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From Metaphor to Theory: The Role of Resonance in Perceptual Learning

Vicente Raja

The Rotman Institute of Philosophy
Western University
Western Interdisciplinary Research Building
1151 Richmond Street North
London, Ontario, Canada, N6A 5B7
https://westernu.academia.edu/VicenteRaja

Abstract

Unlike dominant cognitivist theories that take perceptual learning to be a process of enriching sensory stimulation with previous knowledge, ecological psychologists take it to be an enhancement in the detection of already rich perceptual information. The difference between beginners and experts is that the latter detect better information to support their task goals. While the study of perceptual learning in terms of perceptual information and perceiver-environment interactions is common in the ecological literature, ecological psychology still lacks a story regarding the way perceptual information is detected by perceptual systems and the plasticity of such detection in learning events. In this paper, I propose the ecological notion of resonance—along with biophysical resonance, nonlinear resonance, and metastability—as a plausible foundation to account for the process of detection of perceptual information both in perceptual events and in events of perceptual learning.

1. Introduction

Rodney Brooks (1990) famously claimed that elephants don’t play chess in one of his seminal papers on behavioral robotics. Behavioral robotics aimed to open a new path for the development of artificial intelligence (AI) that avoided the assumption of the dominant approach to AI founded on the symbol system hypothesis (see Newell 1990), that regards cognitive systems as hierarchies of modules that operate on symbols subsequently integrated by a central system (or central reasoner; or central controller). In this sense, perceptual and motor systems, for example, are two different symbolic interfaces or modules. The perceptual system provides an input of symbols to be manipulated by the central system by applying rules and algorithms to them. The outcomes of such manipulation are new sets of symbols that make the motor system execute a given motor program.

The symbol-system approach to AI has been very successful, for example, in generating artificial devices that play chess better than the majority of human beings. Chess is easily characterized in terms of symbol systems. The position of the chess pieces can be symbolically described (e.g., e4, c7, g8) and their possible movements can be described in terms of explicit rules (e.g., kings can only move to its immediately surrounding squares, bishops can only move through the same-color diagonals that cross its current—black or white—square). Thus, an AI device based on symbols and rules can successfully instantiate a chess game where the only problems are a matter of capacity of processing but not of cognitive architecture. However, such a success of the symbol-system approach to AI can be potentially uninformative about the real adequacy of the symbol system hypothesis to capture the functioning of cognitive systems and of intelligence. After all, elephants don’t play chess.

The significance of Brooks' statement has to do with the central role of perception and action in what we take to be intelligent systems, and his framework of behavioral robotics provides a new understanding of the architecture of cognitive systems to account for such a role. We take elephants to be intelligent. Although they don't play chess, elephants are sensitive to their environments and are able to control their own behavior to survive, to safely locomote, to find food, etc. These abilities, however intelligent, are not as easily implemented in a symbol system as the ability to play chess.[1] The implementation of perception/action abilities in AI devices is what drives Brooks to reject the symbol system hypothesis in favor of the physical grounding hypothesis (Brooks, 1986, 1989, 1990). According to him, instead of taking cognitive systems to be based in a symbolic-processing architecture, we need them to be understood as systems that are in constant perceptual coupling with their environments and which behavior emerges from the interaction of simple motor effectors as they are affected by that coupling. In this sense, AI devices do not need the ability to manipulate symbols with sets of rules, but just need to have sensors to constantly track their environment (perceptual coupling) while moving through it and simple motors (e.g., go-forward, go-backward) which interactions are constrained by the perceptual coupling itself.

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[1] There is no space in this paper to go through the several problems symbol systems face to implement abilities that have to do with perception and the control of action. Some of them are as old as the symbol-system approach to AI itself, like the frame problem (McCarthy & Hayes, 1968); others have to do with the set of explicit rules symbol systems need to manage in an ever-changing environment, like the problem of the loans of intelligence (Dennett, 1978; Kugler & Turvey, 1987); and others with the coordination of all the effectors of a system to generate the desired behavior, as the issue labeled as "the Charles V problem" in the literature on motor control (Meijer, 2001). Many other instances of the same families of problems are commonly reported in the specialized literature.

