large-scale dynamics can have a predominant influence on local neuronal behavior by 'enslaving' local processing elements. This idea of top-down would not require a processing hierarchy, but the dynamic 'capture' of neurons into a larger assembly could occur between areas at the same processing level or within an area. This kind of organization works by creating top-down dynamical loops between different cognitive levels. Also, as we are going to see below, these loops are not only limited to internal activity of the brain, but across the whole brain-body-environment system, allowing the brain to anticipate change in a fluctuating world.

Extending the loop: anticipation in brain oscillations

If the brain is considered as an active and adaptive system, comparison of sensor input with existing knowledge is essential for perception. Experimental data suggest that this is achieved by top-down modulation of sensory information processing, mediated by context-depending modification of the temporal patterning of neural responses, particularly by influencing their coherence. According to this view (Engel *et al.* , 2001), top-down factors would lead to states of 'expectancy' or 'anticipation', expressed in the temporal structure of activity patterns in the brain.

These process would be carried by large-scale assemblies where the entraining effects of neural assemblies carrying high-level representations over assemblies involved in the processing of new information would allow a continuous prediction of environmental inputs in a dynamical top-down process. Local patterns would be constantly subject to modulation by specific synchronizing and desynchronizing influences carrying predictions about specific feature constellations.

Top-down dynamical loops are not limited to neural assemblies but, in order to build anticipatory responses, have to cut across the brain-body-environment system. These top-down modulatory effects on neuronal activity have been seen to be played by attention, working memory and behavioral context. These kinds of processes would be the link between the self-generated temporal dynamics in neuronal networks with the view of the brain as an active and adaptive device.

2.5.2 Cognitive functions of cell assemblies

In previous sections, cell aggregation and disaggregation in the brain by means of synchronization has been presented as a fundamental mechanism for building cognitive states. These transient distributed subsets of neurons with strong reciprocal connections have been called *cell assemblies* or *neuronal ensembles*. A cell assembly can be activated or ignited from any of its smaller subsets, due to the assumed strong interconnections, and they must "hold" after its activation during an determined lapse of time.

Varela (2006) proposes that a singular and specific cell assembly underlies the emergence and operation of every cognitive act (perception-action, memory, motivation, etc.). Here, cell assemblies would emerge through fast, transient phase locking of activated neurons, understood as some kind of temporal "glue" that allows neural coherence. Cell assemblies would incorporate or discard external and internal information into its coherent activity, while different assemblies are evaluated until one is transiently stabilized and expressed behaviorally. The entire process takes the form of a bifurcation from a noisy background to the emergence of a transiently stable, distributed structure bound by synchrony.

The interpretation of transient coherency-generating process generated by the nervous system would constitute mental-cognitive states. As both external and internal influences are fundamental in the generation of cell assemblies, the sensorimotor loop must be taken as a whole. Since mental states must have a immediate neural consequences at the level of behavior and perception, they will have subsequently a direct effect on neural events (in the form of a downward causation). As well, mental states are always bound to the body, embedded in a particular field of sensation.

Metastability and Consciousness

Other theories about metastability in the brain stress its importance for explaining consciousness. A central role in these theories is given to the so-called Dynamic Core, a parallel and distributed dynamic process constituted by a large but distinct sets of distributed neuronal groups believed to be the integration center of consciousness (Werner & Jirsa, 2006). The Dynamic Core Hypothesis associates cognitive events with the formation of distributed clusters of neurons that, at the same time, are quite differentiated from the rest of the system, being able to detect features of particular signal inputs, and are able to functionally integrate, by temporal correlation and synchrony, these features into particular objects and background. A crucial point of the Dynamic Core Hypothesis is that, instead of thinking about integration and non-integration as binary and conflicting concepts with nothing in-between, the metastable nature of the Dynamic Core allows a continuum of integration.

Another inspiration for theories of consciousness and metastability is the Global Workspace Hypothesis proposed by Baars (1997). The theory postulates the existence of a multitude of small and unconscious processes that gain access to a limited capacity "global workspace", which is able to integrate competing and cooperating processes and is the gateway to consciousness. This global workspace would allow widespread interactions between otherwise independent brain functions, recruiting different unconscious processes when needed for solving problems or dealing with new situations. Different works have address the issue of supplying dynamics to the Global Workspace Hypothesis, allowing mechanisms by which sub-networks with synchronized activity can be transiently formed. This transient formation of functional neural complexes would be driven by phase transitions in metastable dynamics, being responsible for the existence of different cognitive events.

Anyway, despite of the importance of neural dynamics, it is necessary to describe conscious situated agents in terms of how neural dynamics are embedded in the somatic and environmental context of the animal's life (Thompson & Varela, 2001). In higher primates three kind of cycles are distinguished:

- The organismic regulation of the body, which is the base of emotional states (a primal consciousness or sentience, the feeling of being alive). This cycle would include biochemical interaction between brain and body, linking sensors and effectors to neural processes.
- Sensorimotor coupling, which links what the organism senses as a function of how it moves and how it moves as a function of what it senses. Here, neural assemblies would mediate the coordination of sensory and motor functional areas, and sensorimotor coupling with the environment would constrain and modulate this neural dynamics, allowing the organism to be a situated agent.
- Intersubjective interaction, which includes signaling of affective states and sensorimotor coupling to create different forms of social cognition. The former will be based in the mechanisms which make us able to perceive our own or others emotional states, while the latter would include mechanisms as the so-called 'mirror neurons', which generate sensorimotor loops necessary to recognize gesture of others.

2.6 Coordination for the engagement of Sensorimotor Loops

In conclusion, despite the advances of neuroscience describing the kind of dynamics that allow the emergence of cognitive behavior, the study of these dynamics in isolation seems not to be enough. As the dynamical approach to cognitive science have insisted during the last two decades, cognitive dynamics have to be understood within the different loops coupling internal neural dynamics with bodily and environmental dynamics.

So far, the main proposal is to study relative phase information as the order parameter in self-organized neural dynamics coordination. Two different behavior are hypothesized to take place in the human brain:

- Non-equilibrium phase transitions in synchronized systems, which establish different phase relations between the elements of the system, giving place to coding, binding and representation of information in the brain.

- Metastable dynamics, which allows the brain to rapidly switch between behavioral states, being able to create and vanish coherent patterns of neural activity, as well as flexibly engage and disengage subsystem of the neural substrate.

This two mechanisms would be responsible of generating top-down loops of dynamically capture of neurons in larger assemblies and, eventually, trespass the neural system to form part of sensorimotor loops. Thus, coordination dynamics would be responsible for the emergence of precisely regulated attraction and repulsion forces to form transient forms synchronization and metastability, allowing thus the engagement of stable or metastable sensorimotor loops.

The following chapter will address the great difficulties both in the experimental and theoretical levels for the study of how sensorimotor loops could arise based on these coordination mechanisms. We will analyze both the methodology and the tools necessary for studying the role of coordination in the behavior of embodied and situated agents.

Chapter 3

Tools for Designing Emergent Cognitive Behavior

In previous chapters, we have presented a conceptual framework to study cognition, based on the features of self-organized coordination in dynamical systems. These coordination mechanisms, based on different forms of synchronous and metastable entrainment of oscillating systems, would be the base for the emergence of sensorimotor loops. This view of cognition assumes that cognitive behavior is an extremely complex process emerging from tightly coupled physical, genetic, neural and environmental factors. Therefore, divide-and-analyze methodologies will not lead to a correct understanding of it.

In this chapter, we will introduce a methodology for understanding the emergence of cognitive behavior from sensorimotor loops: the synthesis of artificial agents that exhibit emergent adaptive behaviors, with the objective of understanding the processes of self-organization that lead to the engagement of sensorimotor loops in cognitive tasks.

Due to the limitations of analytical observation, we will go the other way around, trying out to discover the self-organized mechanisms that allow synthetic agents to display emergent behaviors, and observe how they are related with the natural phenomena we are interested in. We will propose to use evolutive techniques in minimal models to find the coordination mechanisms that allow agents to exploit sensorimotor couplings in ways that are not obvious for a designer. Additionally, we will propose two different tools for studying coordination within neural systems: continuous-time recurrent neural networks and Kuramoto oscillatory networks.

3.1 The Synthetic Approach: Understanding by Building

The approach we are proposing is the so-called constructive or synthetic approach. This approach is presented as a methodology used by the sciences of the artificial (e.g. artificial intelligence, robotics, or cognitive modeling) to contribute to the scientific research in life and cognition. These sciences increasingly claim to go beyond a mere engineering approach, and provide a purely scientific approach to crucial topics of natural sciences (like biology, psychology and neuroscience). Their proposal would conform a new methodology for these sciences to find the hidden mechanisms in natural systems.

This methodology, whose objective could be summarized in the idea of "understanding by building", presents a shift in the usual order of behavior analysis and model building. It requires the researcher to embed first basic hypothesis about life and cognition within a working model, and only then to examine the behaviors they produce. The objective behind this is to provide simple scientific explanations of complex natural systems (Damiano & Cañamero, 2010).

The hypothesis proposed by the synthetic approach allow us to consider artificial cognitive system models as knowledge generators by themselves. Once a model is situated in an environment, it can express behaviors that are unexpected even for the ones that constructed them, giving us new insights and feedbacks about the hypothesis on life and cognition we introduced in it. In this sense, models act as guides to discovery, helping us to advance by making predictions for future experimentation, extending the reach of a research program to new phenomena, solving conceptual problems within the program, casting empirical findings in a new light, and so forth (Barandiaran & Chemero, 2009). The 'understanding by building approach' demands the researcher to think and develop science as a form of knowledge which actively creates, and does not passively reflect, the phenomena explored.

If our objective is to gain insights into the studied phenomenon, we should make sure it is modeled at an appropriate level of abstraction. Frequently, neural dynamics models are criticized because they lack some set of features and are not a good representation of the nervous system. However, a more detailed model is not necessarily superior. Even when simulations can never substitute for empirical data, they are valuable tools for re-organizing and proving the internal consistency of a theoretical position (Di Paolo *et al.* , 2000).

As the reader will realize, the models presented in the following chapters are purposefully idealized. Since we are dealing with complex non-intuitive phenomena, the value of the models lie in their suitability for being analyzed to find the hidden mechanisms that allow the emergence of complex behaviors. The models presented here do not want to be an accurate representation of biological organisms but a minimal abstract representation of the mathematical principles that allow the emergence of cognitive behavior in living beings, regardless of how complex they are.

For this objective, simulations that use evolutionary techniques and dynamical systems agents are a good choice for build our models, since they require fewer assumptions than most other approaches.

3.2 The Evolutionary Approach: Building Systems Without Designer

When trying to follow the synthetic approach to construct cognitive systems that model biological functions, we find a major problem: hand-designed systems are not necessarily similar to the systems that have evolved (e.g. the brain). Engineering systems, and particularly AI systems, use to display behavior and properties that are quite different from living organisms. Features such as modularity, simple interfaces or strong rigid synchrony are usually showed by engineered designs not necessarily for their final performance but their feasibility of the design to be developed and managed. That is why evolutive techniques are an important tool for beginning to learn how to understand evolved systems (Izquierdo, 2008).

One of the most popular approaches to model brain-body-environment systems that exhibit characteristics shown by living beings is to mimic the evolutionary process by which these brain-body-environment systems are produced in nature (Nolfi & Floreano, 2000). Evolutionary algorithms have become a standard class of search techniques which are loosely based on biological evolution. They consist on an initially random population of genetic strings that encode relevant phenotypic characteristics of an agent. Genetic information is repeatedly subjected to evaluation, selection and reproduction using mutation and crossover operators. There are many different modalities of these basic techniques, including different genetic string encodings, different mutation and crossover operators, different evaluation and selection procedures, etc. The principal advantage of the evolutionary approach is the possibility of getting rid of a priori assumptions when modeling the behavior of synthetic agents.

Evolutionary algorithms can be used to model the shape or body properties of an agent, but in general they are used just to model the “nervous system” of the agent to achieve some behavior of interest. In the next sections we will analyze some of the possibilities for modeling this nervous system. Evolutionary algorithms have been used for evolving sensorimotor couplings, exploring the different strategies that solve a particular problem, evolving learning behaviors, etc. (Beer, 2008).

The use of genetic algorithms combined with general neural controllers has two advantages for the design of cognitive systems. First, it allows us to minimize the built-in preconceptions of how an agent must solve a cognitive task. Even when we already know how to solve a problem, we are interested in solutions that are different from what was expected. These counterintuitive solutions provide us with new ways of thinking about the task

A second reason is that genetic algorithms are going to make us easier to explore and exploit the dynamics of the sensorimotor loop. Situatedness and embodiment can play unexpected roles in the agent’s behavior, and genetic algorithms can exploit interactions and couplings that are not obvious for a designer. Thus, the exploratory power of genetic algorithms allows us to explore the complex dynamics of sensorimotor loops in a deeper way.

In the next sections of these chapters we introduce two candidates for neural controllers to model coordination dynamics by evolutionary techniques. The first is an already classical neural model within the dynamical systems approach community: continuous-time recurrent neural networks, which claims to be a general model of dynamical neural networks. The second is the Kuramoto model of oscillatory networks, which aims to model the behavior of non-linearly coupled oscillator networks. We will see how both models try to be as simple as possible while preserving the dynamical richness of the phenomena they represent.

3.3 Continuous-Time Recurrent Neural Networks

As we saw in chapter 1, the study of recurrent networks supposed a breaking point for connectionist approaches, allowing to study the temporal deployment of neural behavior. Since them, recurrent neural networks have become a popular tool for modeling dynamical controllers of embodied and situated agents. Even when there has been a great progress on computational modeling of specific neural circuits, it has been recognized the need for a more general theory of such circuits. Such general theory of neural circuits would help us to characterize the general parameter space structure of neural circuits, and the different dynamical behavior that lies in different regions of the system.

One approach towards this general theory of neural circuits are Continuous-Time Recurrent Neural Networks (CTRNNs), which are the *“simplest possible nonlinear continuous-time neural models”* (Beer, 2005). An N-neuron CTRNN is defined by a set of N ordinary differential equations:

$$\tau_i \dot{y}_i = -y_i + \sum_{j=1}^{N} w_{ji} \sigma(g_i(y_j + \theta_j)) + I_i \tag{3.1}$$

where y_i is the state of the i^{th} neuron, τ_i is the neuron’s time constant, w_{ji} is the weight of the connection from the j^{th} to the i^{th} neuron, θ_i is a bias term, g_i is a gain term, I_i is an external input, and $\sigma(x) = 1/(1 + e^{-x})$ is the standard sigmoid output function. CTRNNs have a plausible neurobiological interpretation, where the state y is often associated with a nerve cell's mean membrane potential and the output $\sigma(y)$ is associated with its short-term average firing frequency (Beer, 1995b).

CTRNNs are equivalent to the continuous neural network model that was popularized by Hopfield (1984), except that Hopfield placed restrictions on his networks such that only equilibrium points were possible. Even when the dynamics of CTRNN neurons are quite trivial, small CTRNN networks can reproduce qualitatively the full range of nerve cell phenomenology, including spiking, plateau potentials and bursting (Beer, 2005). And perhaps more importantly, CTRNNs are known to be universal approximators of smooth dynamical systems (Funahashi & Nakamura, 1993) if they are sufficiently large. In fact even small and simple dynamical neural networks can exhibit dynamics of significant complexity that may have important neurobiological implications (Beer, 1995b).

Within the scope of this thesis, we are interested in the use of CTRNNs as neural controllers of autonomous agents developing sensorimotor behavior. That is, how embodied and situated agents utilize their neural dynamics to coordinate the actions of its body with the spatiotemporal structure of its environment so as to accomplish the task necessary to its survival and reproduction. Following this idea, different works show how agents can be evolved to solve task like chemotaxis, locomotion of legged agents, learning behavior or discrimination between approaching objects (for a review, see Beer (2008)). Furthermore, CTRNNs have been applied to a wide variety of problems, including associative memories, optimization, biological modeling and many others (Beer, 1995b), also, a variety of learning algorithms for CTRNNs have been developed (Pearlmutter, 1990).

An analysis of the surprisingly rich dynamical behavior of quite simple neural networks can be found in Beer (1995b). In there, it is shown how different phase portraits can be found in two-neuron circuits (11, according to Beer), each one being able to show different local behaviors. In some of these phase portraits stable limit cycles (which imply self-sustained oscillatory behavior) coexist with equilibrium points, making it possible to switch this system between rhythmic behavior and two different quiescent states with appropriate input pulses. If three-neuron circuits are analyzed, too many different phase portraits are found with interesting properties, including circuits with up to 27 equilibrium points, circuits with two distinct periodic orbits, doubly periodic orbits, or circuits with chaotic dynamics. Also, an analysis of the effect of different types of inputs in these networks is performed.

The steady-state input/output (SSIO) curve of a single CTRNN neuron will play an important role to understand its dynamics. As we study the parameter space of CTRNNs, we find a special set of combination defined as center-crossing circuits, given by the condition $\theta_i = \sum_{j=1}^{N} w_{ij}/2$ (Beer, 1995b). When this condition is satisfied, the null manifolds of each neuron intersect at their centers of symmetry, or, equivalently, the SSIO of each neuron is centered over the range of synaptic inputs that it receives from the other neurons. Center-crossing circuits are important for a variety of reasons. First, the richest possible dynamics can be found in the neighborhood of such circuits. Second, the bifurcations of the central equilibrium point of a center-crossing circuit can often be fully characterized analytically. Finally, for any given weight matrix, the corresponding center-crossing circuit serves as a symmetry point in the net input parameter space for that circuit.

Further, theoretical analysis of the parameter space of CTRNNs has been performed (Beer, 2005), dividing it into regions of topologically-equivalent dynamics by bifurcation manifolds. Bifurcations can be either local or global. Local bifurcations involve changes in the neighborhood of a limit set and can be explicitly defined by algebraic conditions on the vector field and its derivatives in that neighborhood. For example, the change of stability of an equilibrium point as parameters are varied is a local bifurcation. In

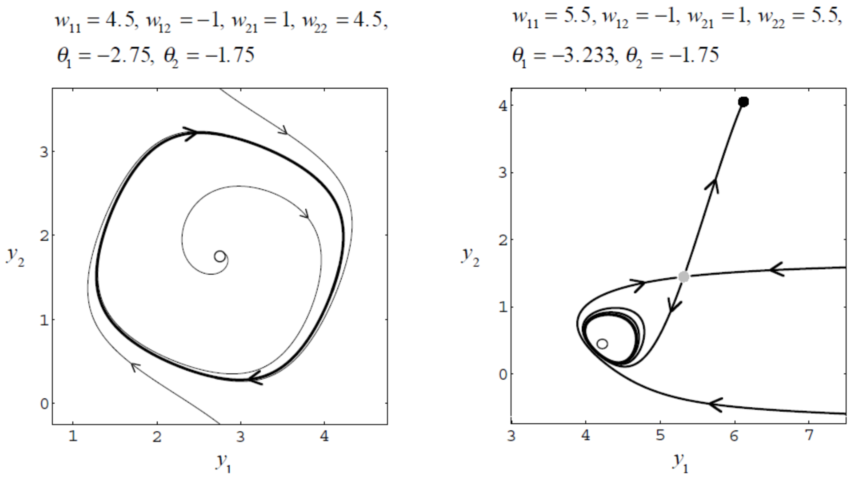


Figure 3.1: Two examples of qualitatively distinct phase portraits that can occur in a 2-neuron circuit. Stable equilibrium points are shown as solid disks, unstable equilibrium points are shown as circles and saddle points are shown as gray disks. Invariant trajectories (limit cycles and the stable and unstable manifolds of saddle points) are shown as thick lines. Taken from Beer (2005).

contrast, global bifurcations involve changes that are not localized to any particular limit set and can usually only be studied numerically. For example, saddle connections are global bifurcations in which the unstable manifold of one equilibrium point coincides with the stable manifold of another.

