Metastable dynamical regimes in an oscillatory network modulated by an agent's sensorimotor loop

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***Abstract*—The last two decades have witnessed an increasing focus on oscillatory brain dynamics as a means of understanding a variety of cognitive phenomena. Most theoretical and mathematical approaches in this area have mainly worked under two assumptions: a) that the most significant aspect of oscillatory brain dynamics is synchronization; and, b) that most part of functional brain dynamics can be understood without incorporating the sensorimotor loop into the picture. Although significant progress has been achieved with these assumptions, we believe they might limit future development of dynamical approaches to brain functioning and cognitive behaviour. Looking at the whole picture of brain dynamics, rather than only moments of synchronization, and analysing it inside the sensorimotor loop can provide new insights on how the brain operates. In this paper we present a robotic agent capable of performing phototaxis controlled by a Kuramoto-model based oscillatory neural network. The network parameters were optimized using a genetic algorithm. The resulting brain and behavioural dynamics are analysed within Kelso's Coordination dynamic framework. We found that: a) during a whole behavioural episode of phototaxis the robot's brain undergoes different metastable dynamical regimes of phase-lock and phase-scattering, represented by the relative phase and phase coherence among oscillators; b) even for a simple task, metastable coordination patterns and functional behaviour emerges without the need for a specific synchronization signature; and, c) sensorimotor loop dynamics plays a critical role generating and sustaining functional metastable regimes of brain activity by modulating the network's control parameter.**

I. INTRODUCTION: BRAIN OSCILLATIONS, SYNCHRONIZATION AND BEHAVIOUR

The so-called artificial-life-route-to-AI [1], originally emphasized the situated, emergent, self-organized, often non-representational, and dynamic nature of cognition. Design principles were also claimed to be biologically inspired. Such biological inspiration was mostly limited to state that cognitive systems had to be built from the bottom-up (from the simplest to the more complex, like evolution proceeded for natural cognition) and to favour insect-like behavioural patterns. In some cases "biological inspiration" meant also the use of artificial neural networks as control systems but rarely did such networks bear much relevance to neurobiology. The scientific context has radically changed since those early years of AL. Neuroscience has made considerable progress developing empirical and theoretical frameworks where self-organization, emergent patterns, phase-synchrony, and oscillatory rhythms are now common issues in studies of brain dynamics [2]–[4]. Whereas the AL approach to cognitive science still has much to explore within this framework, large-scale neuroscience has yet to be integrated with insights into the situated and embodied nature of cognitive dynamics. The current paper aims to help fill this gap, merging situated and evolutionary robotics with some current trends in large-scale neuroscience.

The last two decades have witnessed an increasing focus on oscillatory brain dynamics as essential for a variety of cognitive phenomena. In neuroscience, oscillatory phenomena are present in different levels of the nervous system's activity. At the individual neural level, neurons undergo cyclic alterations on its membrane potential following different dynamical regimes depending on the cell properties [5]. At higher levels, global oscillations is a collective phenomenon generated by groups of neural cells that fire synchronously (entrained by pacemaker cells or as a result of recurrent network activity with inhibitory-excitatory connections). Such oscillations generate magnetic and electric fields which can be measured by Magnetoencephalography (MEG) and Electroencephalography (EEG), respectively. By investigating these signals, coherent dynamical properties can be found and systematically related to sensorimotor activity and cognitive phenomena [3].

The main theoretical and mathematical approaches for analysing such signals have mostly worked under two main assumptions: a) that the most significant aspect of oscillatory brain dynamics is synchronization; and, b) that most functional brain dynamics can be understood without incorporating the sensorimotor loop into the picture (that is, the continuous and recurrent interaction with the environment, the online coupling of brain and environment through sensor and motor activity). Despite the significant progress achieved under these assumptions and the experimental evidence to support aspects of them, we believe they might be limiting future development while the role of sensorimotor loops and the functional relevance of metastable dynamical regimes still remains underexplored.

Regarding the first assumption, work on empirical neuroscience dealing with (oscillatory) brain dynamics usually focuses on moments of phase locking (synchronization) in different spatial and temporal scales in the brain and leaves out of the equation moments of phase scattering (desynchronization). The main reason for this approach is that neuronal synchronization is believed to be the mechanism used for integration and segregation among spatially different areas [6], [7]. Roughly speaking, researchers have been claiming that phase locking among functionally distinct neuronal groups represents meaningful periods of brain dynamics by correlating with specific cognitive moments (e.g. perceptual states). The main evidences for such claim come from investigations on local scale integration in the visual system, the well-known visual binding problem [8], [9]. Researchers on the visual binding problem try to find how functionally distinct areas in the brain dynamically relate to each other in order to produce a coherent whole. For instance, the representations of different aspects of the same object (e.g. its colour, shape, location and direction of movement) are processed by distinct areas showing specific dynamic coordination properties when the object is perceived. Phase locking has become a widespread explanatory hypothesis to explain such global coordination and appears to be correlated with moments of perceptual binding. Synchronization, understood as phase locking, has since become a signature of cognitive processing. The functional significance of moments of phase scattering (i.e. desynchronization), however, might also remain meaningful for brain functioning and should not be left out of the explanatory picture; that is, desynchronization should not be considered merely as moments where the brain is transiting between meaningful or functional brain patterns. As Kelso puts it:

> If, instead of artificially partitioning the brain data (or any dynamical data for that matter) into isolated epochs of pure integration [i.e. moments of phase locking] and pure segregation [i.e. moments of phase scattering], one considers the entire epoch [the whole phase dynamic], one discovers that the behavior seems to be relatively coordinated. [10, p.148].