Brooks' behavioral robotics have witnessed a great deal of scientific and commercial success, but the framework is interesting for two other reasons. On the one hand, behavioral robotics are inspired in the principles of ecological psychology (Gibson 1966, 1979; Chemero, 2009), where perception has to do with the on-line detection of environmental information (perceptual coupling) and not with the manipulation of symbolic information. On the other hand, behavioral robotics offer a new understanding of the kind of AI architectures that can hold perception/action processes based on the simple new principle of the physical grounding hypothesis. In this paper, I aim to offer the prospects of a conceptually similar move regarding perceptual learning in ecological psychology. In other to do so, I will build upon the ecological concept of *resonance* (Raja, 2018), that may serve as the foundation or a complement for an ecological cognitive architecture able to implement processes of perceptual learning as it is understood within the ecological tradition. This is not a paper on robotics, though, and the model I pursue here is—at least for now—strictly theoretical.

In general, for ecological psychologists, perceptual learning consists in enhancing the detection of adequate environmental information to correctly control behavior in a given task. Both in its classic formulation (Gibson & Gibson, 1955) and in a contemporary, more refined ecological account of perceptual learning, *direct learning* (Jacobs & Michaels, 2007), the foundational idea is that learning to perceive is learning to detect the right perceptual information in every situation. In the following, I defend that such learning process may be carried out by a system based on the principle of resonance that, although metaphorically present in the ecological theories of perceptual learning such as direct learning, is still underdeveloped. More concretely, I claim that the process of perceptual learning may be carried out by a system based on the same physical principle of resonance operating in guitars when played. Guitars don't learn though, so the way resonance can be also applied to systems that do learn must be explained. To do so, first, I introduce a few principles of ecological psychology and perceptual learning (section 2). Second, I analyze the relevant concept of resonance for perceptual learning, its roots in ecological psychology, and its relations with the usage of the term “resonance” in neuroscience (section 3). Third, I evaluate some aspects of resonant systems and the concepts and tools they offer to explain perceptual learning (section 4). And finally, in the conclusion, I propose some future directions for the research on perceptual learning based on resonance.

2. Ecological Psychology and Direct Learning

Ecological psychology is a theory of perception (and action) first developed by J. J. Gibson (1966, 1979). There are many different ways to introduce the main tenets of ecological psychology, but here I will just sketch the aspects of the theory that are relevant for the subsequent discussion on perceptual learning and resonance.[2] Probably, the most interesting aspect of the ecological approach to perception is that it takes perception to be direct. Unlike classic, information-processing accounts of perception that take it to be a matter of building up an internal model of the environment by manipulating symbol-like perceptual information with a set of computational rules (e.g., those based on symbol systems), the ecological approach to perception take it to be the detection (not the processing!) of the environmental information that is useful for goal-directed behavior.

The reasons why perceptual information can be detected without further processing is that it is rich, specific of the environment, and available in it. According to ecological psychologists,

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[2] The literature on ecological psychology is already vast and constantly growing. Thus, beyond Gibson’s works, it is not difficult to find other complete introductions to the theory—e.g., Turvey et al. (1981), Michaels and Carello (1981), Reed (1996), Richardson et al. (2008), Chemero (2009), Turvey (2019).

perceivers do not deal with simple, ambiguous perceptual information. Instead of that, they detect complex and specific information available in the environment. This idea regarding perceptual information is based on the rejection of the argument of the poverty of the stimulus (Chomsky, 1980). For classic computational theories of perception, stimuli arriving at the sensory receptors of perceivers are unspecific, ambiguous, and generally insufficient to support any cognitive task. Such insufficiency entails that internal processing of environmental stimulation must be taking place at some point of the perceptual process to enrich and disambiguate the stimulus and make it suitable for being used in a particular cognitive task. According to Gibson and other ecological psychologists, there is no reason to hold the argument of the poverty of stimulus if we describe perception and perceptual information in terms of the relations between perceivers and their environments; that is, if perception is described at the ecological scale.

More concretely, the core idea underlying direct perception is that there is sufficient information available in the environment to know what it affords—i.e., to know its *affordances*, the opportunities of action in the environment that are perceived by an organism, like the "climbability" of a stair or the "graspability" of a cup, for example (Turvey, 1992; Chemero, 2003). For this reason, there is no necessity for a mechanism that enriches the environmental stimulation gathered by organisms in order to make that stimulation really informative of the states of the environment. This is what direct perception means: there is no need for internal states of organisms (e.g., representational models of the environment) to mediate their perceptual relation with the environment.