The previous study used probabilistic calculations to characterize the most likely behavior under various conditions, finding the probability that a random parameter sample will encounter a region of M-dimensional dynamics in an N-neuron circuit. Such calculations provide estimates of the dynamical complexity of randomly-chosen circuits. In addition, given that circuit boundaries become increasingly complex in higher dimensions, a statistical description can provide a very useful summary of the overall scaling of the structure of N-neuron CTRNNs. Probabilistic calculations are also important for the application of stochastic search techniques such as evolutionary algorithms to CTRNNs. Also, the probability of a circuit to show oscillatory behavior can be computed, characterizing when the network, instead of finding equilibrium points, shows periodic, quasi-periodic or chaotic dynamics.

Having this theoretical analysis of the behavior of CTRNNs and given our interest in the dynamics of coupled oscillators, another design possibility already pointed by Beer could be to start with two-neuron circuits exhibiting oscillations of different frequencies and amplitudes and evolve their coupling to achieve some overall dynamics of interest.

For a more detailed description of the properties and possibilities of CTRNNs we suggest the reader to revise the references given so far, where excellent reviews and analysis of the dynamic behavior of recurrent neural networks is encountered. In the next sections, we review other different tool which seems to be appropriate for the study of dynamically coupled oscillator networks and has been barely used as a neural controller for embedded and situated models.

3.4 Kuramoto Oscillatory Networks

In chapter 2 we have stressed the role of oscillations and synchronization in neural activity. Although recurrent neural models are able to model oscillations, it seems appropriate to have models that more directly address the nonlinear coupling effects in oscillator networks, taking relative phases of oscillators (our favorite order parameter, as we have seen in chapter 2), as the main variable of the system.

The oscillator network model described by Kuramoto (1984) was originally proposed to study the phenomenon of collective synchronization, where large numbers of oscillators with different intrinsic frequencies spontaneously lock to a common frequency. Such system have plenty of biological examples, as pacemaker cells in the heart, circadian pacemaker cell in the brain, metabolic synchrony in cells, flashing fireflies, chirping crickets, arrays of laser or microwave oscillators (Strogatz, 2000).

Kuramoto networks exhibit the temporal analog of a phase transitions: after a certain threshold is crossed, clusters of oscillators suddenly freeze into synchrony. This could explain the spontaneous emergence of rhythms in non-equilibrium open systems. In this sense, the Kuramoto model is more general than other models like the HKB model, and has become a widespread theoretical model for brain oscillations (Breakspear *et al.* , 2010). These oscillators might be interpreted as individual oscillatory neurons, the activity of neuronal groups, tissues or brain regions or as the result of the activity of interactions between such regions, like EEG recordings. Anyway, according to the objective of this work what matter to us is not the level of empirical accuracy of the model but its capacity to raise theoretical issues and open new insights into dynamical modeling and analysis of brain-behavior patterns.

The Kuramoto model consists on a reduction of the oscillatory system to a phase model, where the long-term dynamics are given by phase equations representing a sinusoidal coupling:

$$\dot{\theta}_i = \omega_i + \sum_{j=1}^{N} k_{ij} \sin(\theta_j - \theta_i) \tag{3.2}$$

where θ_i is the phase of the i^{th} oscillator, ω_i is the oscillator's intrinsic frequency, N is the number of oscillators and k_{ij} is the coupling factor from the j^{th} to the i^{th} oscillator.

Complex Order Parameter

According to Kelso (1995), the differences among intrinsic frequencies and coupling coefficients would constitute the control parameter of the system, and relative phases would be the coordination variables (order parameters) of the system. But, as we have now more than two oscillators, it may be necessary to find a higher level variable which captures the network dynamic. A good candidate is the macroscopic phase coherence of the system (Kuramoto, 1984), representing the relative phases among the oscillators of the whole network. This variable, which we will call the order parameter of the system, consists in averaging all the oscillators, being represented as a swarm of points running around the unit circle in the complex plane:

$$r\, e^{i\psi} = \frac{1}{N} \sum_{j=1}^{N} e^{i\theta_j} \tag{3.3}$$

This complex order parameter is a macroscopic quantity that represents the collective rhythm produced by the whole population. It corresponds to the centroid of the phases. The radius $r(t)$ measures the phase coherence and $\psi(t)$ is the average phase (Strogatz, 2000). For example, if $r \approx 1$ the whole system would act like a giant oscillator, and if $r \approx 0$ the oscillators would behave incoherently and no macroscopic rhythm would be produced.

Phase transitions

The easiest way to get an insight about the behavior of Kuramoto oscillatory networks is perform simulations and see how does $r(t)$ evolves. And the simplest Kuramoto network is the one in which all k_{ij} have the same value K. For this simple oscillatory network, simulations show (Strogatz, 2000) that for all K less than a certain threshold K_c, the oscillators act as if they were uncoupled: the phases become uniformly distributed around the circle, starting from any initial condition, and $r(t)$ decays to 0. But when K exceeds K_c, the previous *incoherent state* becomes unstable and $r(t)$ grows exponentially, reflecting the creation of a small cluster of oscillators mutually synchronized. The oscillators with intrinsic frequency near the mean frequency of the system will become part of this synchronized cluster. The rest of the oscillators will run near their natural frequencies and drift relative to the synchronized cluster. With further increases in K, this *partially synchronized state* will evolve to a full synchronization as more and more oscillators are recruited into the synchronized clusters and $r(t)$ grows towards 1 (figure 3.2.)

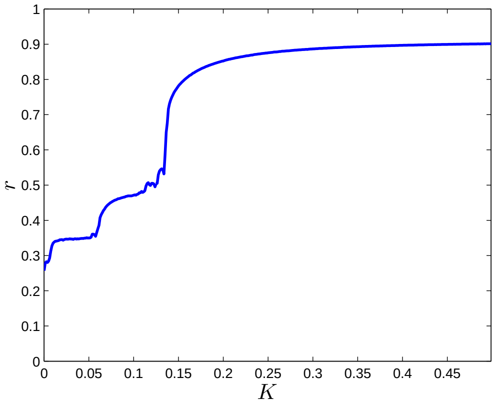


Figure 3.2: Phase transition in a network of 10 oscillators with random frequencies when we increase the value of the coupling factor K, which is the same for all oscillators. We observe how more and more oscillators are recruited into a cluster of synchronized oscillators.

3.4.1 Plasticity and Learning in Oscillatory Networks

Mechanisms of adaptation and learning have been a fundamental topic of interest in cognitive sciences. Most adaptive models of neural networks use different types of Hebbian learning rules, based on the idea that synaptic coupling between two neurons is enhanced if both neurons are simultaneously active (Hebb, 1949).

Kuramoto networks usually have a connectivity matrix which is imposed externally to achieve the desired network dynamics, a task which present difficulties when operating with networks with a large number of oscillators. In contrast, in biological neural networks this task is performed in a self-organized way, via mechanisms of synaptic plasticity, i.e., via potentiation or depression of synapses in response to the dynamics of presynaptic and postsynaptic neurons. In neural networks external stimuli affects directly just to the dynamics of individual neurons, not their connections. However, synaptic plasticity is achieved as a result of the interneuronal interactions.

An adaptation of Hebbian learning rules to Kuramoto networks was proposed by Seliger *et al.* (2002), assuming that the coupling coefficient for a link between two oscillators is a slow function of their phase difference:

$$\begin{cases} \dot{\theta}_i = \omega_i + \sum_{j=1}^{N} k_{ij} \sin(\theta_j - \theta_i) \\ \dot{k}_{ij} = \epsilon(\alpha \cos(\theta_i - \theta_j) - k_{ij}) \end{cases} \tag{3.4}$$

representing that the coupling coefficient grows fastest for two oscillators that are in phase and decays fastest for out-of-phase oscillators, as would correspond for the Hebbian rule. The speed of the coupling coefficient dynamics is going to depend proportionally on ϵ, while α is going to determine how effectively the connection between two oscillators is strengthen by their degree of synchronization. The result of this rule is a multistable behavior, in which a group of oscillators can either be stably synchronized or nonsynchronized depending on the initial conditions of their coupling coefficient.

Another interesting property of this learning rule is that, if we consider a small value of ϵ, the coupling coefficients are either non-stationary and small, for oscillators operating at different frequencies, or fixed for two oscillators that are synchronized. So, as we approach to the limit $\epsilon \to 0$, we can neglect all k_{ij} for nonsynchronized oscillators, and define $k_{ij} = \alpha \cos(\theta_i - \theta_j)$ for synchronized oscillators. Substituting this into Eq. 4.4 we obtain that oscillators within the same synchronized cluster follow the equation:

$$\dot{\theta}_i = \omega_i + \sum_{j=1}^{N} \frac{\alpha}{2} \sin(2(\theta_j - \theta_i)) \tag{3.5}$$

while for the oscillators that do not belong to a cluster $\dot{\theta}_i = \omega_i$, which would be equivalent to the Kuramoto model for the double phases.

3.4.2 Information Measures in Oscillatory Networks

When studying complex systems, due to the inherent nonlinear nature of local interactions, the whole system must be simultaneously considered. In consequence, generally it is hard to know much about the relative importance of individual nodes within a system. This is the case for synchronization in oscillator networks, which usually are analyzed as a whole, being the process of synchronization somewhat like a 'black box', with the initial state of the system as an input and synchrony as an output.

Ceguerra *et al.* (2011) proposed to use an informationally-based approach to analyze local dynamical process occurring in oscillator networks during the synchronization process at an individual level. Concretely, they proposed an emerging technique in complex system science: *local information dynamics* (Lizier, 2010). Information dynamics refers to the storage, transfer and modification of information by the elements of a system performing a distributed computation, and it particularly focuses on how these operations vary in time and space.

Information storage refers to the amount of information in the past of a variable that is relevant to predicting its future. The *local active information storage* for a variable X is the local (un-averaged) mutual information between its semi-infinite past $x_n^{(k)} = \{x_{n-k+1}, ..., x_{n-1}, x_n\}$ (as $k \to \infty$) and its next state x_{n+1} at time step $n+1$:

$$a_X(n+1) = \lim_{k\to\infty} \log_2 \frac{p(x_{n+1}|x_n^{(k)})}{p(x_{n+1})} \tag{3.6}$$

Finite-k estimates are represented as $a_X(n,k)$. And the active information storage is the average over time: $A_X = \langle a_X(n) \rangle_n$. The meaning of the local active information storage $a_X(n+1)$ is the stored information that is currently in use by variable X in computing its next state x_{n+1} at time $n+1$.

Information transfer is the information provided by a source about a destination's next state that was not contained in the past of the destination. The local *transfer* *entropy* from a source Y to a destination X is the mutual information between the previous state of the source y_n and the next state of the destination x_{n+1}, conditioned on the semi-infinite past of the destination $x_n^{(k)}$ (as $k \to \infty$):

$$t_{Y\to X}(n+1) = \lim_{k\to\infty} \log_2 \frac{p(x_{n+1}|x_n^{(k)}, y_n)}{p(x_{n+1}|x_n^{(k)})} \tag{3.7}$$

Again, $t_{Y\to X}(n+1, k)$ represents the finite-k estimates, and the transfer entropy is the time average $T_{Y\to X} = \langle t_{Y\to X}(n)\rangle$. The transfer entropy measures directed, dynamic flows of information, removing any stored information from being considered as transfer.

Ceguerra *et al.* apply these measures on the time-series of differentials $\dot{\theta}_i$, computing how much of the change in phase each time step for a given node can be predicted from its own past (A_X) and how much can be predicted from each of its neighbors that was not in its past ($T_{Y\to X}$). Since the values of the model are continuous-valued, they computed the measures using kernel estimation (Schreiber, 2000), finding that values of $k = 2$ were enough for accurately computing the measures.

Their results show that, during the phase transition from incoherence to synchronized behavior, information storage falls while transfer increases; reflecting decreased unilateral behavior and increased coordination between nodes. Once a synchronized state is reached, information transfer vanishes between nodes, because the nodes' behavior is then predictable from its own past. Also, information measures show that information transfer stops much earlier than the moment when the order parameter shows that a coherent state has been reached, i.e., the distributed computation by the system which makes synchrony possible is complete much earlier than it would appear synchrony is actually achieved. Meaning that the process of synchronization just points the system in the correct direction and lets it go to run its course.

3.4.3 Kuramoto Networks as Neural Controllers

Evolutionary robotics have been recognized as a useful tool in investigating biological hypotheses capturing essential elements of the brain-body-environment interactions that underlie the generation of behavior, in a way that studies of disembodied neuronal dynamics cannot achieve (Beer, 2003). The interesting point of evolutionary robotics is that, even when there are insufficient details to fully specify a system in advance, it allows the exploration of classes of mechanisms and the automatic creation of working models (Harvey *et al.* , 2005).

There has been plenty of work on coupled oscillator networks as controllers of complex motor behaviors, particularly in the field of locomotion (Ijspeert *et al.* , 2005). However, to date there has been very little research on the wider issues of neuronal synchronization and phase information in the generation of embodied cognitive behaviors. One of the pioneer steps in this direction is the work of Moioli *et al.* (2010) in which they used a network of oscillators as the nervous systems of simulated robotic agents engaged in some minimally cognitive tasks. Their main contribution to the Kuramoto model, is to suggest how oscillatory networks can be provided with input and output mechanisms, so they are able to engage in sensorimotor brain-body-environment loops.

Thus, they propose to modify the original Kuramoto equation in a way that the frequency of each node is the result of the sum of its natural frequency of oscillation with the scaled value of the sensory input related to that node:

$$\dot{\theta}_i = (\omega_i + z_i I_i(t)) + \sum_{j=1}^{N} k_{ij} \sin(\theta_j - \theta_i) \tag{3.8}$$

where $I_i(t)$ is the value of the different sensory inputs at instant t and z_i is the scaling value. As well, the outputs of the system can be defined as the sine of the phase differences of two particular oscillators (Santos *et al.* , 2011) or as the linear combination of the sine of ensembles of phase differences (Moioli *et al.* , 2010).

Santos *et al.* (2011) also showed how measures used in neuroscience for the detection on neural assemblies (especially those working in the binding problem, seen in section 2.3.2), like the measure of the moments of (quasi) phase-locking, by filtering out moments of phase-scattering, could be useful for understanding the nature of sensorimotor loops.

3.5 Synthetic Minimal Cognitive Agents for Understanding the Emergence of Sensorimotor Loops

As we have claimed at the beginning of this chapter, our objective is to analyze the emergence and function of sensorimotor loops in cognitive behavior. However, due to the nonlinear and counterintuitive properties of self-organized emergent systems this is not an easy task. That is why our research approach involves to analyze the behavior of minimal models, solving simple tasks in dynamical environments, as our contribution will show.

At first glance, it could seem that we are building nothing but ‘toy models’ that have little to do with real-world problems. However, as the reader will observe, even in quite simple systems can perform surprising behaviors when we design our agents as dynamical systems. Even in these simple models it is not intuitive to understand how the agent’s behavior arises, especially when we generate our models with genetic algorithms. And it is by analyzing the behavior of our agents how we are going to gain insights about the role of their different dynamical couplings.

We deliberately want our models to be simple to get rid of some of the constraints we have to face in more complex environments (like robotics), and go straight to analyze the mathematical models that are behind the properties we want to study. We are not interested in practical implementations but in the general abstract mechanisms that are behind the emergence of intelligent behavior.

In this sense, these simple models will be a first test to prove the consistence of the proposals we have made about the role of coordination dynamics and sensorimotor loops in the generation of cognitive behavior. We have hypothesized that cognition is built upon sensorimotor coupling generated by synchronous and metastable entrainment of neural patterns. In the next part of the thesis, these ideas will be embedded in two different synthetic models. We will present two case studies for testing the claims made in this first part. Firstly, we will explore the implications of metastable dynamics in the organization of behavior at different levels of the biological dominion, through the resolution and implementation of a model related to different instances of “intermittent behavior” in diverse living beings. In a second place, we will built an embodied and situated agent facing a simple phonotaxis task, with the objective of analyzing the role of coordination mechanisms for building a sensorimotor loop.

Part II

Metastability and Synchronization in the Sensorimotor Loop

Chapter 4

Intermittency and Metastability in Organism's Behavior

The brain makes use of metastable dynamics in which neural patterns continuously fall outside their natural equilibrium state, rapidly switching from one state to another. This principle is necessary for the brain's ability to make sense out of seemingly random environmental cues. In this chapter, we compare these intermittent mechanisms observed in the brain with the behavioral patterns of organisms that display intermittent behavior. These organisms continuously alternate behavioral patterns when they have to adapt to complex situations, similarly to metastable brain dynamics.

Thinking that these phenomena are based in a common principle, we formulate an abstract model trying to capture the essence of both of them. In this way, intermittency could be a general strategy broadly used in biological organization (from neural to behavioral and cognitive levels) for adapting to unknown changing environments. This model shows how a system that maximizes its interactions with its environment and displays suboptimal solutions to a problem is more suitable for adapting to a changing environment than steady models that try to maximize their current fitness at a given time.

Finally, we analyze the minimal mechanisms necessary for implementing a system that follows an intermittent strategy and we search for the conditions to embed them in the sensorimotor loop.

4.1 Intermittent Strategies

As we have seen in chapter 2, the brain is a device of great complexity whose dynamics are built upon highly flexible metastable states. By living between stable (attracting) and unstable (repelling) influences, our mind can switch gracefully between distributed neural states. Rather than using an active force to destabilize and switch from one stable state to another, mental states consist in intermittent, short-lived, transient events that vanish to leave room for new ones. In this way, we could say that neural coordination dynamics does not possess any stable states at all, since they are constantly flowing from one state from another.

The way the brain handles the complex task of adapting to unpredictable and changing environments is becoming intermittent. By the transient integration of numerous, distributed, constantly interacting parts of the brain, neural subsystems are flexibly engaged and disengaged to adapt to changing situations. Accordingly, phase synchronization and desynchronization allows the brain to rapidly switch among suitable mental states. However, neural dynamics is not the only domain where we can find this kind of intermittency between metastable states. We see in nature how different organisms happen to act alternating different short-lived states at different levels of behavior. Indeed, many organisms' behaviour is intermittent: they move, pause, and move again (Kramer & McLaughlin, 2001).

We could wonder whether intermittent behavior is 1) just a epiphenomenon, i.e., a consequence derived from the intermittent nature of neural organization; 2) a consequence of physical or dynamical constrains (e.g. the muscles needing to rest after some time of activation and therefore acting intermittently); or 3) a strategy developed by organisms to face the challenge of dynamically adjusting their behaviour to changing environments. If the latter is true, we could ask ourselves if the alternation of intermittent modes of behavior could be a general strategy developed at different levels of biological organization to adapt to complex, ever-changing environments the same way as the brain does.