Regarding the second assumption, despite the great amount of mathematical and simulation modelling in current large-scale neurodynamics, there is still little systematic exploration of the coupling between brain, body and environmental dynamics and, more generally, how oscillatory signals operate together in closed sensorimotor loops. Most theoretical approaches have focused on how oscillatory coordination can carry information within the brain. Models are generally build leaving out the body and the environment and often assuming a representational theory of brain functioning (that is, assuming that the main job of the brain is to create a representation or model of the environment and focusing on neuronal mechanisms capable of supporting the processing of such a model, isolated from its environment). This assumption is partly due to experimental limitations with current brain scanning techniques and partly due to the underlying theoretical framework. Explorations into the dynamics of oscillatory "brain" dynamics coupled to the sensorimotor loop in robotic simulation can potentially help overcome such limitations.

Following the Artificial Life tradition of using a synthetic artificial model to understand cognitive systems, the goal of this paper is to explore metastable dynamical regimes of phase relation in oscillatory networks modulated by the sensorimotor loop. We first introduce Coordination dynamics [11] as a general framework for the study of oscillatory dynamics in brain and behaviour. Next we explain the architecture and design of our simulation model, a Kuramoto-model based oscillatory neural network controller that is capable of performing phototaxis. The network parameters were optimized using a genetic algorithm. The resulting brain and behavioural dynamics are then analysed and experimentally explored with special focus on a) metastable dynamical regimes of phase-lock and phase-scattering of the robot's brain during the behavioural episode of phototaxis; b) the role of sensorimotor loop on such dynamical regimes. Finally we recapitulate the main results and extract some conclusions regarding diversity of functional oscillatory regimes and the essential modulatory role played by the sensorimotor loop.

II. COORDINATION DYNAMICS, SYNCHRONIZATION AND METASTABILITY

Coordination dynamics is a consistent framework which can be used to investigate brain dynamics and behaviour, it was proposed and developed by Kelso [11] based on Haken's work on synergetics [12]. It combines experiments and theoretical models formulated mathematically to study how the components of a system interact and produce coherent coordination patterns. This framework is aimed at studying the coordination of living systems acting in their environments and can be applied to describe the interaction of components at different levels of observation. For instance, it offers a means to relate the coordination dynamic of parts of the brain to the stimuli and responses given by whole living system interacting with its environment [11], [13], [14]. As Kelso and Jirsa put it:

> Coordination dynamics - the science of coordination - describes, explains and predicts how patterns of coordination form, adapt, persist and change in natural systems. [...] [It] seeks to identify laws, principles and mechanisms underlying coordinated behavior in different kinds of system at different level of description. [...] [It] aims to characterize the nature of the coupling within a part of a system (e.g. the firing of cells in the heart or neurons in a part of the brain), between different parts of a system (e.g. parts of the brain, parts of the body, members of an audience) and between different kinds of systems (e.g. stimuli and responses, organisms and environments, perception and action, etc.). Ultimately Coordination dynamics is concerned with how things come together in space and time, and how they split apart [13, p.VIII].

The driving model-example for Coordination dynamics is the extended HKB (Haken-Kelso-Bunz) which describes the dynamic of the relative phase between two non-linearly coupled oscillators [15]. Despite its simplicity, this model has been capable of capturing the dynamics of different behavioural, neural and social coordination dynamics [16]–[18] and still remains a paradigmatic example of dynamical and embodied cognitive science [19]. One of its main properties is the metastable dynamics in which the coordination variable (relative phase) engages when a control parameter crosses a given threshold. The equation governing the dynamic of the relative phase is presented in Eq. (1).

$$\dot{\phi} = \delta\omega - a\ sin\ \phi - 2\ b\ sin(2\phi) + \sqrt{Q}\xi t \qquad (1)$$

where ϕ is the relative phase between two interacting components (oscillators); $\delta\omega$ are the intrinsic differences between the components; a and b are strength of the coupling; and ξ represents the presence of noise fluctuations of strength Q (see [11, p.54] for a detailed description of this equation). The graphic in Fig. 1 depicts the stable and unstable points (filled and unfilled circles, respectively) of the relative phase and its derivative for different values of $\delta\omega$ and constant coupling (a=1; b=1). Observe that, for small values of the intrinsic difference between the components ($\delta\omega$), the system is multistable with stable points ($\dot{\phi} = 0$) near the in-phase and anti-phase dynamics, 0 and π radians, respectively. As the intrinsic difference increases the fixed points move and eventually disappear. Over this threshold of the intrinsic difference the system no more presents fixed points and the relative phase engages in what Kelso calls a "metastable dynamic".