This description of direct perception can be further explained and justified in terms of two other foundational commitments of ecological psychology. The first commitment is the intrinsic relation between perception and action. Often enough, ecological psychologists claim that perception and action are two sides of the same coin. The metaphor of the coin attempts to highlight the fact that perception depends on action and action is guided by perception. For example, and regarding visual perception, perceivers generate optic flow when they move around, and some features of this optic flow constrain their own movements. When perceivers move around the environment, their visual field undergoes transformations that depend on the movements executed. These transformations carry information about both the layout of the environment and the movement of the perceiver and are used for controlling the movement itself —e.g., a centrifugal transformation of the visual field informs about the forward locomotion of the perceiver and its direction.

The second commitment is that the relevant information for perception consists of high-order variables. In the example of visual perception, the information gathered from the optic flow does not consist of basic, physical features of the environment (e.g., retinal-image shape/size, pressure on the skin, etc.). On the contrary, perception deals with other informational variables such as patterns of flow, expansions or contractions in the visual field, texture gradients depending on distance, patterns of occlusion, etc. These informational variables are of higher-order than the physical ones as they are relations between the latter and the action of the perceivers. Also, they are specific of the environmental layout and the movements of the perceivers as they are fully dependent on both of them.[3] The specificational character of environmental information allows for

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[3] In the case of visual perception, the specificational character of information is explained by *ecological optics* (Gibson, 1958, 1960, 1961). Ecological optics address the properties of an illuminated environment that allows for the availability of visual information. In any environment with a transparent medium (e.g., air), light coming from the sources of light bounces off the surfaces it reaches and reverberates in the medium. As the position and orientation of the surfaces with respect to the sources of light depend on the layout of the environment, the structure of the

an understanding of perception that avoids the need for the construction of an enriched representation of the environment. Perception can be understood as the detection of the specific information available in the environment and, insofar such a detection is not mediated by any cognitive process of construction or enrichment, perception can be understood as direct. Summing up, the basic framework of direct perception is that there are high-order variables that specify the features of the environment and that perceivers detect them without any kind of cognitive load or information processing. In this sense, to explain perception is to describe this environmental information and the lawful way in which perceivers detect it.

Building upon the idea of direct perception, James Gibson and Eleanor Gibson (1955) also proposed a new way to understand perceptual learning. Unlike cognitivist theories of perceptual learning, the "Gibsons" take it to be a refinement in the detection of adequate information to perform a given task. In the last years, David Jacobs and Claire Michaels (2007) have developed this idea and have proposed a full-fledged ecological theory of perceptual learning coined as *direct learning*. As direct perception and the first ecological proposal on perceptual learning championed by the "Gibsons", direct learning is proposed as a radical departing from the cognitive approach

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reverberated light in the environment also depends on such a layout—aka *ambient optic array*. At any point of the ambient optic array the structure of light that is specific of the layout of the environment and the position of perceivers. And, as perceivers change their position through the environment, the transformations of the structure of light are specific of their movement. Finally, these transformations can be described in terms of high-order variables that constitute visual information. This is not the place to further characterize ecological optics or ecological information, but there are many examples of theoretical and empirical developments of these notions in the ecological literature—e.g., Turvey et al. (1981), Michaels & Carello (1981), Warren (1998), Warren et al. (2001), Wilkie & Wann (2003), Lee (2009), Segundo-Ortin et al. (In Press).

to perceptual learning that remains based on the idea of the enrichment of environmental information:

> Enrichment theories might hold… that expert perceivers outperform novices because of the knowledge they have added to their memories during the process of learning, allowing them to make more accurate inferences. (Jacobs & Michaels, 2007, p. 321-322).