Trying to offer an answer to this question, in this chapter we depict intermittent behavior view from the perpective of coordination dynamics. We have worked recently in what we called *the adjustment-deployment dilemma* (Aguilera *et al.* , 2011) in which an agent has to find an equilibrium between two complementary behaviors. This dilemma captures the difficult compromise between the time spent in adjusting a response and the time used to deploy it: the adjustment process improves fitness with time but it is also assumed that such fitness decays with time (e.g. environmental conditions change), if you spend very little time adjusting the fitness of the action is poor, but if you spent too much time before deployment the result is no longer valid. We review the mathematical model of the dilemma, with the objective of (1) analyzing whether intermittency could be an universal mechanism to deal with adaptation to complex situations and (2) gaining insights about how metastable regimes could be responsible for the intermittent solutions that different organisms find for adaptation to their environments.

4.2 Introduction: Intermittent Behavior and the Adjustment-Deployment Dilemma

Most models of biological behavior are based on steady state assumptions, considering that actions occur at constant speeds. However, many organisms' behavior (ranging from protozoans to mammals) is intermittent: they move, pause briefly, and move again. These pauses last from milliseconds to minutes, being part of a dynamical system by which organisms adjust their behavior to changing environments (Kramer & McLaughlin, 2001).

Intermittent behavior is a widespread biological pattern. Despite the energetic costs of acceleration and deceleration, a variety of benefits arise when pauses are alternated with action. Intermittent bounding and undulating flight modes in birds (which alternate periods of flapping with pauses where wings are either extended to permit gliding or held close to the body) save mechanical power compared to continuous flight over a broad range of speeds (Rayner *et al.* , 2001). A similar effect takes place in fishes 'burst-coast' swimming (Videler & Weihs, 1982). Many species, when chasing a prey, alternate pauses and moves to stabilize their sensory field. Thus, while moves tend to be straight, both pursuits of a prey and changes of direction are initiated after pauses (Lock & Collett, 1979; Evans & O'Brien, 1988; Tye, 1989). 'Saltatory search' in foraging animals (from insects and lizards to mammals) minimizes the search time by alternating phases of fast motion and phases of intensive search (Anderson *et al.* , 1997; Bénichou *et al.* , 2005).

Additionally, intermittent behavior has benefits that are related not that much with external physical behavior but also the dynamics of mental processes like attention to the visual field. For example, when examining the visual field, eye movement is not smooth but alternates rapid eye movements (saccades) in which perception is suppressed, interspersed with stable intervals (fixations) in which the brain is able to process and recognize central objects of the scene and locate peripheral objects which will be target in the next saccade (Schall & Thompson, 1999). Other examples in that sense are primates pausing briefly while moving between trees in the canopy, being the pauses related to the requirement to identify a route for the next movement sequence (Cannon & Leighton, 1994)

All these examples, all along the biological spectrum, follow a common underlying pattern that combines two mutually-exclusive stages:

- *Adjustment* would be a behavior that improves the position of an organism or increases its possibilities of making the most of its situation. This could be done by increasing potential energy during flapping, augmenting perception in a pursuit to localize the prey, moving to non-explored areas in searches, perform exploratory eye movements, or pause to process the different possible routes through the trees.
- *Deployment* would be a behavior that takes advantage of the possibilities generated in the previous phase. Here is where our examples can keep flying without further energetic costs, moving towards the chased prey, scanning the new area, fixate the eye position for allowing mental processing of the image, or keep moving through the forest.

Interestingly, the intermittency between adjustment and deployment is not a mere sequencing of complete or autonomous behavioral patterns, but poses a problem of functional coordination dynamics: How long do I have to spend gliding before I flap again? How much time do I need to spend focusing and pointing before I shoot? What is the best ratio between stopping for orientation and walking in a changing environment? A correct dynamic equilibrium between adjustment and deployment is crucial in most cases and might change under different circumstances. We have coined the term *adjustment-deployment dilemma* to name a generic characterization of this problem. To our knowledge, no explicit theoretical, mathematical or simulation approach has yet explicitly addressed it.

Despite the ubiquity of this intermittency between adjustment and deployment, most computational and theoretical models typically operate on two broad categories of modeling frameworks: a) continuous and situated steady behavior (e.g. the agent approaches a light source but does not stop to rest, orient or propel itself) or b) some kind of action selection or decision making procedure that operates over a perceived situation and then triggers a behavioral response (without much consideration of the temporal dimensions of the interaction). In both frameworks the temporal structure of the adjustment-deployment dilemma is either absent (due to abstraction and simplification assumptions or due to the constrained scope of the modeled behavior) or is hidden to explicit analysis (since the focus typically remains on global task performance or specific mechanisms and procedures).

4.3 Formalization of the Adjustment-Deployment Dilemma

In order to explore the adjustment-deployment dilemma we have simplified the problem to its minimal form. In general terms we have an organism adjusting its behavior (or solution to a problem) and then executing or deploying it. We can take for example the case of a toad chasing a prey, having to alternate movement with pauses for stabilizing its visual field (Lock & Collett, 1979). In the absence of obstacles the toad is going to move towards the position where the prey was just the instant before the toad started to move. Prey velocity has no influence on the direction of the toad's movement. Also, when the toad is moving it is not going to correct its course if the prey is changing its position. The distance the toad walks in a single bout is going to depend on the initial separation between the toad and prey, and it is not altered if the prey vanishes or moves during the toad's approach. Both the distance moved and the direction of the toad are not corrected by visual feedback until the toad stops its movement (figure 4.1).

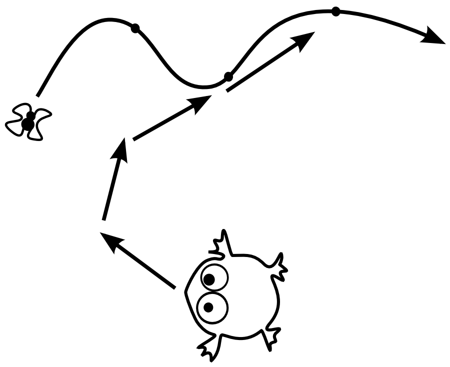


Figure 4.1: Representation of a toad moving intermittently while chasing a prey. The toad only can change its direction when it stops, due to the visual blurring while it is moving.

In terms of our adjustment-deployment dilemma, the toad has to alternate between a 'move' state, where it can approach the prey, and a 'stop' state, in which it can stabilize the image it perceives and update the information about the prey's position. Thus, the toad has to find an equilibrium between adjusting its orientation and deploying a pursuit behavior. We also can see how the relative amount of time expended in either state is going to depend on the dynamics of the problem. When the prey move slowly or when it is far away, the toad has less necessity of adjusting its behavior, and can move during longer amounts of time, while when the prey moves fast or it is too close, the toad has to stop and adjust its orientation more frequently, having less time for effectively moving towards the prey.

Table 4.1: Minimal intermittent behavioral model: concepts

Concept	**Notation**	**Behavior**	**Description**
Suitability	$f(t)$	Adjustment: $f(t) = (1 - e^{-t/\tau})$ Deployment: $f(t) = (e^{-t/\varepsilon})$	Mean ability of an organism of maximizing the achievement of its goals.
Choice	$\gamma(t)$	Adjustment: $\gamma(t) = \gamma_0$ Deployment: $\gamma(t) = \gamma_1$	Binary exclusive choice of an organism between adjustment and deployment.
Performance	$\overline{p}(t)$	$\overline{p}(T) = \frac{1}{T}\int_0^T \gamma(t) \cdot f(t)dt$	Mean results obtained during deployment.
Optimal solution	$f_{opt}(t)$	$f_{opt}(t) = \underset{f(t)}{\arg\max}\ \overline{p}(t)$	Behavior that maximizes performance.

More explicitly, we have expressed the model in a series of mathematical terms, which are seen in Table 4.1. We introduce them below.

Suitability (Fitness)

It represents the mean ability of an organism of maximizing the chances of achieving its goals, i.e., obtaining a successful solution for a given problem or situation. The suitability (or the quality) of a solution in an instant t is denoted by a fitness function $f(t) \in [0, 1]$. We will assume that:

1. The organism has an adjustment mechanism for improving its behavior over the environment. It is known the functional relation between the quality of a solution and time during adjustment. Generally, it is a nonlinear function (the effort in obtaining better results grows in relative terms with time), and we assume it to be exponential, $f(t) = K(1 - e^{-t/\tau})$, where τ is the adjustment speed.
2. We assume that the solution degrades throughout time as the environment changes. Also being exponential the functional dependency between quality of a solution and time, i.e., $f(t) = K(e^{-t/\varepsilon})$, where ϵ stands for the degradation rate.

In the case of the toad, the fitness will correspond to the difference between the prey location and the toad's orientation. When the toad is pointing the prey fitness is 1, and it starts decreasing when the prey moves.

Choice

The resolution structure of the dilemma can be captured with a single variable denoted by $\gamma(t) \in \{\gamma_0, \gamma_1\}$, that is, as the binary exclusive choice of the system over time, γ_0 representing adjustment and γ_1 deployment.

Now, the following equations to describe the behavior of the system result from the previous formalization:

- **Adjustment:** $f(t) = 1 - e^{-t/\tau}, \quad \gamma(t) = \gamma_0$
- **Deployment:** $f(t) = e^{-t/\varepsilon}, \quad \gamma(t) = \gamma_1$

The structure of the dilemma can thus be reduced to finding the strategy (i.e. the value of $\gamma(t)$) that obtain the better results.

Performance

In order to compute the quality of the obtained results by a specific choice function $\gamma(t)$, we will define the evolution of the fitness over time:

$$\dot{f}(t) = \begin{cases} \frac{1}{\tau}(1 - f(t)), & \gamma(t) = \gamma_0 \\ -\frac{1}{\varepsilon} f(t), & \gamma(t) = \gamma_1 \end{cases} \tag{4.1}$$

The agent performance will be obtained just integrating the fitness of the system during the deployment periods (the ones in which the agent is obtaining a benefit from the world, so we will take $\gamma_0 = 0$, and $\gamma_1 = 1$). Both previous functions can be combined, obtaining the global behavior equation:

$$\dot{f}(t) = -\gamma(t) \cdot \frac{1}{\varepsilon} f(t) + (1 - \gamma(t)) \cdot \frac{1}{\tau}(1 - f(t)) \tag{4.2}$$

And the quality of the obtained results will be defined by the performance of the agent, $\overline{p}(T)$, evaluated in an interval $(0, T)$:

$$\overline{p}(T) = \frac{1}{T} \int_0^T \gamma(t) \cdot f(t) dt \tag{4.3}$$

4.4 Formal Solution of the Adjustment-Deployment dilemma

Once the problem is defined, we proceed to compute the values that offer a maximum value of $\overline{p}(T)$. We have,

$$\begin{cases} \dot{f}(t) = \frac{1}{\tau}(1 - f(t)) - \gamma(t) \cdot (\frac{1}{\tau} + f(t) \cdot (\frac{1}{\varepsilon} - \frac{1}{\tau}) \\ \dot{p}(t) = \gamma(t) \cdot f(t) \end{cases}$$

where $\gamma(t) = \{0, 1\}$ and we want to find the set $\{\gamma_k(t_k)\}$ that maximizes $p(t)$. If we discretize,

$$\begin{cases} f_{k+1} - f_k = -h(\frac{1}{\tau}(1 - f_k) - \gamma_k \cdot (\frac{1}{\tau} + f_k \cdot (\frac{1}{\varepsilon} - \frac{1}{\tau})) \\ p_{k+1} - p_k = h(\gamma_k \cdot f_k) \end{cases}$$

where h is a temporal step, $k = 0, 1, 2, ..., N$, so $f(0) = f_0$, $p(T) = p_N$, given $T = \{t_1, t_2, ..., t_N\}$. For the sampled version the problem can be reformulated by the following statement (knowing that h is constant):

"Find the set of decisions $\{\gamma_k(t_k)\}$ that maximizes $\sum\limits_{k=0}^{N} \gamma_k f_k$". That is, the $\{\gamma_k(t_k)\}$ values must be computed providing that,

$$p_N = \underset{\gamma_0, \gamma_1, \cdots \gamma_N}{max} \sum_{k=0}^{N} \gamma_k f_k \tag{4.4}$$

which, since it starts in a_0 will be denoted by $p_N^{MAX}(a_0)$.

For solving the problem it is applied the Bellman Algorithm: *"An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision"* (Bellman, 1957). The Bellman algorithm computes the complete sequence $(\gamma_0, \gamma_1, ...\gamma_N)$ in a recursive way and backwards:

$$p_N^{MAX}(f_0) = \max_{\gamma_0}[\gamma_0 f_0 + \max_{\gamma_1, \cdots \gamma_N} \sum_{k=1}^{N} \gamma_k f_k], \text{ where}$$

$$\mathrm{p}_{N-1}^{MAX}(f_1) \max_{\gamma_1, \cdots \gamma_N} \sum_{k=1}^{N} \gamma_k f_k,$$

Iterating, we obtain the sequence:

$$p_N^{MAX}(f_0) = \max_{\gamma_0}[\gamma_0 f_0 + \max_{\gamma_1}[\gamma_1 f_1 + \max_{\gamma_2}[\gamma_2 f_2 + ... + ... + \max_{\gamma_N}[\gamma_N f_N]]...]$$

For solving the system, we must start from the last decision to the first. Since the last does not affect to the future, the maximization is local. In our case, it is:

$$\gamma_N(t_N) = \begin{cases} 1, & \text{if} \quad f_N \in (f_M,\, 0), \ \dot{f}_N < 0 \\ 0, & \text{if} \quad f_N \in (0, f_M), \ \dot{f}_N > 0 \end{cases}$$

and therefore,

$$p_0^{MAX}(f_N) = \begin{cases} f_N, & \text{if} \quad f_N \in (f_M,\, 0), \ \dot{f}_N < 0 \\ 0, & \text{if} \quad f_N \in (0, f_M), \ \dot{f}_N > 0 \end{cases}$$

that is, depending on if the system is in an adjustment or a deployment phase. Once we know what is the optimal decision in $\gamma_N(t_N)$, the previous instant $\gamma_{N-1}(t_{N-1})$ is computed, applying the following equation:

$$p_1^{MAX}(f_{N-1}) = \max_{\gamma_{N-1}}[\gamma_{N-1} f_{N-1} + p_0^{MAX}(f_N)]$$

we know that

$$f_N = f_{N-1} - \tfrac{h}{\tau}((1-f_{N-1}) - \gamma_{N-1}\cdot(1+f_{N-1}\cdot(\tfrac{\tau}{\varepsilon}-1)), \text{ therefore}$$

$$p_1^{MAX}(f_{N-1}) = \max_{\gamma_{N-1}}[\gamma_{N-1} f_{N-1} + p_0^{MAX}(f_{N-1} - \tfrac{h}{\tau}((1-f_{N-1}) - \gamma_{N-1}\cdot(1+f_{N-1}\cdot(\tfrac{\tau}{\varepsilon}-1)))]$$

Given $\gamma_{N-1} = \{0,1\}$, we only have to compute which one of the two cases is larger:

$$f_{N-1} + p_0^{MAX}[(1-\tfrac{h}{\varepsilon})\cdot f_{N-1}] \gtrless p_0^{MAX}[(1-\tfrac{h}{\tau})\cdot f_{N-1} + \tfrac{h}{\tau}]$$

The equilibrium condition meets for a critical f_{N-1} value, denoted as f^*_{N-1}, that allows to rewrite the equation in the following way:

$$p_1^{MAX}(f_{N-1}) = \begin{cases} f_{N-1} + p_0^{MAX}[(1-\frac{h}{\varepsilon})\cdot a_{N-1}], & \text{if } f_{N-1} > f^*_{N-1} \\ p_0^{MAX}[(1-\frac{h}{\tau})\cdot f_{N-1} + \frac{h}{\tau}], & \text{if } f_{N-1} \leqslant f^*_{N-1} \end{cases}$$

The procedure can be repeated for $(k = 2, ..., N)$ obtaining the values of $\{f^*_0, f^*_1, ..., f^*_{N-1}, f^*_N\}$ by iteratively solving the equation:

$$p_{N-k}^{MAX}(f_{N-k}) = \max_{\gamma_{N-k}}[\gamma_{N-k} f_{N-k} + p_{k-1}^{MAX}(f_{N-k} - \tfrac{h}{\tau}((1-f_{N-k}) - \gamma_{N-k}\cdot(1+f_{N-k}\cdot(\tfrac{\tau}{\varepsilon}-1))),$$

$$k = 1, ..., N. \tag{4.5}$$

Figure 4.2 shows the solution of the problem for given values of τ and ϵ. We see how the optimal strategy for solving the adjustment-deployment dilemma is not the one that maximizes the fitness in a given instant of time. Instead, the best solution is actually the one that reaches a suboptimal solution and, instead of keep enhancing it, maintains it constant throughout time. Our results show that the global result does not depend on the quality of the chosen solution, but in how it is coupled in the available time window.

4.5 Intermittent Adaptation: Maximizing Interactions with the Environment

What do the previous results mean? As seen in Figure 4.2, the obtained optimal strategy for solving the adjustment-deployment dilemma tends:

- not to maximize the fitness but to reach a intermediate value (f^*_n) which is kept until the process is about to end.
- to maximize the number of behavioral changes (i.e the alternation between adjustment and deployment).

Let's go back to the toad's example. We have an agent that had to act in a changing environment. Also, when the toad is performing a task in this environment (chasing the prey), the toad does not know how the environment is changing. In our model we suppose that the toad 'knows' how fast the environment (the position of the prey) is changing, so the toad can have a measure of how much time it can move until the direction of its

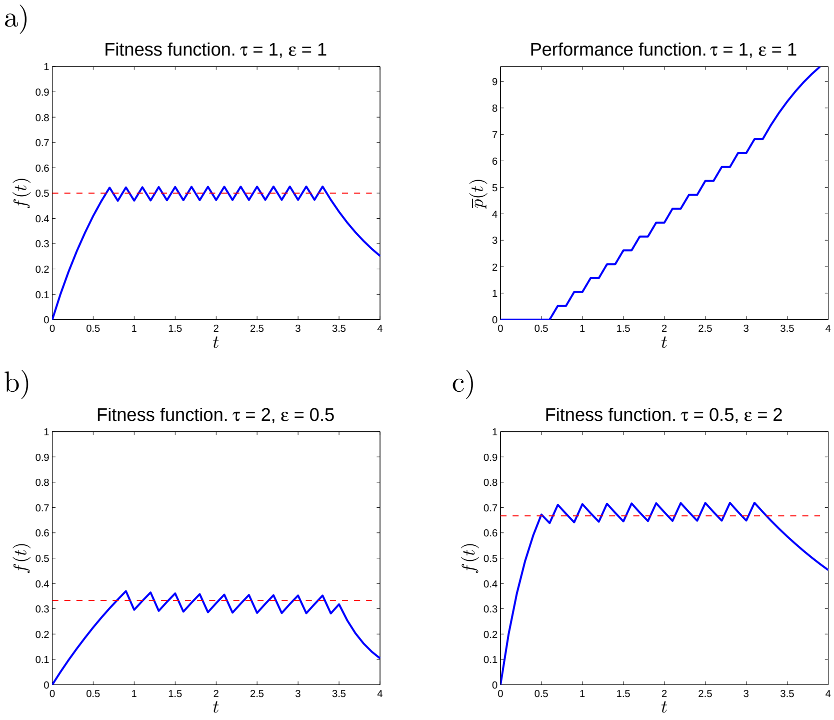


Figure 4.2: Representation of the optimal strategy for different situations: a) fitness and performance functions for $\tau = 1, \epsilon = 1$, b) fitness function for $\tau = 1, \epsilon = 0.25$, c) fitness function for for $\tau = 0.25, \epsilon = 1$. The dashed line represents the value of f_n^*.

movement is no longer valid. In an intuitive first approach to the problem, we could think that what the toad has to do is just change its orientation to point to the prey, and start moving until it reaches a point where its orientation is no longer valid.