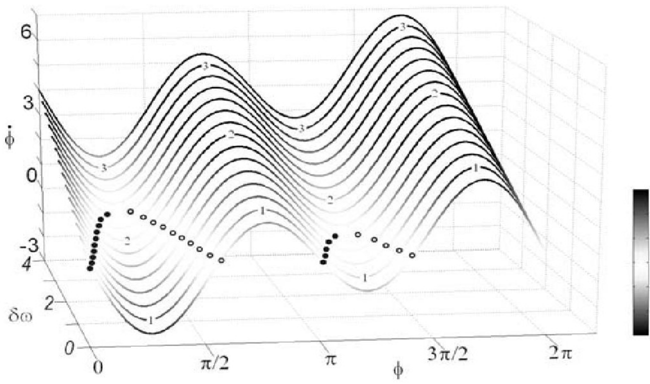

Fig. 1. Surface of the relative phase (ϕ) for increasing values of the intrinsic difference between components ($\delta\omega$) [14]. See text for a description.

The region where the system is metastable is of particular interest for it is this kind of dynamics that have been the least explored in large-scale neuroscience and yet potentially the most relevant (as shown by the recent interest on criticality and phase transitions in the brain [20]). In the metastable region the system achieves a compromise between the intrinsic dynamic of its component oscillators and the global coupling, allowing for a flexible tradeoff between integration and segregation (the mark of brain complexity [21]). In other words, within the metastable region, the system shows the capacity for flexible response without getting trapped in a strong attractor.

Besides the metastable dynamic depicted by this model, *coordination variable* and *control parameter* are also important concepts in Coordination dynamics. A *coordination variable* is an "upper level" variable which captures the collective dynamics of "lower level" interacting components; in Eq. (1) it is represented by the relative phase (ϕ). In Haken's framework this variable is denoted as *order parameter*. A *control parameter* is a variable which qualitatively changes the collective dynamics of the system when a threshold is crossed. In Eq. (1) the *control parameter* can be either the coupling strengths (a, b) or the intrinsic difference between the interacting components ($\delta\omega$). We know that two variables are *coordination variable* and *control parameter* when varying the latter leads to collective dynamic transitions which are captured by the former.

Despite the emphasis on system-environment coordination dynamics and the significance of metastability, to our knowledge, no theoretical studies have yet explored metastable dynamical regimes (dynamics in the region of the surface where the attractors have disappeared - Fig. 1) modulated by the sensorimotor loop. In order to do so we designed and evolved an artificial agent capable of doing phototaxis and whose controller system is made of a small network of non-linear coupled oscillators (the Kuramoto model).

III. THEORETICAL MODEL

The model consists of a two-dimensional simulated environment, an agent and a light source. The agent's movement is controlled by a network of coupled oscillators which receive signals from two sensors and control the activation of two motors. In order to obtain the right set of parameter values for an agent performing phototaxis, a genetic algorithm is used. The range of each parameter, which defines the search space, is presented throughout the description of the methodology together with the description of each variable.

The dynamic of the network of oscillators is governed by the Kuramoto model [22]. This model was originally motivated to study collective synchronization among interacting oscillators with different intrinsic frequencies. Some examples of biological phenomena and engineering applications involving collective synchronization are: pacemaker cells in the heart, circadian pacemaker cell in the brain, flashing firelies, arrays of lasers and microwave oscillators [23]. The first implementation of the Kuramoto model as a controller of situated agents, which has motivated the present work, was done by Moioli, Vargas and Husbands [24]. In their work, they investigate the dynamic of neural synchronization and phase of an agent evolved to discriminate between moving circles and squares.

The Kuramoto model was chosen, instead of the HKB model, because it is more general and has become a widespread theoretical model for brain oscillations [25]. These oscillators can be interpreted in various ways: a) as individual oscillatory neurons, b) as the activity of neuronal groups, tissues or brain regions c) as the macroscopic result of the activity of interactions between such regions, like EEG recordings. In the current work it is not necessary, however, to adhere to any of these levels of interpretation, we take the oscillators to be theoretical entities at an undetermined level of abstraction. What matters to us, at this stage, is not the level of empirical accuracy of the model but its capacity to raise theoretical issues and its potential open new insights into dynamical modelling and analysis of brain-behaviour patterns.

A. Agent and its Network of Coupled Oscillators

The agent (Fig. 2) has a circular body of 5 units diameter; two sensors separated by $120^\circ \pm 10^\circ$ whose output signal is given by $I_q = e^{-0.04 d_q}$, where q represents each sensor, and *d* is the distance from sensor q to the light source; it also has two diametrically opposed motors which activation is defined by $(sin(\theta_4 - \theta_3) + 1)/2$ and $(sin(\theta_5 - \theta_3) + 1)/2$, respectively; where θ_n is the phase of the oscillator *n*.