Unlike cognitivist theories, direct learning is a theory of change. According to theories of change, "learning entails mere changes, for example, changes in which properties of ambient energy arrays perceptual systems respond to." (Jacobs & Michaels, 2007, p. 322). In this sense, rather than deriving from the enrichment of perceptual inferences, direct learning comes from the improved fit of experts to their environment. Insofar as direct learning is a theory of change, perceptual learning is explained by accounting for the environmental information that guides perceivers in their actions and the way they make the learning path—i.e., the change—from less useful to more useful information (that is, from beginner to expert). In other words, perceptual learning is not about adding memories to the perceptual process to improve perceptual inferences, but about being able to detect better and better informational variables available in the environment during the learning path.[4]

In the theory of direct learning, the learning path is defined by three concepts: *education of intention*, *education of attention*, and *calibration*. Succinctly, education of intention is coming

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[4] As a scientific theory, direct learning has already provided a good amount of interesting results. See, for example, Fajen and Devaney (2006); Jacobs, Runeson, and Andersson (2001); Jacobs, Runeson, and Michaels (2001); Jacobs and Michaels (2006); Jacobs, Silva, and Calvo (2009); Jacobs, Vaz, and Michaels (2012); Michaels, Jacobs, and Bongers (2006); Wagman et al. (2001); Withagen and Michaels (2004, 2005).

to choose the right behavior—also of having the right goal or intention—for the task the perceiver wants to perform, and calibration is having the perceptual system adjusted to the requirements that the environment imposes on the perceiver; that is, having perceptual variables scaled to the perception-action requirements of the environmental situation. While the three concepts are important for perceptual learning, I will be focusing on education of attention because it makes the major work regarding the selection of adequate environmental information for every task.[5] Put simply, education of attention is the process of coming to attend to the more useful variables within an informational space. For example, a skier may learn how to go faster downhill in giant slalom while successfully avoids the gates. Some of the adequate variables of perceptual information (but surely not all of them) for such a faster performance are in the optic flow generated by the skier as she goes down the hill. The patterns and amounts of expansion of the gates in her visual field, for instance, are the informative variables of the right way to avoid them. The path of learning to detect such variables in the visual field—i.e., the high-order variables of perceptual information—to support a successful performance in giant slalom is a matter of educating the skier to attend to those variables.

Although both direct perception and perceptual learning have witnessed a good amount of theoretical and empirical support in the ecological literature, ecological psychology still faces the challenge to explain the process by with perceptual information is detected by perceivers and, therefore, used for controlling their action. How is the skier able to *detect* the variable(s) that specifies the position and the approaching speed of the gates in her visual field (direct perception)? And, if the variable detected is not the most accurate one to control the movement of avoiding the

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[5] Education of intention and calibration are more relevant to frame the task to perform and to the status of the abilities of a system to perform the task itself.

gates, how is the skier able to *switch* to a better variable for that task (direct learning)? The rest of this paper aims to offer the prospects of a theory that accounts for these issues while staying true to the main tenets of ecological psychology. To do so, I will sketch the fundamental properties of a system able to detect environmental information and able to learn how to detect better informational variables in terms of ecological and biophysical notions of resonance.

3. Resonance

The concept of resonance is often invoked in the sciences. In its most fundamental, physical sense, resonance occurs when a system B is driven by a system A to oscillate at a greater amplitude at one or more specific frequencies. The phenomenon of resonance is easily observed in our everyday life. For example, if a tuning fork is near to another one when the latter is hit, the first tuning fork will vibrate at a frequency related to the vibration of the second one. A simpler example is a person pushing a swing. When the swing is pushed at an appropriate moment in its cycle its amplitude of swinging increases, while when the swing is pushed in other moments of the cycle, the pushing goes against its motion. The specific moments in which the swing has to be pushed for the pushing to increase the swing's amplitude are related to its resonant frequency.

Another very good example of a resonant system is the acoustic guitar. It is composed by a body, a neck, a head, and strings that are connected from the bridge (in the body) to the tuning pegs (in the head). When the guitar player plays a string, the body of the acoustic guitar resonates to its vibration. The resonant body is what gives the acoustic guitar its characteristic sound—as opposed, for example, to the characteristic sound of a violin due to its specific resonant body. For this event of resonance to be possible, strings and body must share fundamental resonant frequencies, although the characteristic sound of the acoustic guitar needs specifics regarding the guitar's body; for instance, its shape to generate concrete harmonic frequencies. Although the harmonics of the acoustic guitar makes its resonance more complex than other simpler resonant events, the basic physical principle still holds: a system A (the body of the guitar) is driven by a system B (a string) to a greater amplitude in its oscillation (in the case of the guitar, to a specific vibration).