Nevertheless, our result shows that this intuitive view of the problem is not right, at least not always. If the movement of the prey is fast enough compared with the times it takes to the toad to perceive where the prey is and to change its orientation, the optimal solution to the problem implies that the toad do not have to change its orientation to point towards the exact position of the prey. Instead, a less accurate but faster to obtain orientation is going to be a better option. From that moment, fast alternations between movement and orientation are going to result in the optimal strategy. Also, the precision of the toad's orientation is going to be kept fixed at a suboptimal point. The value of this point of optimal behavior at any instant of time, $f^*(t)$, is going to depend on the relation between τ and ϵ (Figure 4.3).

In a nutshell, the optimal solution to the adjustment-deployment dilemma can be captured under the following dictum: 'when the environment changes, the best behavior is the one that maximizes the number of interactions with the world, being the optimal fitness level determined by the dynamics of the environment'. The last part of the conclusion is especially interesting, since it adds a new condition for adaptation by means of metastability and intermittent behavior. According to this result, adaptation to the environment is not always going to require too adjusted solutions. Instead, suboptimal solutions combined in an intermittent way are going to be best strategy to cope with changing environments.

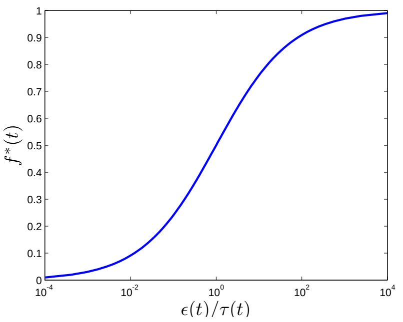


Figure 4.3: Quality of the solution for the optimal strategy $f^*(t)$ for different values of $\epsilon(t)$ and $\tau(t)$.

4.6 Comparison with Experimental Data

Another interesting result of the presented model is that $f^*(t)$ is going to determine the amount of time that the agent spend in adjustment and deployment. Specifically, when execution time tends to infinity, the relative time spent in deployment, r_{dep}, is going to be equal to the mean of the optimal fitness value:

$$\lim_{T\to\infty} r_{dep} = \lim_{T\to\infty} \frac{T_{\gamma(t)=1}}{T} = \lim_{T\to\infty} \frac{1}{T}\int_0^T \gamma(t) = \lim_{T\to\infty} \frac{1}{T}\int_0^T f^*(t) \qquad (4.6)$$

This result represents that, for example, when adaptation is slower than environment changes, an organism will spend more amount of time in adjustment and will develop strategies with poorer solution quality. That is coherent with empirical data:

- In adult viviparous lizards r_{dep} is around 0.7 and 0.8 for general locomotion, while it is reduced to nearly 0.25 when the lizards are actively searching for prey (Avery *et al.* , 1987). That is, when an agent has enough time to exploit its adjustment, it can afford high fitness strategies (Figure 4.2.c), while low fitness strategies will be developed by an agent when available deployment time is smaller (Figure 4.2.b).

- Several studies pointed out behavioral changes of animals looking for preys as the searching environment changes. When preys are more difficult to detect or when environments are visually more complex, the value of r_{dep} decreases (O'Brien *et al.* , 1989; Sonerud, 1992).

The percent of the time spent in deployment varies greatly among different organisms. As seen in (Kramer & McLaughlin, 2001), r_{dep} ranges from 0.04 to 0.94 for different tasks and species. Also, according to experimental data (Bénichou *et al.* , 2005), r_{dep} follows a binomial distribution in foraging animals, meaning that most foragers either spend more time searching than moving or spend more time moving than searching. Being very little the number of foragers that spend similar amounts of time searching and moving. These results can be hinted in Figure 4.3, where, if ϵ/τ is assumed log-uniformly distributed, in most of the cases r_{dep} would be either small or big, and only a little percent of the cases r_{dep} would have medium values.

4.7 A Minimal Model-Implementation of the Adjustment-Deployment Dilemma

Assuming the model presented before, is it possible for an agent to implement this optimal strategy in a changing environment? And if so, what structure is necessary to implement such behavior coupled with the dynamics of the environment? As it is shown if figure 4.4, an agent performing an intermittent behavior must engage in a sensorimotor loop that determines if an adjustment or deployment behavior is performed.

In this way, an agent which acts intermittently needs to have 1) a metastable mechanism which is able to switch between the autonomous patterns of behavior of adjustment and deployment and 2) a regulator mechanism which engages the previous mechanism in a intermittent sensorimotor loop.

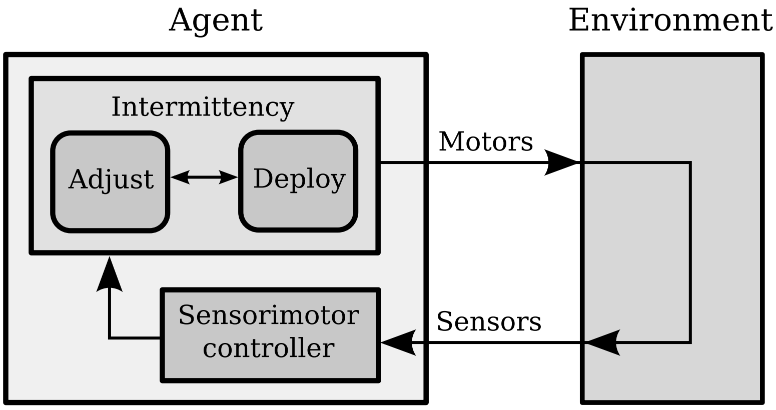


Figure 4.4: Schema of an agent implementing the adjustment-deployment dilemma. Two functional blocks would model the emergence of intermittent behavior and the sensorimotor coupling with the environment.

We can model these two blocks independently as long as we accept the following assumptions:

- When modeling the sensorimotor controller, we can consider that changes between behavioral patterns are fast enough compared with pattern duration to consider transition times as instantaneous.
- As we proved on equation 4.6, the only requisite for reaching certain optimal value of fitness is to obtain an adequate relationship between the time expended in any of the two behaviors in a given window, concretely $r_{dep} \approx \underset{T\to\infty}{lim} \frac{1}{T}\int_0^T f^*(t)$.
- Both the sensorimotor controller and the intermittency mechanism must be able to operate at different dynamic scales, as well as represent with adequate accuracy the ranges of behavior that are found both in the theoretical adjustment-deployment model and experimental data of intermittent behavior (figure 4.3).

If we assume this, we can model the sensorimotor controller dismissing how the intermittency mechanism is modeled and viceversa. In the first place, we are going to model an intermittency mechanism based in the HKB model, and then, the regulation of the sensorimotor loop with a neural network controller.

4.7.1 Intermittency Mechanism

The first part of our task consists in building a model that can switch between two states. The model must be able to operate in different timescales and reproduce the results of intermittent behavior observed in both the adjustment-deployment dilemma and experimental data from real animals behaving intermittently (figure 4.3). We will use coordination dynamics to build a model representing the coupling of different oscillating nodes.

In chapter 2 we described the HKB model, which reproduces the different types of behavior that the human brain is hypothesized to develop: synchronized and metastable modes. We simulate both modes of behavior in the HKB model to analyze whether their behavior fits (or not) to the theoretical assumptions and experimental data related to the adjustment-deployment dilemma.

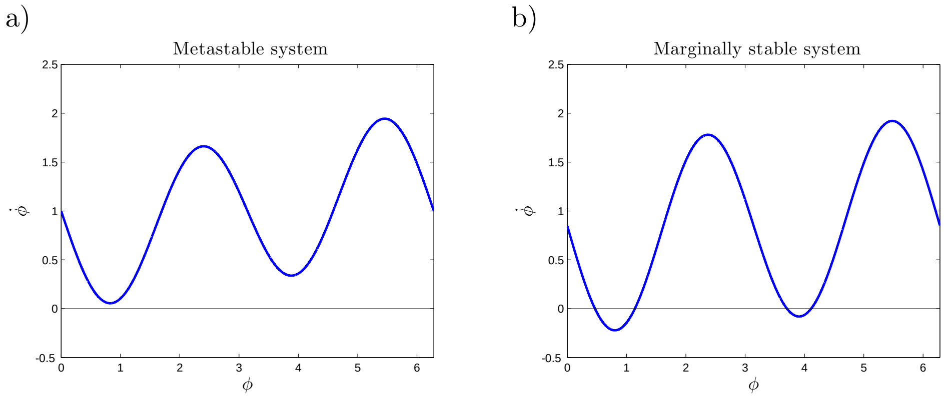


Figure 4.5: a) Metastable HKB model. Switching is periodical and internally generated b) Marginally stable HKB model. Switching is noise-driven.

Pure metastable system

Pure metastable systems are constantly shifting from one state to another. In our case, we model a metastable system of two ever-switching states based in the HKB model (figure 4.5.a):

$$\begin{gathered}\dot{\phi} = \delta\omega - a\ \ sin(\phi) - 2b\ \ sin(2\phi) + \sqrt{Q}\,\varepsilon \\ \delta\omega,\, a,\, b \ni \dot{\phi} > 0 \quad \forall\phi\end{gathered} \tag{4.7}$$

where ϕ is the relative phase between the two interacting oscillators; a and b are the coupling coefficients; $\delta\omega$ represents the difference between the intrinsic frequencies of the pair of oscillators; and ε represents the presence of noise fluctuations of strength Q. In our pure metastable system, in the absence of fluctuations ($Q = 0$), the amount of time the system spent in each state will be a deterministic amount (i.e., it is periodic).

We can define a parameter, r, which, similarly to r_{dep}, represents the relative time the system stays in, let's say, state 1 and not in state 2. When we analyze the distribution of time between the two states for the different values of the control parameters (figure 4.6), we differentiate between two regions of the state space. Region A is the part of the space state where the amount of time spent in each of the two states is similar (i.e. the center of the graph, around $r = 0.5$), and region B is the part where we spend much more time in one state than another (r around 0 or 1). In the case of a pure intermittent system, we can observe that in region A it is very easy to find a precise relationship

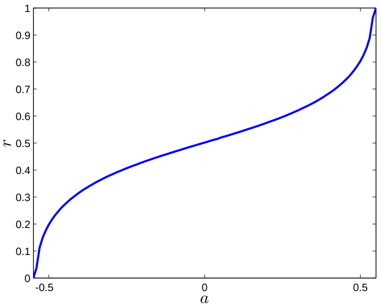


Figure 4.6: Value of r for different values of a with $\delta\omega = 1$, $b = 0.3$ and $Q = 0$. The values are arbitrary and similar results are got for other combinations, including the situations where fluctuations are present.

between state 1 and 2 (i.e., determining the value of r), while, in region B, the task is much harder. This result contrasts with the results we found both in natural data and the adjustment-deployment dilemma, where most of animals display strategies that spend much more time in one state than another, since they find more situations where the best strategy is to favor one state of behavior over another.

Marginally stable system

The previous situation change when we allow one or both of the previous metastable states to reach a quasi-stable or marginally stable state (figure 4.5.b). That is, we define a synchronized system whose stability will be threatened by the presence of internal fluctuations:

$$\begin{gathered}\dot{\phi} = \delta\omega - a\,\sin(\phi) - 2b\,sin(2\phi) + \sqrt{Q}\,\varepsilon \\ \delta\omega,\, a,\, b \ni \dot{\phi} > \dot{\phi}_0 \quad \forall\phi, \quad \dot{\phi}_0 < 0\end{gathered} \tag{4.8}$$

where $\dot{\phi}_0$ is a arbitrary value which is relatively small compared to the noise. In this way, we put them in a situation where there is stability but any small perturbation makes the system to loss its stability (i.e., metastability is not going to be intrinsic to the system but caused by external perturbations). In this case, we found that transitions are not periodic anymore, but noise-driven.

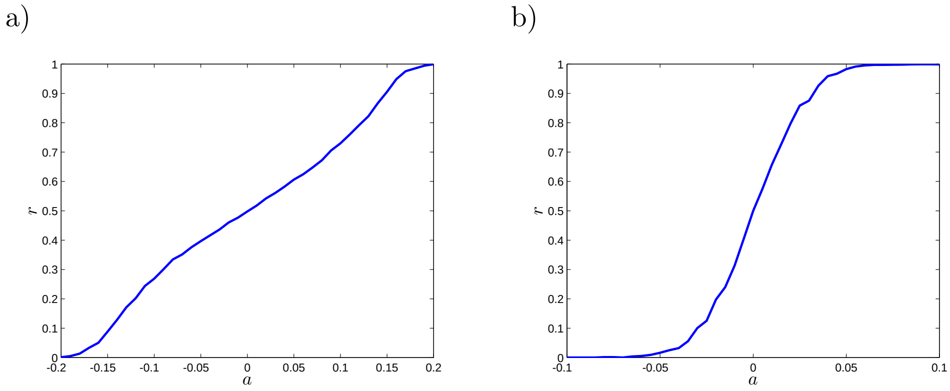


Figure 4.7: a) Value of r for different values of a with $\delta\omega = 1$, $b = 0,45$ and $\varepsilon = 0.4$. b) Value of r for different values of a and $\delta\omega = 1$, $b = 0.5$ and $\varepsilon = 0.4$.

As we increase the value of b we see that both metastable states approach the region of stability (and eventually one or both of them will fall into it if we use the correct value of a). Our strategy will be the following: we will try increasing values of b with its corresponding span of values of a, computing the shape of the corresponding r function. Along the process, we will analyze how the appearance of the r function changes. The results reveals that r changes its form from the tangential function we had before to a sigmoid function, with an almost linear function for intermediate values of b.

In this new situations, we can see that the properties of region A and region B change drastically (figure 4.7). Now, the graphs can show the same kind of sigmoid-like functions that we observed in the solution of the adjustment-deployment dilemma (figure 4.7.b). Therefore, the proposed intermittency behavior based in a marginally stable mode seems to account for the results of the adjustment-deployment dilemma, being it a more suitable choice than pure metastable modes for modeling intermittent behavior.

4.7.2 Sensorimotor controller

Once we have characterized a switching behavior with enough precision, we need to model a controller to trigger alternation of behavioral patterns by driving the HKB model to the desired modes of behavior. However, we will simplify our model to a one-output network which decides whether the agent has to deploy or adjust. We leave apart the task of converting these choices into parameters of the HKB model.

We used continuous-time recurrent neural networks (CTRNNs, see chapter 3) in order to implement a dynamical system capable of developing the optimal strategy in any possible situation. CTRNNs are a good choice for the proposed task because (1) they are the simplest nonlinear, continuous dynamical neural network model; (2) despite their simplicity, they are universal dynamics approximators in the sense that, for any finite interval of time, CTRNNs can approximate the trajectories of any smooth dynamical system (Beer, 1995a). The general form of a CTRNN with N neurons is:

$$\dot{y}_i = \frac{1}{\tau_i}(y_i + \sum_{j=1}^{N} w_{ij}\sigma(g_j(y_j+\theta_j)) + I_i) \tag{4.9}$$

where $i = 1, 2, ..., N$, y is the state of each neuron, τ is its time constant ($\tau > 0$), w_{ij} is the strength of the connection from the j^{th} to the i^{th} neuron, θ is a bias term, g is a gain term, $\sigma(x) = 1/(1+e^{-x})$ is the standard activation function, and I represents a constant external input. In this case, the only knowledge the network is coding about the world is the current quality of the solution being implemented, i.e. $I = K_f \cdot f(t)$, where K_f is a gain term.

One of the neurons (e.g. $i = N$) was considered as the output of the system. This output will determine the values of $\gamma(t)$, and therefore the following $f(t)$.

$$\gamma(t) = \begin{cases} 0, & y_N(t) \leq 0 \\ 1, & y_N(t) > 0 \end{cases} \tag{4.10}$$

Once the neural networks were defined, by using a genetic algorithm we find a network that develops an optimal behavior, tending to select with more probability the networks that achieve a higher value of $\overline{p}(T)$.

Adaptation Without Learning

The objective is to obtain a system which is able to display a suitable behavior for a given dynamics. In the first place, we define the $\tau(t)$ and $\epsilon(t)$ functions, which represent the dynamics of the world at each moment. These functions will determine the value of $f^*(t)$.

For the training, we tried a situation with constant rates: $\tau(t) = 1$, $\epsilon(t) = 1$, $f^*(t) = 0.5$ was selected. Given these dynamics, the genetic algorithm was executed for various sizes of neural networks. The result showed that even for CTRNNs with $N = 1$ (one single neuron), the network was able to obtain the optimal results for the given dynamics (Figure 4.8).

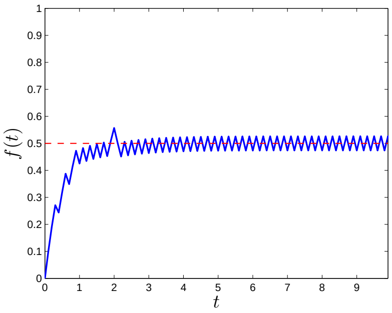


Figure 4.8: Fitness function $f(t)$ for f$^*(t) = 0.5$ (red dashed line). Response of a single-neuron network.

From now on, it was taken the single-neuron network adapted to a constant situation of $f^*(t) = 0.5$ without any change. The following objective was to observe the response of this neuron to environments with dynamics which were different than the one of the training. The experiment consisted in defining $f^*(t)$ as a) a ramp function, b) a step function, c) a triangle wave and d) $f^*(t)$ as result of defining $\tau(t)$ and $\epsilon(t)$ as sinusoidal functions.

We obtained that the neuron was able to adapt to any of these changing dynamics obtaining an optimal performance (i.e., with $f(t) \approx f^*(t)$) as seen in figure 4.9. Therefore, the mechanism implemented for a single neuron for adapting to a particular world dynamic (f$^*(t) = 0.5$) was able to adapt to any other smoothly changing dynamics without any further training.

The same results were observed when the genetic algorithm obtained in the first place a neuron adapted to any other situation different to $f^*(t) = 0.5$. The resulting neuron was always able to adapt to the new changing forms of $f^*(t)$.

System Behavior

The robustness of this result was achieved because of the resulting structure of the neuron and its consequent behavior. Its, behavior is based on the coupling between the external (the environment) dynamics and the internal (the neuron's) dynamics of the system. The system external dynamics were represented by the variations of the fitness function $f(t)$, that is, $\dot{f}(t)$ (representing the effect of the agent behavior on its own situation in the world). Similarly, we took $\dot{y}(t)$ for representing the system internal dynamics, determined by the variations of the internal state $y(t)$. With the purpose of seeing intuitively the effects of the different dynamics ($\dot{f}(t)$ and $\dot{y}(t)$ are quite spiky functions), the systems dynamics were represented by the variables $\dot{f}_m(t)$ and $\dot{y}_m(t)$, being the filtered moving averages of $\dot{f}(t)$ and $\dot{y}(t)$.