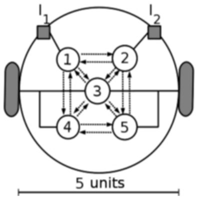

Fig. 2. The agent's controller ("brain") is composed of five oscillators.

The agent's behaviour is controlled by a network of five coupled oscillators, using the Kuramoto model [22], defined by Eq. 2:

$$\dot{\theta}_i = (\omega_i + I_q s_{qi}) + \sum_{j=1}^{N} k_{ji} sin(\theta_j - \theta_i) \tag{2}$$

where θ is the phase of the i^{th} oscillator which is integrated with time step 0.015 using the Euler method, ω is the oscillator's intrinsic frequency (range [1,10]), I_q is the q^{th} sensory signal (out of 2), s_{qi} is the sensory input strength from the sensor q^{th} to the oscillator i^{th} (range [0.01,20]), *N* is the number of oscillators (here 5), and k_{ji} is the coupling factor from the j^{th} to the i^{th} oscillator (range [0,5]).

Following Kelso's model, we also use the intrinsic difference between oscillators as the control parameter. The difference is that while the control parameter in his model is "manually" controlled by changing $\delta\omega$, in our model it is modified by the agent's sensors $(\omega_i + I_q s_{qi})$.

B. Optimization with Genetic Algorithm

A total of 27 network parameters encoded in a genotype as a vector of real numbers in the range [0,1] (linearly scaled, at each trial, to their corresponding range) were evolved using the *microbial genetic algorithm* [26]. There is no specific reason why this algorithm was chosen; the system is relatively simple and could have been optimized with other genetic algorithms. The genetic algorithm setup is: population size (80); mutation rate (0.05); recombination (0.60); reflexive mutation; normal distribution for mutation $\left(\mu = 0, \sigma^2 = 0.1\right)$; trial length (150 secs); and trials for each agent (30). At the end of the 30^{th} trial the worst fitness (out of 30) is used as the selective fitness of the agent. The fitness function is defined by (3):

$$F = \begin{cases} 1 - \frac{d_f}{d_i}; & if\ d_f < d_i; \\ 0; & otherwise; \end{cases} \tag{3}$$

where F is the fitness; d_i and d_f are the initial and final distances to the light source, respectively.

IV. DYNAMICAL ANALYSIS

The dynamical analysis of the model were done using the fittest agent found by the genetic algorithm. This agent is run for one trial and the states of the variables are recorded for future analysis. Important variables that will be carefully analysed are the relative phase, phase coherence and their respective derivatives. The relative phase (ϕ), shown in Eq. (4), represents the phase difference between the i^{th} and j^{th} oscillators. As there are five oscillators, the number of $\phi_{i,j}$ is 10 (C_2^5).

$$\phi_{i,j} = (\theta_i - \theta_j) \tag{4}$$

Kelso suggests that the relative phase is the coordination variable of the system. In his model such use is feasible as it has only one variable of phase relation. In our case, as the model consists of 5 oscillators and 10 combinations of relative phase, it turns out to be necessary to find a higher level variable which captures the network dynamic. The macroscopic variable of phase coherence [22] is a good candidate. This variable neatly represents the relative phase among the oscillators of the whole network. It is given by the magnitude of the complex number defined in Eq. (5).

$$re^{i\psi} = \frac{1}{N} \sum_{j=1}^{N} e^{i\theta_j} \tag{5}$$

where *r* stands for the phase coherence and ψ stands for the mean phase of the network. The higher the value of phase coherence, the more similar the phase among oscillators. If *r=1*, the relative phase among the oscillators is zero; and if *r=0*, the relative phase is π. The derivative of *r* informs how the relative phase changes over time. When $\dot{r} = 0$ the oscillators are in phase-lock.

V. STUDY OF BRAIN-BEHAVIOUR METASTABLE DYNAMICS

A. Brain-behaviour dynamic

The behaviour of the fittest agent during its lifetime and the distance to the light source are presented in Fig. 3. The agent follows the increase of light intensity moving in circles and then starts moving around the light when it is near it. The sensor activations, which work as control parameters for the network, are presented in Fig. 4.

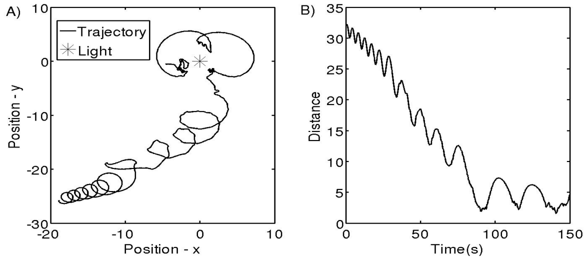

Fig. 3. **A)** Agent's behaviour in the two-dimensional environment (x and y coordinates) . **B)** Distance from the agent to the light source.

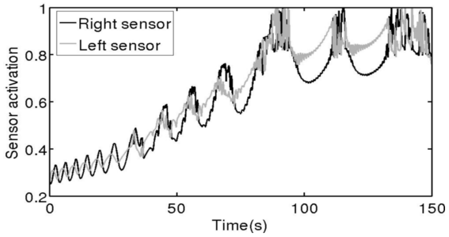

Fig. 4. Right and left sensor activations during phototaxis.