The physical notion of resonance provides the basis to understand what is the feature of resonance that makes it a concept often invoked in different scientific fields, including the cognitive sciences: the dynamics of two systems that enter into a resonant state are coupled in terms of some specific variable. When two systems vibrate together (tuning forks or acoustic guitars) or are mechanically synchronized (the "pusher" and the swing) their relation can be described in terms of some variable that makes possible such a coupling—or synchronization, or phase-locking, etc.

Although the concept of resonance has been often invoked in the cognitive sciences,[6] the ecological concept has its own particularities. In the ecological literature, resonance refers to the process by which perceivers are able to detect environmental information. Such a concept of resonance, though, has not been fully developed since James Gibson first proposed it in *The Senses Considered as Perceptual Systems* (1966), and only a few examples of an operational notion of

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[6] Resonance has been used, for example, to explain certain behaviors of individual neurons (Hutcheson & Yarom, 2000; Gastrein et al., 2011; Kasevich & LaBerge, 2011; Moca et al., 2014; Tchumatchenko & Clopath, 2014), to understand the activity of mirror neurons as motor resonance (Gangitano et al., 2004; Borroni et al., 2011; Press et al., 2011; Cavallo et al., 2013; McCabe et al., 2014), to study of the sequential effect in psychology (Gökaydin, 2015; Gökaydin et al, 2016), or as the fundamental notion of a cognitive architecture (*adaptive resonance theory*; Grossberg, 2013).

resonance may be found in the literature (e.g., Raja, 2018). The basic idea of resonance, though, appears at the very beginning of Gibson's second book:

> Instead of supposing that the brain constructs or computes the objective information from a kaleidoscopic inflow of sensations, we may suppose the orienting of the organs of perception is governed by the brain so that the whole system of input and output *resonates* to the external information. (1966, p. 5; emphasis is mine).

In this famous quote, resonance, as opposed to computation (i.e., inference, information-processing), is characterized as the proper activity of a perceptual system regarding perceptual information, where the brain seems to act as a kind of governor of the process. This understanding of resonance is widespread in the ecological literature and, for instance, has driven to consider the activity of detecting perceptual information as similar to the way a radio is tuned to the specific frequency of a radio station (Cutting, 1982) or as similar to the way a smart device, such as a pole planimeter, is able to perform accurate measurements (Runeson, 1977). However, despite the importance of resonance to understanding the way perceptual information is detected by perceptual systems, the concept has remained underdeveloped for several decades. Resonance has remained metaphorical for the most part of the historical development of ecological psychology. Given that, the first step to characterize a system able to detect perceptual information in a direct way is to offer an operational characterization of the concept.

Inspired by the physical notion of resonance and following in the footsteps of others who have explored the resonant properties of the CNS from different traditions I have analyzed the ecological notion of resonance, defining it as the process by which perceptual systems—including their neural parts (CNS)—are driven by or are coupled to the perceiver-environment dynamics in terms of perceptual information (Raja, 2018).[7] To be more concrete, the activity of the perceiver in her environment (i.e., the perceiver-environment dynamics) generates perceptual information that subsequently constrains the dynamics of perceptual systems (e.g., the neural dynamics of perceptual systems) in terms of informational coupling or synchronization, such that perceiver's perceptual systems resonate to the perceiver-environment dynamics. Following the dominant methodological tradition in ecological psychology (Warren, 2006; Chemero, 2009), these two dynamic scales can be described in terms of dynamic systems, so the proposed operational notion of resonance can be formalized in an abstract theoretical model (Figure 1).

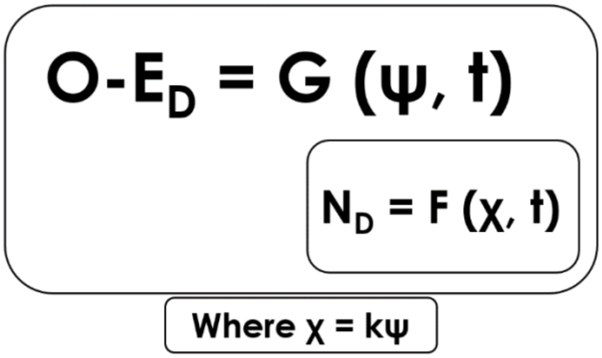

Figure 1. Abstract model of resonance. In psychological events, the perceiver-environment dynamics ($O\text{-}E_D$) can be defined as a function, *G*, of ecological information, Ψ, through time, *t*. The neural dynamics of the perceiver's perceptual

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[7] One important influence in my definition of resonance is the notion of coupling based on informational variables used proposed by Warren (2006). Unlike Beer (1995) or Kelso (1995), for example, who defend a notion of coupling based on the relation of the state variables of a system and the control parameters of the other, Warren proposes a notion that goes beyond parametric coupling and can also be based on the coupling of state variables themselves through informational constraints (see, e.g., Warren 2006, p. 369). Other important influences are the studies on resonance at the neurophysiological level and at the level of neural networks (see below in this section and section 4.3).