According to these parameters the neuron behavior could be explained at different levels:

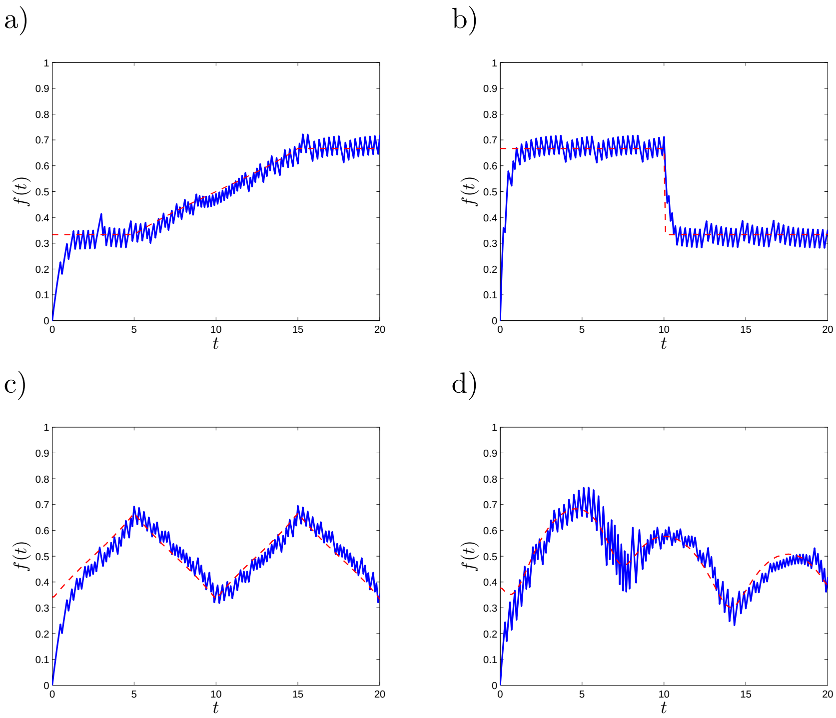


Figure 4.9: Fitness $f(t)$ of the resulting neuron, without any further learning, tried for different world dynamics: a) $f^*(t)$ as a ramp function, b) $f^*(t)$ as a step function, c) $f^*(t)$ as a triangle waveform and d) $f_{opt}(t)$ as results of defining $\tau(t)$ and $\epsilon(t)$ as sinusoidal functions.

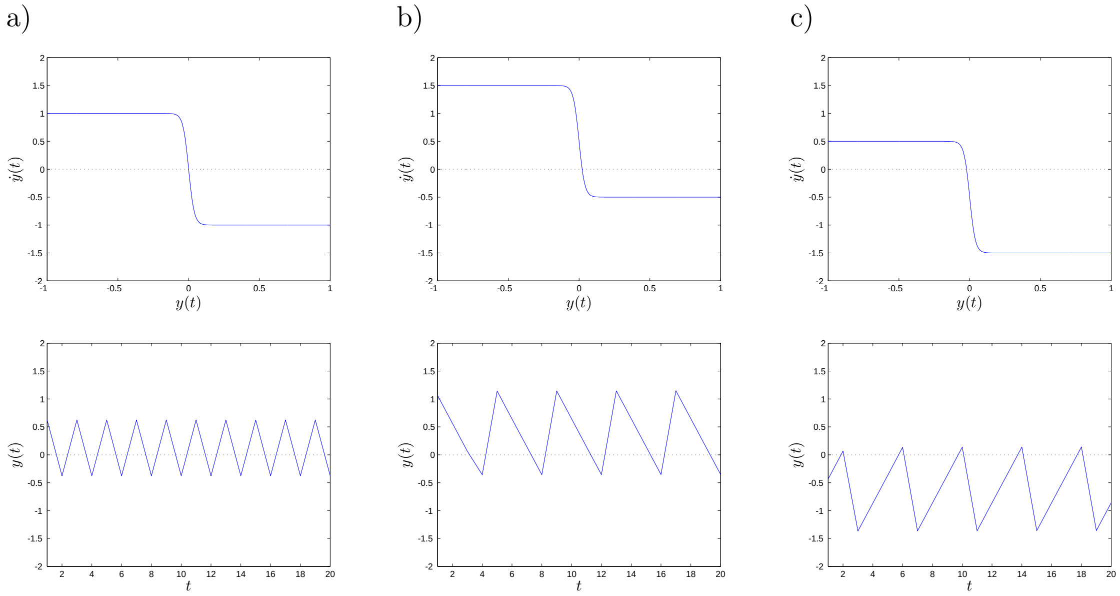


Figure 4.10: Values of $\dot{y}(t)$ and $y(t)$ when a) $f(t) = 0.5$, b) $f(t) = 0.25$ and c) $f(t) = 0.75$. $y(t) \gtrless 0$ determines whether the neuron generates or executes a solution (notice that in each case $r_{dep} = f(t)$). Therefore the functions describe a case where the neuron a) generates solutions as much times as it executes them, b) generates solutions more times than it executes them and c) generates solutions less times than it executes them.

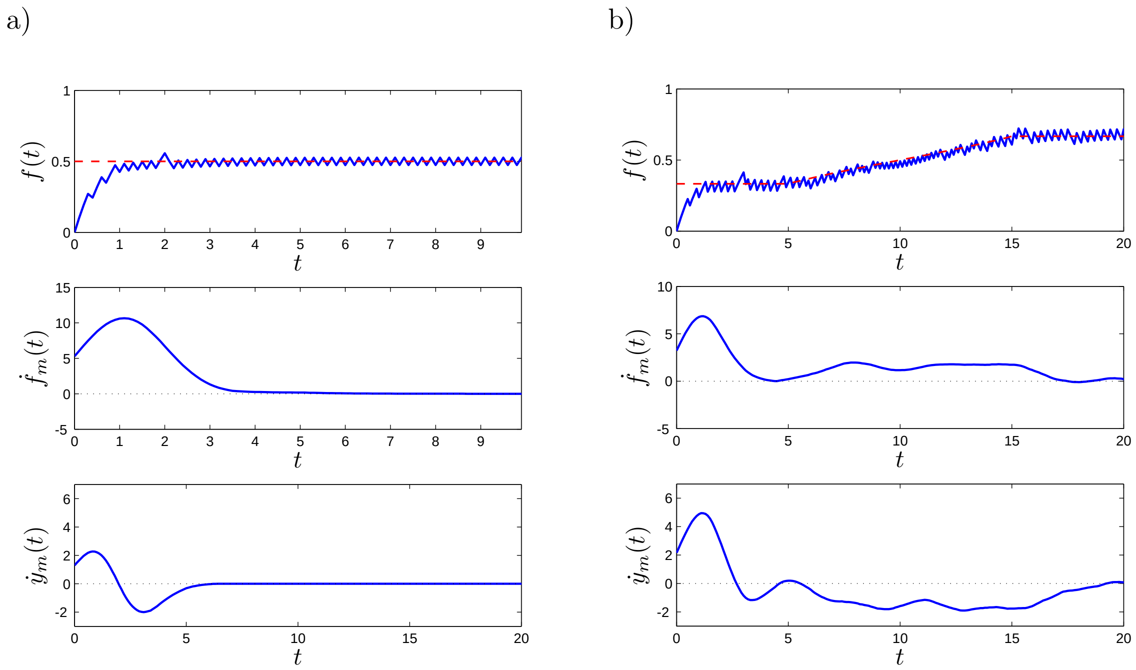


Figure 4.11: Values of the system fitness $f(t)$, the system external dynamics $\dot{f}_m(t)$ and the system internal dynamics $\dot{y}_m(t)$ for different situations. The different situation dynamics are defined by the value of $f^*(t)$, represented by the red dashed line.

1. When $f(t) \simeq f^*(t)$ (figure 4.10), the neuron feedback loop is able to compensate the output deviations. It makes the neuron to behave like a nonlinear oscillator around $f^*(t)$.

2. If $f^*(t)$ shows a constant value, but fitness is not at this optimal value, i.e., $f(t) \gtrless f^*(t)$ (figures 4.11.a), then the system tends to $f(t) = f^*(t)$. Internal and external dynamics ($\dot{y}(t)$ and $\dot{f}(t)$) act together in order to adapt fitness to its optimal value.

3. In the last case, when $f^*(t)$ is changing throughout time (figure 4.11.b), the following happens. If $f^*(t)$ changes, that means that the world dynamics (i.e. the adaptation and degradation rates) are changing, therefore $\dot{f}_m(t)$ changes and $f(t)$ is no longer around $f^*(t)$. Nevertheless, the system dynamics $\dot{y}(t)$ changes in reaction to the changes in $\dot{f}_m(t)$, counteracting them. This will recover the equilibrium of the system in a new point, which will be $f(t) = f^*(t)$.

As seen, the system is able to act in two different time levels. On the first one the agent can respond to transient changes of $f(t)$, keeping the fitness at its optimal value, alternating adaptation and deployment. On the second time level (slower than the first one) the agent can adapt its average fitness value to $f^*(t)$, expanding the adaptive opportunities of the agent.

Nevertheless, these results are preliminary, and more consistent proof of this hypothesis should be obtained from simulation in which both the intermittency mechanisms and the sensorimotor controller should be engaged in embodied and situated agents performing task in an intermittent way.

4.8 Metastable Mechanisms for Intermittent Behavior

In this chapter we have depicted an essential aspect of intermittent behavior, namely the *adjustment-deployment dilemma*, the dynamic interplay between the time spent on adjusting a solution to the environment or bodily circumstances before deploying it, and the execution time taken by the deployment of the solution. Our hypothesis is that intermittent behavior is closely connected with the metastable dynamics observed in the brain, being both part of a more general framework in which intermittency is the mechanism used to couple a system's dynamics with the dynamics of a complex and ever-changing environment.

Despite its ubiquity in biological behavior, to our knowledge, this is the first characterization, formalization and modeling approach to the adjustment-deployment problem. We have formalized mathematically the structure of this dilemma and numerically computed its optimal solution for different values of the problem-structuring parameter which turns out to be the ratio between speed of adjustment and speed of the adjusted solution decay while deployment takes place. The optimal solution to the adjustment-deployment dilemma, for fixed ratio between increasing quality of adjustment and decay-rate while deploying, turns out to require a compromise with non-maximal quality and a high rate of alternation between adjustment and deployment.

The distribution of optimal strategies over the range of parametric values takes a sigmoidal shape, meaning that, overall distribution of solution should show many instances of biological behavior where adjustment is very fast and longer periods of deployment are present or the contrary; i.e. long periods of adjustment followed by quick deployment. The distribution of intermittency in animal behavior seems to match our model's optimal solution distribution.

But what are the mechanisms capable to achieve the optimal solution under changing conditions? A CTRNN composed of a single node was shown to be capable of achieving this optimal solution, being its input an indicator of the success of its deployment. The results suggest that optimal solutions to the adjustment-deployment dilemma could, in principle, be instantiated on very simple mechanisms, if the appropriate conditions occur, and should therefore be accessible even to unicellular systems. We also present some results that show how switching between complementary patterns can be modeled by an HKB model operating in a marginally stable state, better than pure metastable functioning. Thus, systems posed in between the border of stable synchronized and metastable states would be in an optimal situation to adapt to changing environments.

Needless to say the present model is still in need of further development. Some of the underlying assumptions should be relaxed and the model complexified. For instance, many crucial temporal aspects of the adjustment-deployment dilemma were left aside in this study and many of them might provide avenues for future research. The inclusion of forced perceptual delays, evaluation delays (the organisms need to take some time to taste a food source, or to evaluate the outcome of its interaction), the possibility of overlap between adjustment and deployment, constraints on deployment duration, etc. should be included in further development. The measurement of fitness and quality of solution could also be enriched by including additional cost function to deployment (energy expenditure), adjustment (risk of being detected/hunted) or associated with the switching between the both of them, and a variety of spatial and embodiment constraints.

Future development should also include reference-to and modeling-of specific examples of animal behavior that face the adjustment-deployment dilemma, compare the model to existing data and include the necessary adjustments on parameters and, most probably, add more dimensions to the problem.

4.9 Metastable Adaptive Behavior

We have shown that, when faced with the adjustment-deployment dilemma, we gain more by assuming a compromise with a suboptimal quality solution and maximizing our interactions with the environment. Recurrent testing of our solution into the environment renders betters results than indefinitely adjusting our models of the solution. These results show how metastable dynamics can be used as a general adaptive tool when facing uncertain environments. Due to its generality, the presented abstract model could be used at any level of biological organization: from neural dynamics to behavior and higher cognitive functions.

We have also shown how very simple mechanisms can find solutions to relatively complex problems, illustrating how a wide range of living systems could successfully cope with domain invariant adaptive problems like the adjustment-deployment dilemma. Since intermittent behavior is found in organisms such as protozoans which do not possess a neural system, we hypothesize that metastable adaption could be a principle of minimal cognition. The generality of the model and the robustness of our results support this idea (van Duijn *et al.* , 2008).

Our model also brings forth the necessity to include the temporal dimension of cognitive processes into our theoretical framework. Speed, intermittency, decay-rates, and deployment duration crucially matters when it comes to real-world problem solving. Including these temporal features into the sensorimotor loop, we obtain a highly robust adaptive behavior. However, how is this temporal dimension successfully embedded in the sensorimotor loop? How can organisms exploit the coupling between temporal patterns of both internal and external dynamics? The next chapter implements a minimal model of an agent performing a phonotaxis task, exploring how robust behavior can result for a sensorimotor loop which embeds critical temporal features of the interaction with the world.

Chapter 5

Robust Coordination in the Brain-Body-Environment System

In previous chapters, we have claimed that coordination dynamics is responsible for the emergence of behavioral patterns which create sensorimotor loops allowing robust and flexible interactions with the world. This leads us to wonder about how dynamical coupling in the brain-body-environment system may face the influence of internal and external perturbations on the actions of an agent.

Some other works in theoretical neuroscience and systems biology consider that robustness is just internally generated (i.e. a property of the internal structure of organisms). However, the dynamical approach we are proposing in this work opens us the door for exploring other perspectives about robustness, which intend to analyze it as a dynamical phenomenon of coupling in the sensorimotor loop cutting across the brain-body environment system (Fernandez-Leon, 2010).

From this point of view, in this chapter we analyze robustness in a simple taxis task, in which an agent has to perform a behavioral response to a directional stimulus or gradient of stimulus intensity. Analyzing previous models of oscillator networks performing similar tasks, we hypothesize that the necessary condition for robust sensorimotor loops to emerge is that both the neural system and the processed stimulus share the same metrics in order to create a structured behavioral space.

5.1 Emergence of Robustness in the Sensorimotor Loop

When we decide what type of neural controller we use for modeling cognitive agents, it could make a difference what kind of predictions our system is generating. Concretely, feed-forward and feedback networks are good at predicting what is going to happen next, while oscillator networks are a good choice for predicting when things happen (Buzsáki & Draguhn, 2004). That is, we can think that, while feed-forward and feedback networks are good at processing input information expressed in terms of amplitudes of input and output parameters, oscillator networks should easily deal with relative phase information.

We can see this clearly in the work of Santos *et al.* (2011), where they evolve a physical agent controlled by a Kuramoto network to perform a phototaxis task, where the input of the network is the the light intensity received by two sensors; using the model seen in section 3.4.3. We can see how they achieve the phototaxis behavior, but the agent movement is somehow awkward and it breaks (becomes unstable) when the agent is too close to the light source. This does not happen when agents are controlled by other type of neural models, as CTRNNs. Also, when the sensorimotor loop is perturbed by temporal delays, it easily dissolves making impossible the phototactic movement.

This leads us to think that robustness may be enhanced when the perceived stimulus and the neural controllers share the same metrics and process the same type of information. Kuramoto networks may not be the best option to compute absolute amplitude information or amplitude gradients from the environment, because their metrics are different from the ones of oscillator phase differences. Maybe they could play a more interesting role if we use them to solve phototactic-like behavior just using phase, or phase-like, information.

These ideas link directly with the fact that human comprehension of the different signals (voice, image, etc.) that we receive depends more in the phase information of the signal than the amplitude information (Oppenheim, 1981), since phase represents locations of different elements in a signal (either in space or time), leaving apart their amplitude. Since the brain is conformed by multiple oscillating processes, it make sense to think that we are especially prepared to easily compute phase information from the environment.

For the following sections we are going to design a phonotaxis task, where an agent has to approach an object just perceiving information about the phase of a wave which is sent from the agent and echoed in the object. We will see how the processing of relative phase information allows the formation of beautifully simple and robust sensorimotor loops with Kuramoto oscillator networks.

5.2 Oscillatory networks as a neural controller in a minimal situated phonotaxis task

In the first place, we designed an scenario with a minimal task to start analyzing sensorimotor loops in oscillatory networks. The model consists or a two dimension simulated environment, an agent and an object the agent must reach. The agent's movement is controlled by a network of four coupled oscillators, being one of them connected to a sensor. The sensor sends an acoustic wave to the environment, which is going to be reflected in the goal object coming back to be detected by the sensor. The phase of the oscillator connected to the sensor is going to be the same than the phase of the travelling wave that is reflected from the object to the agent and received by the sensor. Therefore, we define the oscillator network as:

$$\dot{\theta}_i = \begin{cases} \omega_i + \sum_{j=1}^{4} k_{ij} \sin(\theta_j - \theta_i), \quad i = 1,2,3 \\ \\ \omega_i - \frac{2\pi}{\lambda} 2\dot{d}, \quad i = 4 \end{cases} \tag{5.1}$$

where θ_i is the phase of the i^{th} oscillator, ω_i is the oscillator's intrinsic frequency, N is the number of oscillators and k_{ij} is the coupling factor from the j^{th} to the i^{th} oscillator. Also, d is the distance between the agent and the goal. Thus, the phase of the 4^{th} oscillator is going to be the phase of the acoustic wave the reflected acoustic wave travelling from the goal to the agent.

The agent (figure 5.1) is modeled as a solid circular body radius $R = 0.1$ with two diametrically opposed motors, which can move forward or backwards with different velocities. The agent's mass is quite small (there is no inertial resistance) so the motor output is the tangential velocity at the point of the body where the motor is located. The translational movement can be calculated using the velocity of its center of mass (the vectorial average of the motor velocities), and the rotational movement by calculating the angular speed (difference of the tangential velocities divided by the body diameter). The activation of the motors is going to be defined as $R\sin(\phi_{12})$ for the right motor and $R\sin(\phi_{13})$ for the left motor, being $\phi_{ij} = \theta_j - \theta_i$; that is, the sine of the relative phase

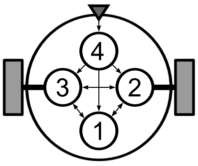


Figure 5.1: Schema of the two wheeled physical agent controlled by a Kuramoto network of coupled oscillators connected to an acoustic sensor.

between oscillators 1 and 2 activates the right motor and the same for the relative phase of oscillators 1 and 3 and the left motor. R will be a gain factor

An elitist genetic algorithm was used to obtain the parameter values that allow the agent to successfully perform the phonotaxis task. The algorithm used 14 genes of 5 bits each, defining the values of ω_i (range $[0, 5]$), k_{ij} (range $[0, 5]$) and $\frac{2\pi}{\lambda}$ (range $[0, 15]$). Moreover, it was used a population size of 80, with a trial length of 400, selecting the 20 fittest individuals and recombining the rest with a mutation rate of 0.01.

The fitness function was defined as the combination of two factors $F = F_D + F_P$, where F_D represents the reduction of the distance to the goal between the initial and final position of the agent $F_D = 1 - \frac{d_f}{d_i}$, being $F_D = 0$ if $d_f > d_i$ and F_P represents the amount of time the agent at a distance less than 10 body lengths to the goal (i.e., a distance of 1). The position of the goal is generated randomly. In 8 generations the agent successfully performed the phonotaxis task (figure 5.2), obtaining fitness values of $F_D = 0.96$ and $F_P = 0.72$.