As previously mentioned, the sensors change the intrinsic frequency of the oscillators to which they are connected. In Fig. 5 we show both intrinsic and real frequencies of each oscillator. The intrinsic frequencies of the oscillators θ_1 and θ_2 change over time as they are the only ones connected to the sensors. As the oscillators are not isolated, their real frequency is a compromise between its own intrinsic frequency and the real frequency of the others. That is why the real frequencies are usually different from the intrinsic ones. The oscillators θ_4 and θ_5, for instance, mainly oscillate below their intrinsic frequency before $t = 30$ secs. and above it after this time. The final frequency dynamic of the whole network is a dwelling among components trying to impose their intrinsic frequency and, at the same time, yielding to the frequencies of the others.

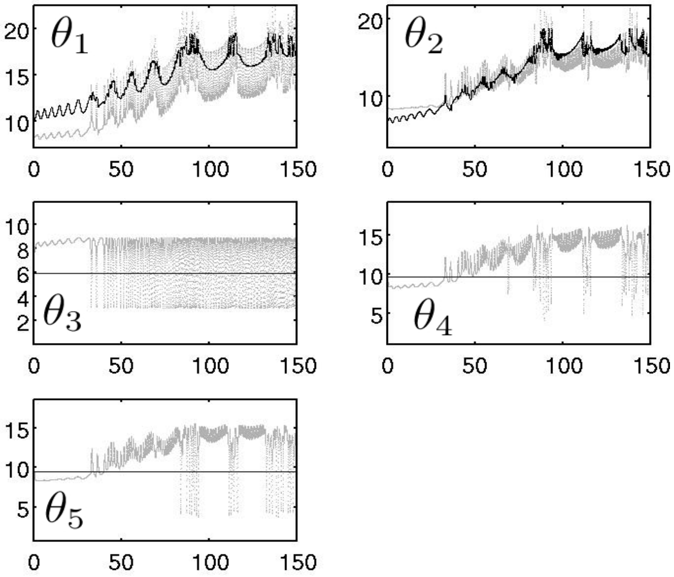

Fig. 5. Intrinsic (black line) and real (gray line) frequencies of the oscillators.

Two possible outcomes of this dwelling are: a) some components could get stuck in a point attractor corresponding to a common frequency; b) some components interacting in a metastable dynamical regime where the frequency of each oscillator fluctuates as a result of a trade-off between different frequencies. Our experiment presents only the second situation where the system is in a metastable dynamical regime. In Fig. 6 we present two different metastable regimes characterized by smooth and fast fluctuations before and after $t = 30$ secs, respectively. The transition between these regimes takes place when the difference between real and intrinsic frequencies of θ_3 crosses a threshold where the coupling factors is no longer enough to maintain the current metastable regime. The time intervals [0,30] secs. and [30,60] will be referred to from now on as T_1 and T_2, respectively.

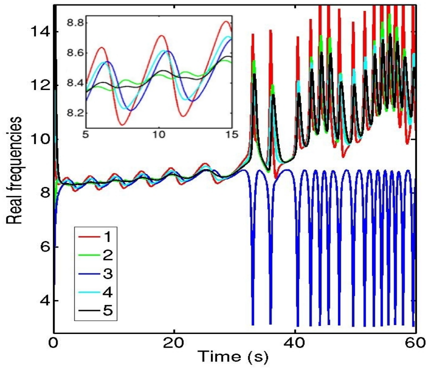

Fig. 6. Smooth and fast frequency dwelling among oscillators. **Inset**:zooms into the time interval [5,10] seconds. Such frequency dynamics before and after 30 secs. characterize different metastable regimes.

The different metastable regimes can also be observed through the relative phase between pairs of oscillators (see Fig. 7). Constant relative phase over time (derivative of the relative phase equals zero) indicates that the pair of oscillators have the same frequency; in this case we say the oscillators are in phase-lock. Relative phase fluctuating around an angle means that the pair of oscillators are dwelling over certain frequency; in this case we say that the oscillators are neither in phase-lock nor in phase-scattering, but in a dynamical regime where the tendencies to be in phase-lock and phase-scattering coexist (the metastable regime). For instance, $\phi_{1,2}$ (red dots) smoothly fluctuates within ≈[0.5, 1] radians during the first 30 seconds and then starts fluctuating faster maintaining their relative phase within ≈[6, 2] radians. In both cases (before and after 30 secs.), θ_1 and θ_2 are engaged in a metastable dynamical regime.