> system(s) during the same event (N_D), can be defined as a function, F, of some variable, χ, through time, t. The key aspect of resonance is that $O\text{-}E_D$ and N_D are coupled in terms of ecological information such that $\chi = k\Psi$, where k is a coupling term (see Raja, 2018; for a technical take on the way information can contribute to the coupling of systems in a non-parametric sense, see also the section on "State Control" in Warren 2006, p. 369).

The abstract model in Figure 1 highlights several aspects of ecological resonance. First, the model establishes a concrete way to understand the different scales involved in the phenomenon of resonance. On the one hand, resonance is characterized as the coupling of two dynamic systems ($O\text{-}E_D$ and N_D).[8] This fact helps us to maintain the importance of the perceiver-environment interactions—e.g., the way perceivers' performance and environmental exploration frame the availability and obtainment of information—for the ecological explanation of perception and learning;[9] and allows us to keep using the dominant methodology in the ecological literature: dynamic systems theory (Chemero, 2009). Therefore, ecological resonance stays true to the main

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[8] The choosing of neural dynamics (N_D) as the "resonant system" is, first and foremost, a pragmatic selection. First, it simplifies the explanation of resonance, but in principle, there is no reason why the "resonant system" could not be described at a different scale of the perceptual system (e.g., neuro-muscular dynamics, muscular-skeletal dynamics, kinematics, and so on). And second, choosing N_D as the "resonant system" may be a good strategy for ecological psychologists (and for neuroscientists!) as it adds up to the exploration of the relations between ecological psychology and neuroscience (see, e.g., de Wit, van der Kamp, & Withagen, 2016; Raja, 2018).

[9] An important aspect of the relation between $O\text{-}E_D$ and N_D is that N_D is not confronted to $O\text{-}E_D$ in the classic epistemological sense in which internal states (N_D) are understood as opposed to external states ($O\text{-}E_D$). The two scales hold a relation of nesting. This fact has its own philosophical consequences regarding the units of analysis within the cognitive sciences (e.g., subject-object distinction vs. organism-environment mutuality).

tenets of ecological psychology. On the other hand, the model highlights the importance of perceptual information for the process of resonance. Perceptual information is the variable that constrains the perceptual system at different scales and that is what allows for its detection.

As the ecological notion of resonance counters most of the basic assumptions of the dominant, cognitivist cognitive science based on information-processing accounts of the activity of the CNS, a concrete example of what is implied by resonance in ecological psychology will help to unpack the different aspects of the concept. Suppose, for example, a situation in which Satoshi must avoid an approaching object. As noted above, according to ecological psychologists, there are some variables in Satoshi's optic flow that can be used to successfully avoid it. In the case of approaching objects, there is a well-known perceptual variable, tau (τ) (Lee, 2009), that specifies the time it will take for an approaching object to hit the visual system that is seeing it coming. Therefore, in the example, if Satoshi is able to detect tau, he will know how much time he has to execute a movement to avoid the approaching object. And, if detection of perceptual information is based on resonance, somehow the dynamics of Satoshi's CNS of must be also constrained by tau.

The way tau constrains the neural dynamics of a perceiver like Satoshi in what can be labeled as an event of ecological resonance was explored by van der Weel and van der Meer (2009). In their study, participants (10 babies) were exposed to a screen in which looming figures that served as "approaching objects" were projected. As tau is described as the relative rate of expansion of an object/figure, its value can be manipulated by different looming rates for different figures. In this setup, van der Weel and van der Meer analyzed the theta-rhythm oscillatory behavior of babies' visual cortex—which is related to cognitive and anticipatory attentional processes (Orekhova, Stroganova, & Posikera, 1999)—during looming situations. They found that the theta-rhythm oscillatory behavior was tau-coupled; that is, that the tau-value of the change in rhythm’s temporal structure was linearly correlated with—or modulated by—the value of the perceptual variable tau generated by the perceiver-environment interaction in the experimental setting. In Figure 2C, van der Weel and van der Meer show how the value of tau of the waveform of the neural activity of babies’ visual cortex (black dots) matches the value of tau of the looming figure over time (blue dots)—starting roughly at 0.10 seconds.