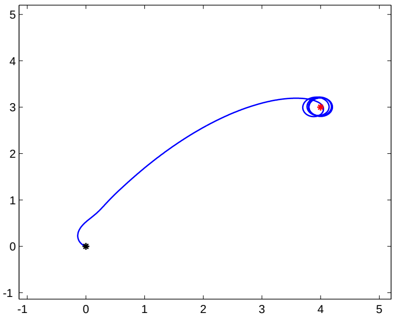


Figure 5.2: Trajectory of the agent reaching an object in a phonotaxis task. The agent does not follow a straight line but follows a slight detour.

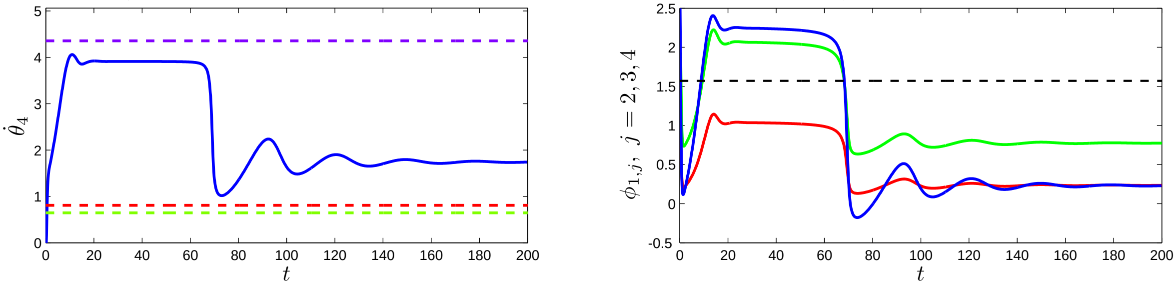
5.2.1 Dynamical Behavior Analysis

We see that the problem was solved performing what apparently seems as a quite simple behavior. However, if we look more carefully what is going on it is not trivial. On a first approach for solving a phonotaxis task, one may think that, at least, two sensors located at different positions are needed to correctly determine the position of an object, as used in previous phonotaxis models (Webb & Harrison, 2000), so the relative phase of the received waves reflects the direction of the sound source. If we have only one sensor, the only way to gain some information about the environment is to move, thus modifying the frequency of the perceived wave because of the Doppler effect. This gives the agent information about its relative speed respect to the goal. However, moving towards the goal is does not give the agent any information about its relative position respect to the object. So, if our agent is solving correctly the problem with just one sensor, it must be sustaining some kind of sensorimotor loop.

Think about the case of the agent approaching the goal-object in a straight line with just one sensor. The signal received by the agent is a periodic sinusoidal wave, not giving to the agent any information but the relative speed between the object and itself, not knowing how far the object is, until it bumps into the object. If we want to have insights about where the object is a different strategy is needed.

a) Frequency of the received signal

c) Relative phases



b) Coordination parameter

d) Activation of the motors

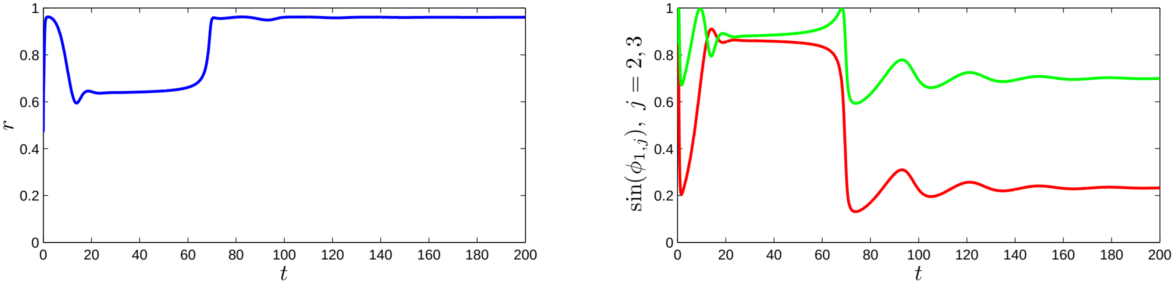


Figure 5.3: a) Frequency of the signal received by the sensor. In discontinuous line the natural frequencies of the network oscillators: ω_1 (red), ω_2 (green) and ω_3 (purple). b) Order parameter of the system. c) Relative phases of the system, $\phi_{1,2}$ (red), $\phi_{1,3}$ (green), $\phi_{1,4}$ (blue). d) Sine of the relative phases, $\sin(\phi_{1,2})$ (red), $\sin(\phi_{1,3})$ (green). We can identify the presence of two different cell assemblies with different levels of synchronization and phase-locking, which are associated with two different kinds of behavior (go straight and turning). For all of them, When $t \in [10, 70]$ the agent is approaching to the goal, while when $t \in [70, 200]$ the agent stays close to the goal turning in circles.

As we can see in figure 5.2, the agent is not approaching the goal in a straight line but taking a slight detour. If we analyze the dynamics of the controller network we can see how this detour is not arbitrary and it is necessary to implement the sensorimotor loop. For the analysis, we are going to represent the values of the frequency of the received acoustic signal, θ_4 (for having a measure of the Doppler effect), the coordination parameter of the system, r (which measures the degree of coherence between the set of oscillators, see chapter 3 for a description), the relative phases of the network, ϕ_{ij} and the sine of the relative phases that activate the right and left motors (figure 5.3)

In figure 5.3.a we can see that when the agent is approaching the goal ($t \in [10, 70]$), it moves in such a way that the frequency of the received signal is kept constant at a value around 4. Also, when the agent has reached the goal ($t \in [70, 200]$), the same happens for a frequency of something less that 2. If we observe the order parameter of the system in figure 5.3.b, we see that the previous phenomenon divides the state of the network in two different behaviors with different levels of coherence: ‘approaching the goal' ($r \approx 0.6$) and 'staying close to the goal' ($r \approx 0.9$). In figures 5.3.c and 5.3.d we can see that the change of the received frequency induces the formation of two different cell assemblies of synchronized oscillators, characterized by the different phase relations in the oscillatory network. Each cell assembly is associated with one of the two possible behaviors. In the 'approaching the goal' assembly both motors are similarly activated, while in the 'staying close to the goal' assembly one of the motors has less activation, making the agent to turn around constantly.

We have seen how the sensorimotor loop is established by computing the frequency of the acoustic wave received. Somehow, the oscillator network is trained to follow phase gradients to reach the objective. In this way, the task is similar to other phototaxis or chemotaxis task. If we force our agent to perform these other tasks, we just need to have oscillatory sensors which transforms light or chemical gradients into phase gradients. However, we do not fully understand yet how the dynamics of the established sensorimotor loop works. Therefore, in the next section we will analyze how this dynamics react when the signals in the sensorimotor loop are perturbed, with the objective of characterizing this dynamics in a broader range of conditions.

5.2.2 Perturbation of the Sensorimotor Loop

We have repeatedly stressed the importance of sensorimotor loops for the emergence of cognitive functions. The main reason is that we consider that the ensemble brain-body-environment constitutes a dynamical complex system in its own. We cannot understand it as a group of independent "boxes" that just do a part of the processing of cognitive information. Instead, we have to be aware that the coupling among different system dynamics is the base for the emergence of the great diversity and versatility of living behavior.

Santos *et al.* (2011) showed how the effect of a disruption of the sensorimotor loop could result in breaking the coupling with the environment, not allowing the agent to perform a phototactic behavior. In this section we will perform some experiments to show how not only behavior is controlled by brain dynamics but brain dynamics are also shaped by behavior. We will see how the perturbation of the sensorimotor loop does not necessarily dissolve it, but if the loop is robust enough, perturbations are going to allow new behavioral strategies to arise, even when they were not pre-specified in the conditions of the genetic algorithm, being instead a consequence of the dynamical richness of sensorimotor loop coupling.

Perturbation of the sensory wave frequency

The first disruption we have tried is to modify the frequency of the acoustic wave that is sent and received by the agent to locate the position of the goal. This is going to perturbs the behavior of the oscillator network, since each oscillator is tuned to couple to a particular frequency of the sensor oscillator (as we saw in figure 5.3.a) . For doing that, we took the oscillator network that resulted from the genetic algorithm with a tuned sensor frequency of ω_4 and we changed the natural frequency of the oscillator sensor to a new value $\omega_4^* = a\,\omega_4$, where a is a real number.

We could think that a change in the wave frequency would "beak" the precise equilibrium of the previous sensorimotor loop, not allowing the agent to behave correctly. Instead, if we analyze the new behavior of the agent for different values of ω_4^* (as for example, the cases shown in figure 5.4), we see that the neural controller dynamics does not respond correctly to the information they receive but, however, the subsequent behavior of the agent shape the neural dynamics to perform a different new strategy, which still allows the agent to reach the goal. Thus, we see in figure figure 5.4.a how, when

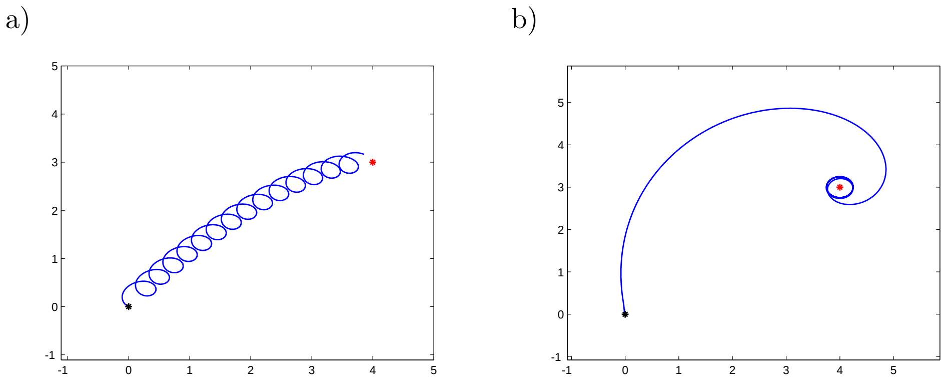


Figure 5.4: Trajectory of the agent when the frequency of the sensory wave is tuned to a) $\omega_4^* = 0.9\,\omega_4$ and b) $\omega_4^* = 1.4\,\omega_4$. It is observed how the agent implements new strategies that were not determined in the genetic algorithm.

$\omega_4^* < \omega_4$ the agent displays a strategy of a cycloidal movement, being one of the motors less activated than the other one most of the time. It is worth to mention that in this case the relative phase of the oscillators is no longer stable, but changes in a cyclic way (being metastable). Meanwhile, when $\omega_4^* > \omega_4$ the agent has to take a larger detour to adapt to the new situation while keeping stable phase relationships.

Delay of sensory information

Other possible perturbation is to add delays to the signal of the received acoustic wave. That is, at instant t the signal the agent perceives is the one received at instant $t_d = t - T$. Obviously, the agent gets better results when $T = 0\,s$ and there is no delay, but when we explore different possibilities of delay times, what we see is not what we expected. First of all, we can see in figure 5.5 that having a larger disruption of the delay do not necessarily means that the behavior is going to be worse. We can see that in figure 5.5.a, where the fitness starts to decrease when $T = 0.9\,s$, but then there is a peak at $T = 1.3\,s$ where the fitness increases. This is also seen in figure 5.5.b, where we periodically find adapted behaviors for very large values of delay (Note that the agent reached the goal in about 70 seconds in the default situation, and we are adding delays up to 100 seconds).

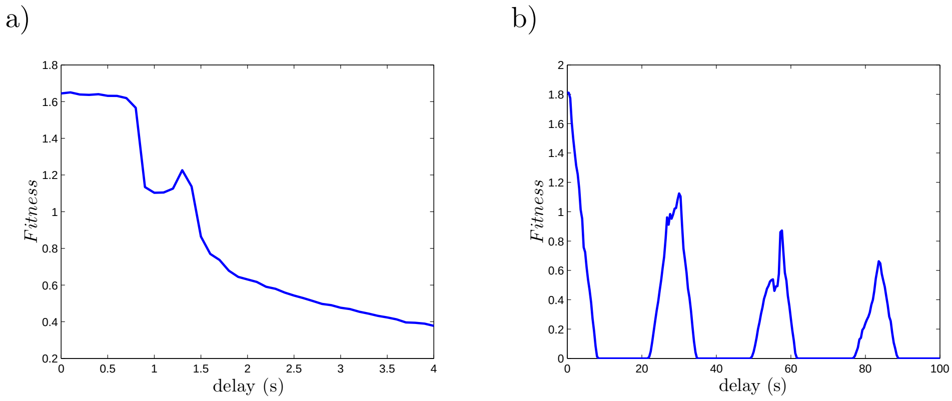


Figure 5.5: Fitness of the agent's behavior for different values of sensorimotor delay. We see how the reduction of the fitness with larger delay is neither linear nor monotonically decreasing.

What is happening here, like in the case of frequency perturbations, is that the agent is exploiting the dynamical richness of the sensorimotor loop dynamics to implement new strategies which were not specified by the genetic algorithm. As we can see in figure 5.6 is that the agent is implementing a similar type of cycloidal metastable solution, with one motor having a smaller level of activation. In both cases, the network tries to have a coherent behavior between the four oscillators, therefore sustaining the sensorimotor (in a metastable state if stability is not possible) loop in the presence of environmental perturbations.

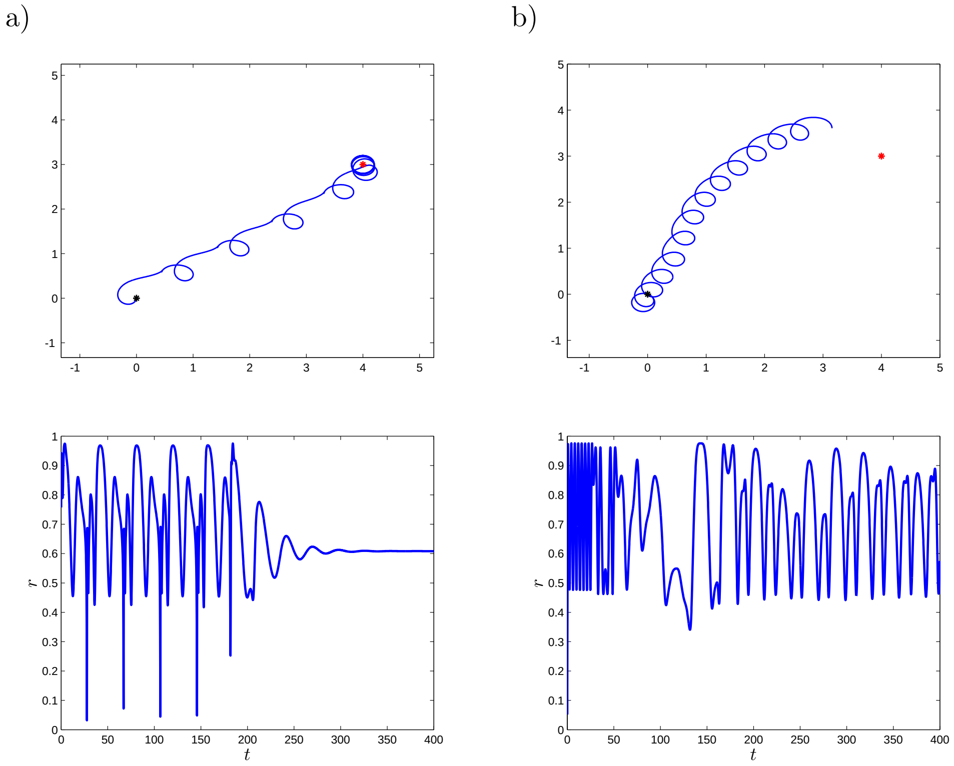


Figure 5.6: Trajectory of the agent and evolution of the order parameter when it is introduced a delay of a) $T = 1.3\,s$ and b) $T = 28.0\,s$. The agent implements a metastable cycloidal solution not specified by the genetic algorithm.

5.3 Sensorimotor Metastability

In figure 5.3 we can intuit that the order parameter r is a good indicator of the state of the system. We have identified two different cell assemblies that define the possible behavior of the agent, which in general terms consist in ‘going straight’ or ‘turning right’ movements, with a subtle modulation in the ‘go straight’ pattern to achieve the detour in the trajectory that allows the agent to locate the position of the goal while keeping the cell assembly stable. In the general un-disrupted case, the ‘go straight’ cell assembly is stable until the agent reach the goal. However, perturbations of the sensory input make the agent to implement different new strategies, which will be based in the activation of these cell assemblies in different ways. Let’s see how.

Marginal stability and frequency perturbation

In the case of modification of the acoustic wave frequency, we could encounter two different cases. In one, when $\omega_4^* > \omega_4$, the system exhibit a stable behavior while moving towards the object and we observe that, like in the standard case, there is established a cell assembly that represents the 'approaching the goal' state, letting space for another assembly representing the 'staying close to the goal' state when the agent arrives to the goal. If we analyze the dynamics of this case, we see that like in the case without perturbation the system maintains a steady activation of the sensor oscillator with a frequency of $\dot{\theta}_4 \approx 4$. However, in this case, since the sensor receives a higher frequency, the agent has to approach to the goal slower in order to maintain the same value of activation of the sensor oscillator. We could say that in this case the situation of the system is more stable, since the agent needs less movement (relative to the goal) to maintain its state.

When, on the other hand, we decrease the frequency of the acoustic wave, there is a different situation with an abrupt change. When $\omega_4^* < 0.97\,\omega_4$ the system loses its stability and it enters in a metastable regime showing a cycloid movement. The system can only maintain the 'approaching the goal' state transiently, switching immediately to the 'staying close to the goal' (which actually makes the agent turn in circles). Both states combined in an intermittent way give place to the cycloidal movement showed by the agent. Therefore, when the system is tuned to display the original (the most adapted) behavior, its neural system is situated at the border of stability. And, crossing the line of stability, is going to lead to the emergence of intermittent strategies.

Intermittency and delay of sensory information

In the case of sensory delay with $T = 1.3\,s$, if we observe the order parameter of the system (figure 5.6), we see that it presents a series of peaks at $r \approx 0.97$ and $r \approx 0.86$. Do these peaks mean something? If we analyze how the order parameter r is related to the movement of the agent (figure 5.7) we realize that when $r \approx 0.97$ the values of the derivative of the distance to the goal $\dot{d}$ are negative. And, when $r \approx 0.86$, $\dot{d}$ is positive. That is, when the low coherence cell assembly emerges ($r \approx 0.86$) the agent is moving towards the goal, while when the high coherence cell assembly emerges ($r \approx 0.97$) the agent start turning.

As we can figure out from above and figure 5.3.b, what happens is the following. In the standard un-perturbed strategy, the 'go to goal' behavior (associated with a low coherence cell assembly) is stable until the goal is reached. However, with the $T = 1.3\,s$ delay perturbation it is impossible for the system to keep this state stable for that long. What happens here is that the stability of the 'go to goal' state breaks, giving place to the other stable state: 'turn right', which leads to the system to a new situation were the 'go to goal' state can emerge again.

What we are seeing is a phonotactic version of the adjustment-deployment dilemma seen in chapter 4. The perturbation of sensory information is going to deviate the movement of the agent, making him to move in a wrong direction. However, when the fitness of current behavior ("how correct is the direction I am taking") is low, the system becomes instable and switches to an adjustment (turning) behavior that is going to correct the situation of the system. How often I have to switch between adjusting and deploying is determined by the dynamics of the system (in this case, the movement of the agent and the delay of sensorial information).