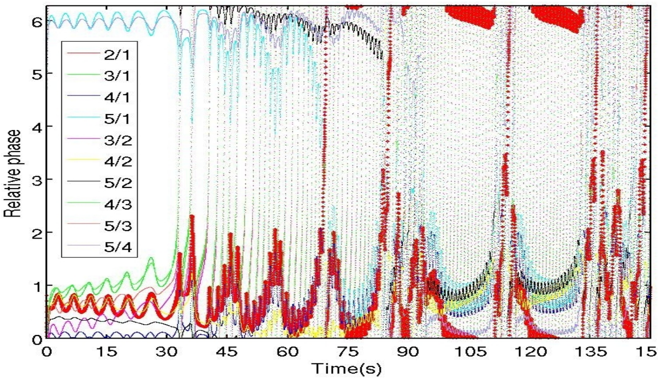

Fig. 7. Relative phase (ϕ) between oscillators (in radians) (see Eq. (4)). Darker red dots highlight the relative phase between the oscillators θ_1 and θ_2. We can see the dynamical regime transition at t=30 secs.

The metastable dynamical regime can also be observed for the pair of oscillators θ_4 and θ_3. In Fig. 8 we show the density distribution of relative phase for this pair of oscillators and its derivative. In these graphics (Fig. 8-A and B) we observe different properties of the relative phase dynamic during T_1 and T_2, which characterize two metastable regime signatures in which the oscillators θ_4 and θ_3 engage from 0 to 60 seconds. The signature of the metastable regime in which the whole network is engaged during a given time slot consists of the relative phases among all oscillators. In our model this signature consists of 10 different combinations of relative phase.

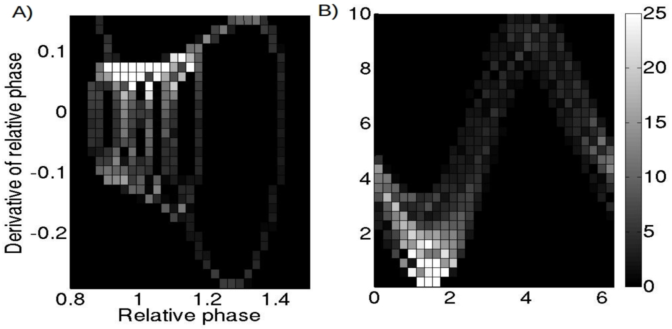

Fig. 8. Density of the relative phase $\phi_{4,3}$ and its derivative ($\dot{\phi}_{4,3}$) for the time intervals T_1=[0,30] secs. (graphic **A**) and T_2=[30,60] secs. (graphic **B**). The whiter areas show where the relative phase and its derivative have a stronger tendency remain during the respective time interval. In **A** and **B** the relative phase mainly fluctuates around 1 and 1.3 radians, respectively. Points where the derivative is zero represent moments of phase-lock and where it is relatively high, moments of phase-scattering. In both time slots the derivative is denser in regions slightly greater than 0, which indicates the presence of metastable regimes (as the relative phase tends to remain in regions of the surface without getting stuck in point attractors). While the metastable regime during T_1 is characterized by moments of quasi phase-lock near 1 radian and moments of phase-scattering with angles within ≈[0.8,1.4], the metastable regime during T_2 is characterized by moments of quasi phase-lock near 1.3 and moments of phase scattering within [0,2π] radians. Though graphics B does not show clearly, the derivative of relative phase is always greater than 0 during T_2.

These 10 different signatures of relative phase can be capture by the *phase coherence r* (Eq. 5), which turns out to be the coordination variable of the network [23]. The dynamic of this macroscopic variable is presented in Fig. 9. We can roughly trace some correspondence between the phase coherence and the 10 relative phases shown in Fig. 7 (observe that we are showing the phase coherence from 0 to 60 secs. and the relative phases from 0 to 150 secs.). During T_1 the phase coherence fluctuates above 0.9, which indicates the oscillators are in a metastable dynamic near 0 radians. This can be confirmed by the relative phase in Fig. 7 (during the first 30 secs.) where the 10 relative phases are slightly fluctuating around 0 radians.

Analogously to the graphics of density distribution we presented for $\phi_{3,4}$ (Fig. 8), we now present the same type of graphic for the phase coherence, which captures the relative phase of the whole network and its metastable dynamic. Fig. 10 shows the density distribution of *r* and its derivative. Differences on the density distribution of phase coherence and its derivative represent different metastable regimes in which the network engages during the first 60 seconds.

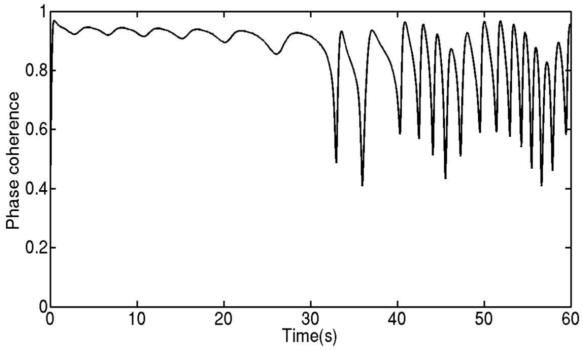

Fig. 9. Phase coherence (*r*) during the first 60 seconds. This variable captures the dynamic of relative phase of the whole network (see text for a description).