Somehow, a system that was designed to be stable and perform a phonotaxis task, becomes intermittent (metastable) when it has to tackle a complex unfavorable situation. Showing how metastable dynamics allow adaptation to complex environments easily

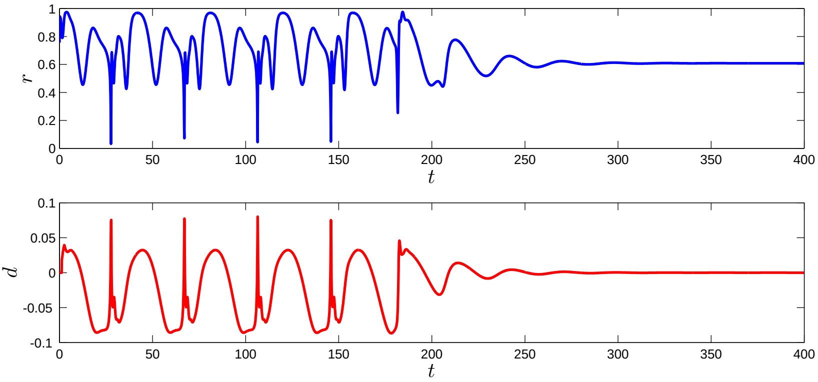


Figure 5.7: Value of the order parameter r and the derivative of the distance to the goal $\dot{d}$ for the case seen in figure 5.6.a. It is observed that periods when the agent is distancing from the goal ($\dot{d} > 0$) correspond with the periods of maximum coherence of r, while periods where the agent is approaching the goal ($\dot{d} > 0$) correspond with the periods of less coherence of r.

than steady dynamics. These results reinforce the hypothesis proposed in chapter 4 where metastability was presented as a general system to adapt to complex changing environments by maximizing the number of interactions with the world.

We now explain the phenomenon seen in figure 5.5.b, in which we see how when the delay increases, we reach a point ($T \approx 8\,s$) where the sensorimotor loop "breaks" and the agent no longer is able to implement any successful behavior. However, if we keep increasing the value of the delay, we periodically found groups of values where the agent is able again to perform phonotaxis, around $T \approx 28\,s$, $56\,s$, $84\,s$, ... How is this possible?

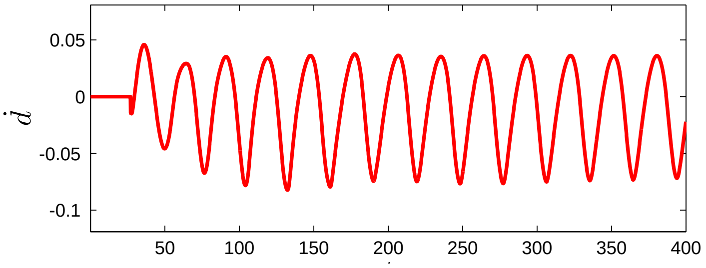


Figure 5.8: Value of the derivative of the distance to the goal $\dot{d}$ for the case seen in figure 5.6.b. We see that the period of the turning cycle is approximately $T_p \approx 28\,s$.

If we display the value of $\dot{d}$ for an arbitrary value with a large delay (we use the case of figure 5.6.b, $T \approx 27\,s$, but the results are valid for any large value of delay, even for the ones that result in a zero fitness behavior), we can see that when the agent is always turning in circles (figure 5.6.b) the period of the cycloidal movement is always around $T_p \approx 28\,s$ (figure 5.8). It means that when the delay is a multiple of T_p, the agent perceives what it received when it was in the same part of the turning cycle in the past. Thus, the agent is going to be able to perform the phonotaxis task because of the coupling between the periodicity of its movement and the sensorimotor delay.

This mechanism allows an agent to solve any situation of sensory delays, because if the agent implements a periodic intermittent behavior, just matching up the sensory delay with the intermittent cycle, the sensorimotor loop is going to emerge again. Also, this effect could be used as a band-pass filter, because it only takes the sensory information that is coupled within the sensorimotor loop.

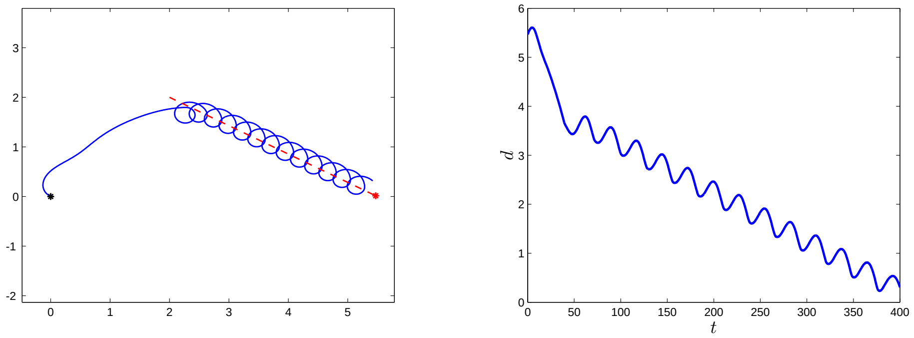


Figure 5.9: Trajectory of the agent chasing a moving goal distance d to the goal over time. When the agent is moving, it loses sight of the goal, so it has to adjust its behavior by turning.

Adjustment-deployment dilemma: chasing a moving goal

We have identified that the agent implements a metastable behavior when it cannot maintain its internal stability. We have linked this fact with the intermittency in the adjustment-deployment model we studied in chapter 4. Is it the same phenomenon? Or it is just a coincidence that both models show an intermittent behavior?

For answering to that question we have modeled a new scenario for the same agent we have been using so far. The new situation is that the agent has to reach a moving goal. The problem the agent has to solve is that, when it is chasing the goal and the goal is moving in the opposite direction, the relative speed of both get slower than when the object was still, making the agent not to perceive correctly the received wave and lose sight of the goal. However, the agent is going to be able to adjust its situation by turning and regaining the sight of the agent (figure 5.9). As in the previous cases, the deployment of the approaching movement is interspersed with turning behavior to adapt to the distortion in the received signal.

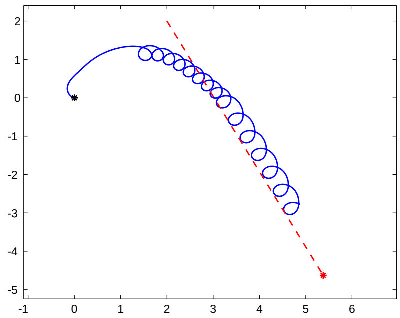


Figure 5.10: Trajectory of the agent chasing a moving goal which moves with two different velocities. At the middle of the simulation the goal velocity is reduced to the 30% of the original velocity, resulting in a change of the movement of the agent.

Is this really an adjustment-deployment strategy? If so, the adjustment-deployment intermittency should be adapted to the dynamics of the environment. We prepared a new simulation, in which the speed of the goal changes at some point. Concretely, at $t = 250$, the speed of the goal is reduced to the 30% of the original speed. In this case, we see in figure 5.10 how the agent modifies its behavior with the change of velocity. After the velocity change, the distortion of the signal perceived by the agent is smaller, thus allowing the agent to deploy the 'approaching the goal' behavior for more time until it has to adjust its situation by turning. The behavior displayed shows a typical characteristic of the adjustment-deployment dilemma: when the environment changes slowly, the agent spends more time in 'deployment' than when the world changes faster and more adjusted solutions to the problem are needed.

5.4 Codification of Distance Information in the Relative Phase

We have designed an agent that is able to perform a phonotaxis task by building a sensorimotor loop that allows the agent to know the position of the goal. If this is true, the agent has to somehow code the information about the goal within its oscillatory neural controller, giving rise to the emergence of a representation. As it has stressed before (O'Keefe & Recce, 1993; Singer, 2007, see section 2.3) representation in oscillatory networks might be coded in the phase relations of the elements of the networks with a precision in the millisecond range.

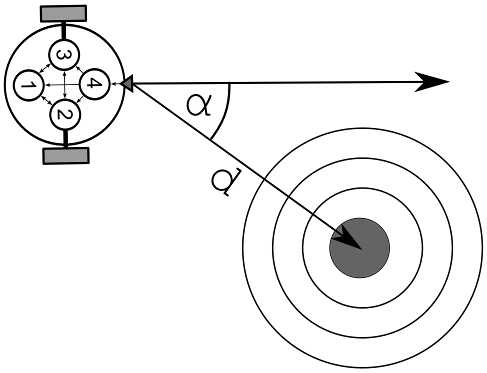


Figure 5.11: Representation of the variables d, which represents the distance to the goal, and α, which represents the angle between the goal and the agent's orientation.

If the agent is able to build a sensorimotor loop gaining information about the location of its goal, we ask ourselves if the information is encoded in the agent's internal neural dynamics. For answering that, we are going to analyze how the relative position of the agent affect the phase of the oscillator network. We analyze the variables d and α (figure 5.11), being d the distance from the agent to the goal and α the normalized angle from the heading of the agent to the goal, and how they are related with the relative phases of the system. For the following analysis, we take the variable ϕ_{12}, the relative phase between the 1^{st} and the 2^{nd} oscillator, but any other choice of relative phase would give us similar results, since they are all phase-locked in the default situation.

The first experiment we have run tests if the phase representation always codifies the same situation in the same way. For that, we run different simulations with different starting points for the agent. If we represent the trajectories of the relative phase respect

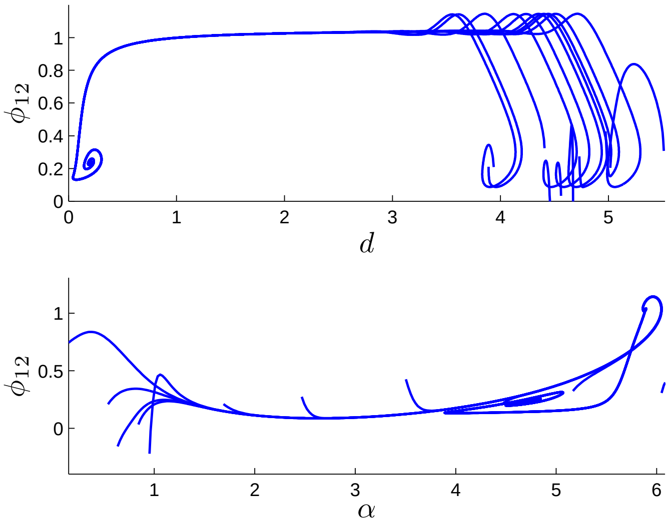


Figure 5.12: Plot of the relative phase ϕ_{12} for 10 different trajectories of the agent. It is seen how all trajectories converge to a unique one. Also, it is seen how the same distance information is codified in a different way depending on the state of the neural oscillator controller.

to the values of d and α (figure 5.12), we can see how all the trajectories converge into a unique path, which uniquely represents the distance and angle information for a concrete state. We also see that information is codified in different ways depending on the state of the agent. In this sense, if we analyze the tridimensional plot of the relative phase respect to d and α (figure 5.13), we can distinguish a first stage when the agent is far from the goal and it is just orienting itself and turning to face the goal; a second stage where the agent starts approaching the goal, and a third stage where the agent start turning to reach the goal.

In the first stage, the distance to the goal does not change much, but we see that the orientation of the agent changes as it turns, while the relative phase also changes. Concretely, as the agent approaches to the goal ($\alpha \approx 6$), the relative phase increases to $\phi_{12} \approx 1$. In the second stage, it is the orientation which is kept constant, while the distance decreases. Phase representation is kept also constant while the agent is far from the goal ($d > 2$), but when the agent is closer to the goal ($d < 2$) the phase information starts changing, while a slight change in the orientation α takes place. These changes become bigger the closer the agent is to the goal. So, in this short range representation not only the orientation angle but also distance to the goal is codified in phase information. Finally, in the third stage, the agent shows an undulating trajectory until it stabilizes in a point where it is continually turning around the goal at a close distance.

We have seen how relative phase is able to represent the orientation information of the agent in the different stages of behavior. Additionally, phase information can codify distance information in the short range. That makes sense if we consider how the agent is perceiving information from the world. The agent can detect the acoustic waves coming from the goal. And, given the size of the agent, when it is far enough we can consider that the agent is perceiving a linear wavefront, so it has no way to know what the distance to the goal is, and it can just know if it is approaching or not. However, when the agent is closer to the goal, the linear wavefront approximation do not hold anymore, and it can perceive not only 'where' but 'how far' the goal is (figure 5.14).

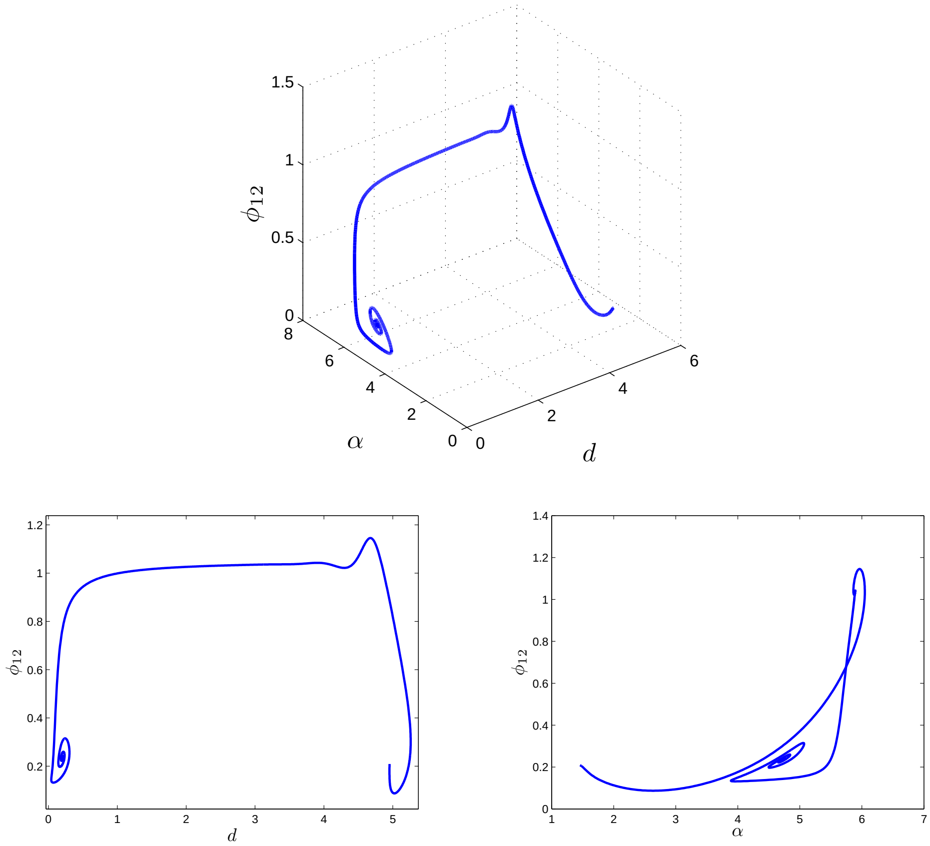


Figure 5.13: Plot of the relative phase ϕ_{12} for the trajectory of an agent performing phonotaxis. Relative phase codifies aspects of both distance (d) and orientation angle (α)

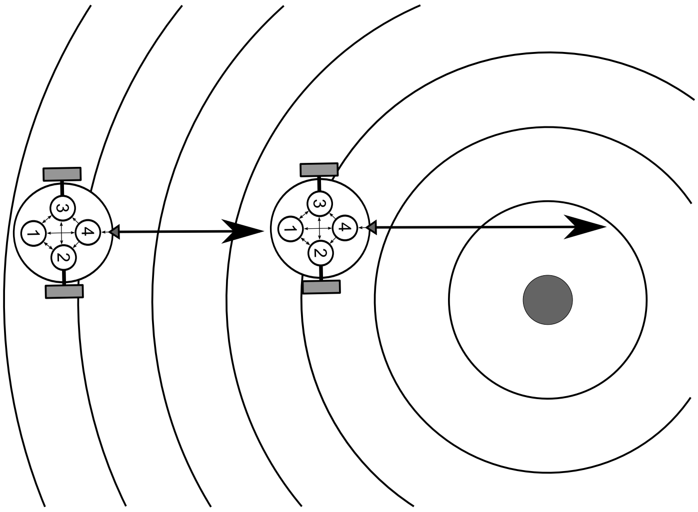


Figure 5.14: Schema of how making a detour allows the agent to embed knowledge of how close is the goal. When the agent is far away, it perceives 'plain' wavefronts. Waveforms start curving as the agent starts getting closer to the goal.

Intermitency and information coding

If we perform the same analysis than before when the agent behaves intermittently, the result is not too different. Again the orientation of the agent is codified in the relative phase as seen in figure 5.15. Nevertheless, since the agent is deploying a cycloidal behavior, it cannot process information about its relative distance to the goal because the instability of the 'approaching to the goal' behavior that allowed to compute it. Thus, relative phase can only code information about the agent's orientation. It is worth to note that the coding of orientation information is performed in the same way than in the default unperturbed case.

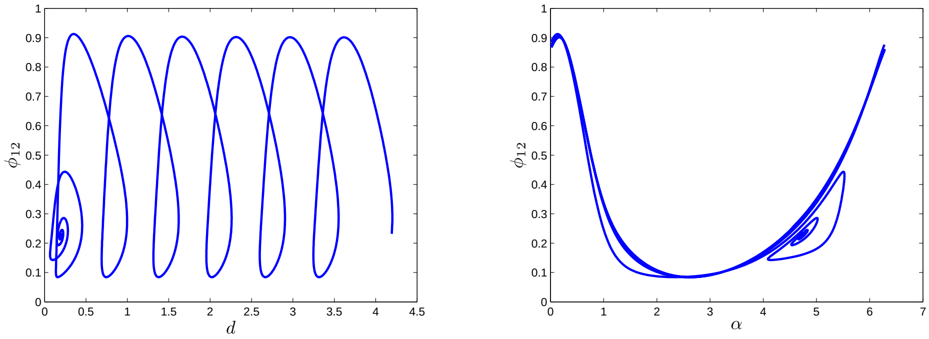


Figure 5.15: Plot of the relative phase ϕ_{12} for a cycloidal trajectory of an agent performing phonotaxis. Relative phase codifies aspects of orientation angle (α). Distance (d) is no longer codified.

5.5 Phase-Locking and Metastability in the Sensorimotor Loop

We have proposed that dynamic coupling between the parts of the brain, and between brain, body and environment allow the emergence of robust behavioral patterns, being this coupling modeled by non-linearly coupled oscillators. In chapter 2 we have defined two different mechanisms to model interaction of brain parts (Tognoli & Kelso, 2009).

1. The first mechanism is **synchronization** of brain dynamics, which is defined as the formation and dissolution of attractors that bind local oscillations into phase locked states. These regimes are hypothesized to correspond to transiently synchronized neural cell assemblies (Varela, 2006).

2. The second involves forms of coordination different that phase-locking, defined as **metastability** in brain dynamics, represent the binding of areas with different intrinsic oscillatory properties which are just partially coordinated. Here, oscillatory patterns show dwelling tendencies in a quasi-phase-lock intermittent mode. This mode of behavior is more robust and allows flexible and versatile behavior (Kelso, 1995).

We have built a simulation model that shows both kind of dynamics for solving a phonotaxis task, making us to think about which is the role of synchronization and metastability in cognitive behavior and how these two are related.