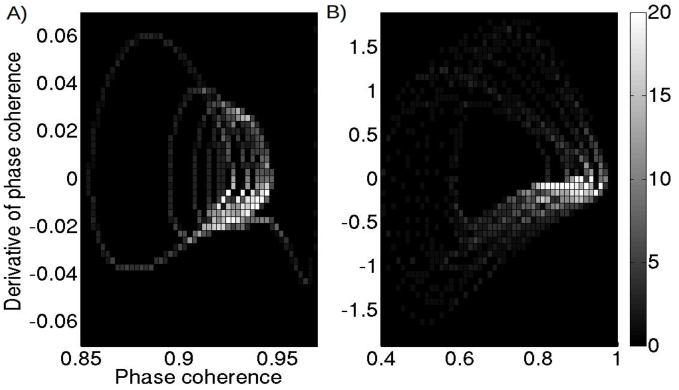

Fig. 10. Density of *r* and its derivative $\dot{r}$ for the time intervals T_1 (graphic **A**) and T_2 (graphic **B**). The whiter the area, the greater the tendency of the pair *r* x $\dot{r}$ to be present. The phase coherence mainly remains between [0.9,0.95] for T_1 and between [0.8,0.9] for T_2, which means that during T_1 the metastable dynamic of phase relation takes place around an angle smaller than the angle during T_2 ($r = 1$ means zero-lag phase-lock; and $r = 0$ means π phase-lock). Regions where the derivative is zero indicate moments of phase locking, and regions where it is higher show moments of phase scattering. As the derivative during T_1 is smaller than during T_2 (see different y axis), the fluctuations of relative phase during T_1 is slower.

We finalize this section presenting the moments of (quasi) phase-lock between oscillators by filtering out moments of phase-scattering from the relative phase dynamic. These graphics exemplify what Lutz et al. [27] call *dynamical neural signature* and what Varela [6] calls neural assembly; topics of great interest among neuroscientists, specially those working on the binding problem (see Fig. 11).

Studying only such moments of (quasi) phase-lock might limit our understanding on neurodynamics; for future developments on this research area one should investigate the whole picture of phase relation dynamics. As a proof of concept for such approach, we have shown that during the behavioural episode of moving towards the light the robot's brain undergoes different metastable dynamical regimes of phase

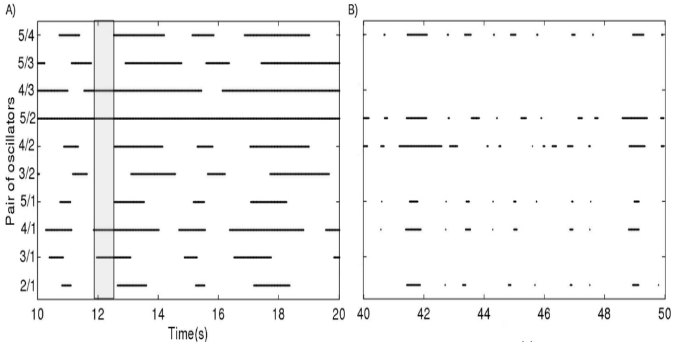

Fig. 11. Each point represents a moment of (quasi) phase-locking ($-0.1 < \phi < 0.1$) between pair of oscillators (y axis) for time intervals [10, 20] secs (graphic **A**) and [40, 50] secs (graphic **B**). For t=[10, 20] secs. the moments of (quasi) phase-locking are greater than for t=[40, 50] secs. The whole time window (e.g. [10,20]) exemplifies what could be a *dynamical neural signature* (local and long-distance synchrony occurring before and after the onset of a task). The gray rectangle shows an example of what could be interpreted as a *neural assembly* (a specific configuration of oscillators in phase-lock in a given time window).

relation which are essential for the functional performance of phototactic behaviour.

We will now show the functional role of the sensorimotor loop modulating the control parameter to achieve coherent phototactic behaviour.

B. Sensorimotor-loop disruption experiment

Brain oscillations are coupled to the sensorimotor loop, meaning that, not only is behaviour controlled by brain dynamics, but also that brain dynamics are shaped by behaviour. In order to explore this, we carried out an experiment as a proof-of-concept in which disruption of the sensorimotor loop through sensor delays alters brain dynamics and behavioural performance altogether. In Fig. 12 we show the fitness (measured according to Eq. (3)) of the same agent studied above (without any further evolution) for increasing sensor delays. The agent's behaviour, its sensor activations and phase coherence dynamic are presented in Fig. 13.

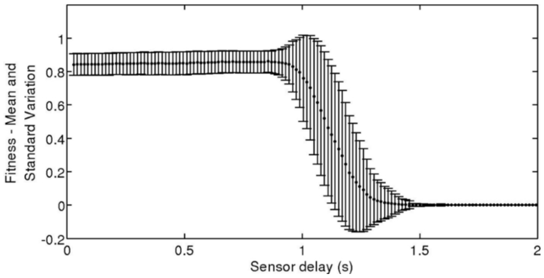

Fig. 12. Mean and standard variation of fitness for different values of sensor delay. For each value of sensor delay we ran the experiment 5000 times. The agent is robust for sensor delays up to 1.0 sec.; within [1, 1.5] secs. its performance decays, and after 1.5 secs. the oscillatory network no longer engages in functional metastable regimes which produce phototactic behaviour.