We start with synchronization. In the first agent that is obtained from the genetic algorithm, when performing the original unperturbed phonotaxis task, we saw that the neural controllers of the agent showed a behavior of full phase-locking with different phase relationships. Typically, neurophysiologist have centered their attention in zero-lag synchronization, although some studies have addressed other phase relationships (Womelsdorf *et al.* , 2007; Palva & Palva, 2009). Tognoli & Kelso (2009), in addition to inphase and antiphase synchronization, consider near inphase or near antiphase entrainment in brain synchronization dynamics as important neural coordination states. In the model simulated here, we can see (figure 5.3) how phase-lockings other than inphase or antiphase can be important for the processing of the information in the sensorimotor loop, being able to code different states of the brain-body-environment system. As well, having a continuous space of phase relationships will be useful for coding environmental information.

Let's continue with metastability. Other result show in our model is that, in the sensorimotor loop, not only the neural dynamics determine behavior, but perception shapes the form of neural dynamics. The coupled sensorimotor loop arises as an order parameter that channels the interactions of the elements of the system, constraining its degrees of freedom. For the unperturbed situation, the sensorimotor loop allows a stable behavior of the agent. Anyway, the unperturbed sensorimotor loop is situated at the border of stability. When the stability of the loop is broken, metastable behaviors arise. These metastable behaviors allow the agent to explore different strategies to solve the problem, showing a more robust behavior than the stable initial one, having all the properties seen in chapter 4.

Thus, stable synchronization and metastable dynamics appear closely linked. We see in our model how the most efficient and robust behavior is the one that lives between stability and metastability, which can show a synchronized predictable behavior when the environmental conditions allow it, and can deploy a metastable intermittent behavior when it is needed a more flexible adaptation mechanism.

5.6 Robustness and Behavioral Pattern Structuring

In sensorimotor loops, while neural dynamics determine behavior, perception is going to shape the form of neural dynamics. This is one of the hallmarks of sensorimotor loops, which allows the emergence of robust behavioral patterns. As we see in our model, the received acoustic wave stabilizes the system in a phase-lock state. Also, the behavior of the agent is going to stabilize the Doppler effect of the received signal in the neural controller. And, if we analyze the metastable modes of behavior, we see that behavior and the signal are intermittently trapped in quasi-phase-locking modes.

There could be four different modes of behavior for our agent: a) attraction to the goal (phonotaxis), b) orbiting at a constant distant to the goal (the behavior we see when the agent reach the goal), c) repulsion from the goal (the opposite to phonotaxis), or d) motion independent to the goal. Just in the latter case, which is also the one that allows a larger variety of behaviors, the agent would not be engaged in any sensorimotor loop, and there will not be any phase-locking. Thus, if we oblige the system to be stable while having an input from the goal, it is always going to engage in any sensorimotor loop.

Indeed, if we modify the natural frequencies of the three oscillators of our system (all of them except the sensor oscillator) and we keep high values for its coupling factors, we can see how the behavior of the agent always lies in the the 'a)', 'b)' or 'c)' modes of behavior (where 'b)' is just a transition in the continuum between 'a)' and 'c)'), either showing synchronous or metastable behaviors (figure 5.16). In this case, when the cases which still maintain high values of motor activation, we show how the agents perform surprising spiral movements towards or away from the goal (figure 5.17.a). If, on the

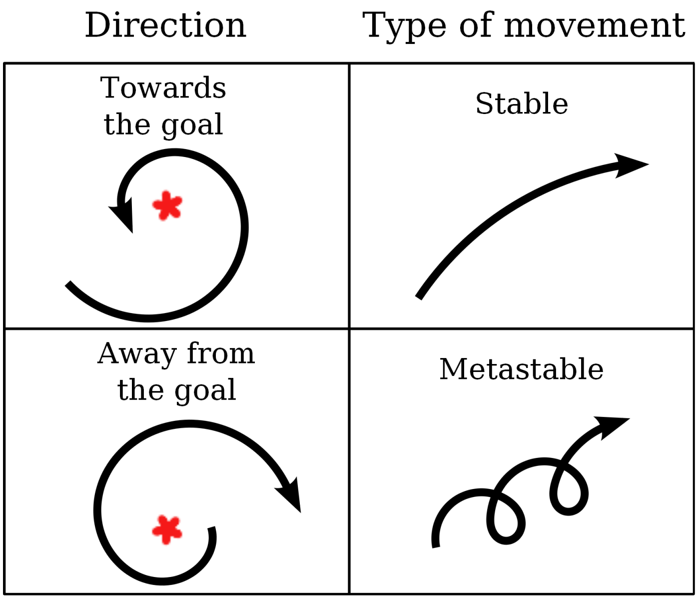


Figure 5.16: Table of possible behaviors when the agent is engaged in a sensorimotor loop with random natural frequencies for the oscillator network and strong coupling factors. The movement of the agent can be either stable or metastable, and approaching or moving away from the goal a different speeds. The possible behaviors also can show different degrees of curvature.

other hand, we cut the connections from the sensor oscillator, we see how the movement is independent from the goal, and the system becomes unstable (figure 5.17.b).

We see how sensorimotor loops not only allow adaptive behavior to arise, but determine what behaviors are actually possible (or not) for the agent. We can easily see how coordination dynamics in the sensorimotor loop is a great advantage for adaptive behavior: they force the agent to implement, from all the set of possible patterns of behavior, only those behaviors that are meaningful respect to its environment and allow a mutual stabilization of the perceived stimulus and neural dynamics. If our behavior is constrained to the set of behaviors seen in figure 5.16, it is much easier to find the parameters of the neural controller that perform the desired behavior just by a random search than in the case where we have no behavioral constrains.

In conclusion, any type of coupling with the environment is not enough for guaranteeing a robust behavior. Instead, robustness emerge when the nature of coordination in the sensorimotor loop organizes the behavioral options of the agent into those that maintain the internal stability of the system. As we have seen, in such structured sensorimotor loops, the agent is able to display a highly robust behavior just by assuring its internal stability. Thus, synchronization and metastable dynamics can be seen as mechanisms to impose the necessary internal stability in structured sensorimotor loops to perform robust structured behavioral patterns.

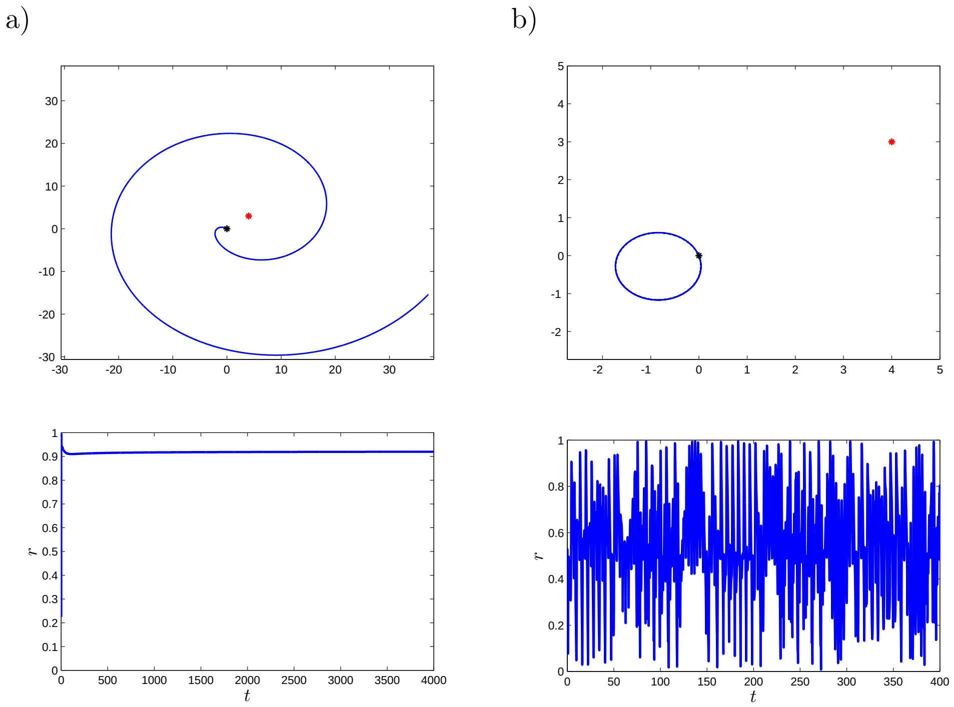


Figure 5.17: a) Agent with modified oscillator natural frequencies moving away from the goal and keeping its internal state stable. b) Agent with removed sensor oscillator connections, moving independently of the goal and having an unstable internal state. The stability of the sensorimotor loops structures what kinds of behaviors are possible to perform for the agent.

Chapter 6

Sensorimotor Coordination for Adaptive Behavior

In this last chapter, we recap what we have seen throughout this work. First, we started refusing some assumptions of the classical artificial intelligence approach, which over-relies on world-modeling and planning capacities that often are completely uncoupled to the agent's interactions with the world. Consequently, we proposed the 'dynamical approach' approach to cognitive science as a more realistic perspective to analyze and explain the emergence of cognitive behavior, by defining cognitive agents as dynamical brain-body-environment coupled systems. This approach is based on how the deployment along time of coordinated neural patterns sustains the emergence of cognitive functions. Assemblies of neurons entrain themselves in coherent transient states, integrating information between different functional sectors by rapidly engaging and disengaging parts of the neural system, at the same time they interlock in coupled interactions with the environment.

In the approach we have presented, we have pointed out what we considered as two of the main hallmarks of cognitive emergence: coordination dynamics and sensorimotor loops.

Coordination dynamics inspires on the organization of pattern activity in the brain to define a mathematical framework for analyzing the formation and coordination of patterns in complex self-organized systems. It tries to understand the role of oscillatory networks in the brain to maintain its autonomy and coherence while preserving the versatility of self-organized criticality.

We have introduced two types of dynamics that the human brain uses to coordinate the oscillating functional parts that compose it:

- Synchronization. It enables the brain to create (transiently) stable states which establish phase relations that are going to define functional cell assemblies. These assemblies would be responsible for the emergence of cognitive functions.
- Metastability. When a stable coordination of different nodes of the brain is not stable or cannot cope with the requirements form the environment, the synchronized regime breaks apart and metastability arises. However, some attraction will remain at the points of the phase space where attractors where placed, giving place to relative coordination between oscillating nodes. This dynamics allows rapid switching between cell assemblies formation and flexible engagement and disengagement between functional parts.

However, despite the great advances brought by neurophysiological studies about the dynamics of the brain, we consider that this research line has showed some limitations for understanding the role of coordination mechanisms in the emergence of self-organized dynamics in the brain. We think that these limitations are founded the following facts: 1) it is difficult to understand the emergence of brain dynamics just by analytical observation and 2) brain dynamics alone cannot tell us much about the cognitive phenomena unless we conceive them as patterns cutting across the brain-body-environment system in a coupled sensorimotor loop.

Sensorimotor loops allow robust and flexible coupling across the brain-body-environment system. They are processes where dynamical patterns are deployed in time to allow the emergence of cognition, structuring the organism's behavior. In contrast to simple input/output processing proposed by classical AI approaches, the sensorimotor loop closure stress that meaningful interaction with the world needs an embodied agent whose effectors and sensor activities become coordinated performing the desired task or un-coordinated during breakdowns.

The problem comes with the question of how to study the emergence and function of the different levels of coupling in sensorimotor loops. Our approach, under the name of the 'synthetic approach', proposes to build simple artificial self-organized agents performing minimal cognitive tasks. With the objective of analyzing how complex emergent behaviors arise from even simple mechanisms when dynamical couplings are introduced. Evolutionary techniques will be an important tool find counterintuitive couplings in brain-body-environment systems, allowing to discover surprisingly robust mechanisms to different task. By doing this way, we seek to obtain models where the intelligence in the system is just the intelligence of the designer, trying the models to have meaning by themselves.

As a first attempt to explore these ideas, we have presented two case studies about the importance of coordination dynamics and sensorimotor loops in the study of cognition. Our main objective with these examples is to boost more ambitious future research lines, taking the ideas presented above as important elements in our approach.

Coordinated Intermittency for Adaptive Behavior

In chapter 4 we have analyzed how intermittent modes of behavior are not just a feature of brain dynamics but can be found at different levels of biological organization We found how metastable systems could provide optimal solutions to generate adaptive behavior to unknown changing environments.

In contrast with classical AI's over reliance on world-modeling and planning, the presented model's solution turns to require a compromise with non-maximal quality and a high rate of alternation between adjustment and deployment behaviors. That is, the most adaptive behaviors wouldn't be the ones that build best models of the world, allowing to higher levels of adaption, but the ones that maximize the interactions with their environment, generating fast short-termed predictions which are going to be constantly revisited. That is, recurrent testing of our solution into the environment renders betters results than indefinitely adjusting our models of the solution. We find our model to match experimental biological data from behavior in different animals, and we checked how the model could be implemented with quite simple mechanisms, if the appropriate conditions are met.

Our model also brings forth the necessity to include the temporal dimension of cognitive processes into our theoretical framework. Speed, intermittency, decay-rates, and deployment duration crucially matters when it comes to real-world problem solving, since the suitability of the performed behavior is going to depend on the coupling between internal and external dynamics of the agent. Thus, the processing of these temporal elements must be embedded in the sensorimotor loop, being the coordination of internal and external pattern dynamics essential for a suitable interaction with the world.

We interpret temporal alternation between complementary behavioral patterns as a widespread adaptive strategy of biological organization. Autonomous patterns have to be combined by flexible metastable and distributed control systems, being the duration of this patterns mediated by temporal processing of both their dynamics and the dynamics of the environment.

Robust Sensorimotor Coupling

How do robust patterns of behavior arise coupled with the world dynamics? In chapter 5 we have modeled a simple agent performing a minimal phonotaxis task. We have evolved a neural controller that allows the agent to follow an acoustic signal just by processing the phase of the signal received by one sensor. Even in this simple task, embodiment and situatedness are key elements for understanding the role of the brain dynamics. We see how the agent achieves its objective by the dynamical coupling of its neural systems with both its body and the environment, being able to move in different ways to achieve its objective even when the environment dynamics are perturbed. We have seen how studying the dynamics of neural controllers in isolation doe not give us much information if we do not consider them as coupled with external dynamics.

We have seen how different coordination dynamics solve the problem in different forms and the role they play embedded in the sensorimotor loop. Synchronization solves the task in a straightforward way, displaying a stable behavior. Anyway, when this stability is threatened by external perturbations, synchronization is broken and metastability arises, allowing a robust behavior that allows the agent to adapt to unknown situations.

Also, we have observed the importance of embedding the processing of temporal aspects in the sensorimotor loop, for example allowing the correct processing of delayed information when it is coupled with the agent movement. In fact, the temporal coordination of sensorimotor patterns ‘structures’ the behavioral coupling with the environment, defining what patterns are behaviorally meaningful and how. In this way, closed sensorimotor loop forces the temporal patterns of the neural controller to fit into the temporal structure of environmental stimulus, which are at the same time determined by the behavior of the agent.

We have seen how, forcing the stability of the neural controller (showing either phase-locking or quasi-phase-locking) the agent always displays behaviors that are coupled with the environment in some way (being either phototactic or anti-phonotactic in different degrees). Just by forcing a system to maintain stable or metastable internal states we reduce the set of possible behaviors to the ones that are meaningful in relation to the environment in some way. This happens because we have defined the information processed by the neural controller in relational terms. Variables have not just meaning by themselves, but related to a system that may be stable or not.

While in the classical perceive-think-act loops of the computationalist approach the meaning of a behavior just could be established only by external evaluation of the researcher, sensorimotor loops allow to interpret behavior from the point of view of the agent, depending on how different patterns could be stabilized or not (and how) in a given environment.

6.1 Future Work: Towards Intelligent Systems Inspired in the Organism

A relation to the world in terms of meaning is the base of all forms of cognitive activity, from the patterns of adaptive regulation in the simplest forms of sensorimotor coupling with the environment to the highest abstract forms of cognition. What makes engagement with the world meaningful for an agent? We have shown how stable sensorimotor loops constitute a necessary element for giving meaning to the different ways of interacting with the environment, constraining the set of stable behavioral patterns to which fit into the metrics of environmental stimulus.

However, it is not clear that the presence of a closed sensorimotor loop does fully solve the problem of meaning in AI. For example, Di Paolo (2010) argued that the generation of meaning should not be divorced from the internal organization of the organism. Meaning should be grounded in the generation of autonomous patterns of behavior, that will be stabilized if they are able to maintain its own autonomy. Di Paolo refers to these stable autonomous patterns of behavior as habits, giving a simple explanation for their emergence. If we assume that the potential for plastic change of an agent is always present, and that plasticity affects the generation of behavior which in turn affects plasticity in an activity-dependent manner and through recurrent engagements in similar situations, then two scenarios are possible: 1) the double link between plasticity and behavior never reaches a stable dynamical regime, in which case it will inevitably run into an adapt-or-die situation, or 2) it may reach a stable regime and this may be unadaptive (with the same result as in the previous case), or adaptive in which case it will be conserved in preference to other viable behaviors.

In that sense, a stable repertoire of habits would constitute self-sustaining dynamical structures, underlying the generation of behavior. And this stable structure will be challenged when behavior is perturbed due to the modification of the environment dynamics. This would explain how behaviors tend to get increasingly attuned to the regularities of the body and its surrounding, being sustained by ecological structures in which actions are perceptions are combined.

Coordination dynamics defines the stability of the system based on the phase-locking or quasi-phase-locking of the system, in contrast to systems that only process absolute variables (as the level of activation in neural networks). This allows a more interesting characterization of stable and unstable states of behavioral patterns, compared to other approaches the at assumed arbitrary definition of thresholds in neural activation to trigger plasticity mechanisms (Di Paolo, 2000). As we saw in chapter 5, when we define sensorimotor loops in terms of structured coordination dynamics, internal and behavioral stability require one another. An interesting further research would be to explore what kind of mechanisms could link internal stability with the degree of adaptivity of the agent's behavior, and how plastic changes could be triggered when this internal stability is challenged.

In contrast to computationalist to AI, in which intentional terms are determined by the designer, dynamical systems perspectives on cognition have difficulties to define terms as motivations, tendencies, goals, etc. as functional states in the cognitive architecture of an agent. Kelso (1995) suggested that it is possible to describe intentional behavioral changes in terms of transitions between dynamical attractors which correspond to different behaviors. We have shown how the meaning of a given behavior is grounded on the dynamics of the sensorimotor loop it is engaged, where intentional and developmental processes re-parameterize behavior and, in turn, interaction with the environment constrains and modulates intentions and development. Our objective for future research is to go further, and explore the types of organization necessary for systems in which different coordinated self-sustaining patterns of behavior that interact with the world in meaningful ways arise, grounding the intentionality of adaptive behavior in an organism.

This master's thesis intends to be the first step of a more ambitions research project towards the completion of a PhD thesis derived from some of the issues and problems presented in this work. The motivation of this research project will be to understand some general principles of biological organization in adaptive and intelligent systems. We introduced our work with the 'computer metaphor', which gave birth to most of the classical approaches to AI, thinking that symbolic processing of information could model all principles of organization in the brain, thereby allowing for the design of human-like intelligence. However, we have claimed that computationalism is not enough to account for the huge capacities shown by the human brain and, instead, a holistic and dynamical perspective is necessary for understanding the systems and processes that are behind of cognition. If we are right, it is time to get rid of some of the old misconceptions about the nature of intelligence and embark ourselves in the quest for find the adequate metaphors to define adaptive behavior at different levels of biological organization.

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