We have seen that without sensor delays the oscillatory network engages and switches between the functional metastable regimes that produce coherent behaviour, namely phototaxis. The present experiment shows that agent's performance is robust to small perturbations of sensory delay (0.0-1.0 second delay in Figure 12) but decays abruptly afterwards and remains incapable of performing phototaxis. Experiments with delay perturbation to the motor output were also carried out with similar results (not shown in this paper).

These results show that the coupling with the environment is not just a precondition to generate a sensory state, in terms of a snapshot-like sensory input, nor is the environment a place where "decisions" taken by the brain are to be executed. The *dynamics of the coupling between agent and environment crucially matter* both for behavioural performance *and* for the resulting brain dynamics. Disruption of the coupling results on disruption of the coordination dynamics that are characteristic of our agent's light detection and approaching behaviours. A 1.5 second delay on the sensorimotor loop coupling suffices for the oscillatory network to no longer engage in the functional metastable regimes that were analysed in the previous section.

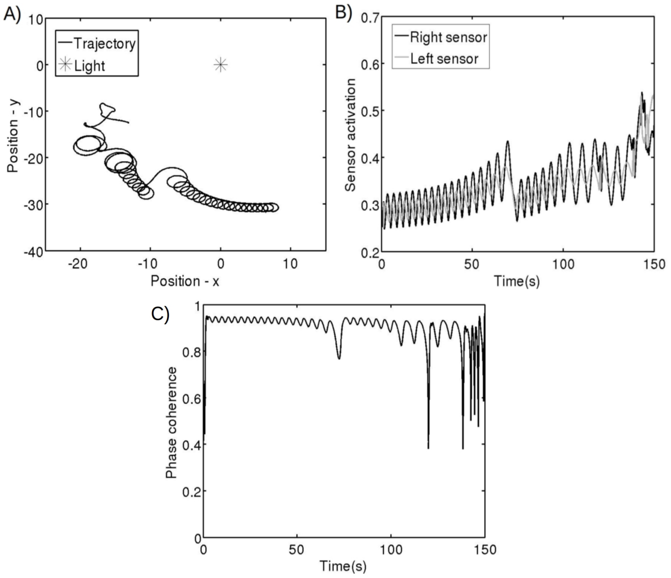

Fig. 13. Agent's behaviour (graphic **A**), its sensor activations (graphic **B**) and phase coherence (r) for 1.2 secs. of sensor delay. The agent does not approach the light within the time given of 150 secs.

VI. CONCLUSIONS

We have modelled an agent controlled by a Kuramoto-model based oscillatory network and analysed it within Kelso's Coordination dynamic framework. We have explored metastable dynamical regimes (trajectories in the region of the surface where the attractors have disappeared - Fig. 1) and found that during phototactic behaviour the oscillatory network undergoes at least two different metastable regimes of phase relation. Such regimes were represented by specific patterns of phase coherence, interpreted as the coordination variable within Kelso's framework. Sensory input operated as a control parameter modulating the patterns of phase coherence. To our knowledge, these aspects of metastability within the sensorimotor loop have not been previously explored in theoretical or empirical studies of brain oscillatory dynamics.

We have observed that, despite its simplicity, a simulated robot can help us better understand some aspects of the complex behavioural role played by oscillatory phenomena. We have shown that, despite the widespread assumption to take synchronized time windows as functional units of cognitive brain activity (as shown in Fig. 11), the whole phase dynamic spectrum might also play a decisive role on the generation of coherent behaviour. In particular our model provides a proof of concept of how *metastable dynamical regimes of phase relation and functional behaviour emerge without the need for a specific synchronization signature that carries a cognitive role (of, e.g. perceptual states or behavioural commands).*

Oscillatory dynamics in the brain can be investigated by both modelling and data collection at many different levels: from individual neurons and very small circuits [28] to the whole cortex and brain activity [3], [6]. The present simulation was not meant to target any such levels specifically. Our goal was rather to reproduce at a merely conceptual level of generality the *type* of macroscopic data from which the significance of phase-locking synchronization is generally privileged and to show how a system that displays analogous patterns does in fact functionally exploit the whole phase dynamic to achieve behavioural performance. Such a proof of concept should not be taken as an empirical model (see [29], for a distinction between conceptual and empirical models).

Disruption of the coupling was shown to be robust to small perturbations but completely destroyed functionality above 1.5 seconds of delay, consequently altering the dynamic patterns that characterize "normal" functioning. The sensory-delay experiment illustrated *that sensorimotor loop dynamics are essential to generate and sustain functional metastable brain regimes*.

We need richer methods to analyse oscillatory phenomena in order to systematically relate behavioural and brain dynamics capable of producing a coherent picture of situated cognition. Artificial Life models can provide the means to explore such methods contributing with proofs of concept, testing empirical assumption and building minimal scenarios that can improve our conceptual and mathematical understanding of the complex interplay between brain, body and world that gives rise to our experience of the world.

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