The study developed by van der Weel and van der Meer (2009) shows what I take to be a clear instance of resonance in the ecological sense. Perceptual information (i.e., the perceptual variable tau) is available in the environment of perceivers due to their dynamical interaction with it—in this case the dynamics of the perceiver-environment interaction were highly controlled (e.g., perceivers were not locomoting but still controlling their posture to look at the screen, the “approaching object” was a looming figure projected in a screen, etc.) but still enough to make tau available. Thus, tau constrains neural dynamics making them be coupled to the perceiver-environment in terms, in this case, of a linear-coupling parameter (see Figure 2D).

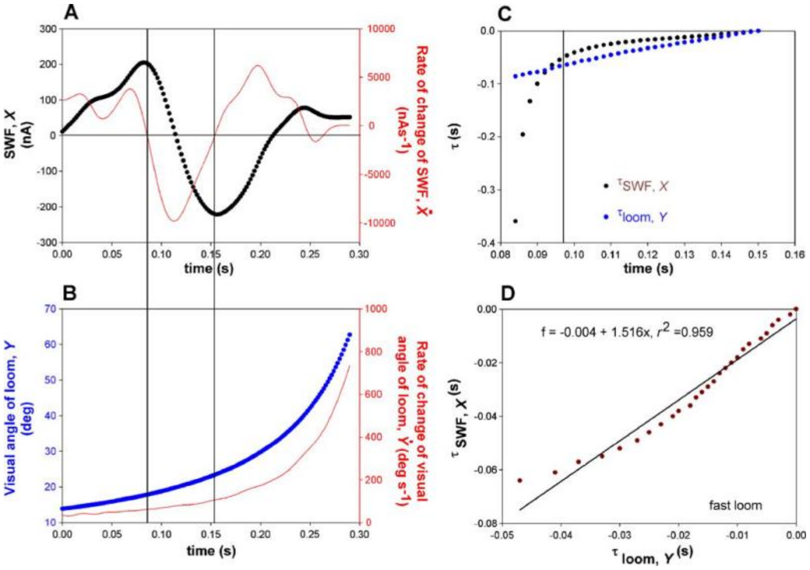

Figure 2. This figure shows the tau-coupling analysis between the two relevant scales: the ecological scale (variable Y) and the neural scale (variable X). Part A and B show the change over time of the neural activity (source waveform [SWF]) and the visual angle, respectively, along with their rates of change during a looming situation. Part C plots the tau value the peak-to-peak of SWF (τ_{SWF}) activity and the corresponding tau value of the loom over time (τ_{loom}). Finally, part D represents τ_{SWF} against (τ_{loom}). A recursive linear regression was run to determine the strength of the coupling between τ_{SWF} and τ_{loom} (r^2 of the regression) and the value of the constant (K) of the equation of tau-coupling, $\tau_{\mathrm{SWF}} = K\tau_{\mathrm{loom}}$ (slope of the regression). Data points of the regression were removed until the r^2 exceeded the criterion level set at 0.95—in practice, this means that the first 7 data points of Fig. 2C were removed in Fig. 2D and the linear model captures the tau-coupling of the event from roughly 0.10 seconds and on. After meeting the criterion level by such an exclusion of data points, the percentage of tau-coupling was 79.4%, $r^2 = 0.959$, and regression slope 1.516. (Image from van der Weel and van der Meer, 2009, p. 1389, figure 4).

This study and others (see Raja, 2018) seem to support the adequacy of the proposed formulation of resonance as the process by which perceptual systems are able to detect perceptual information in an ecological way; that is, without the need for any kind of mediation or processing of information. It is important to stress that, although ecological resonance is not strongly committed with any specific cognitive architecture and may be the foundation or a good complement for different ones, a cognitive architecture[10] able to resonate in the ecological way should meet some minimal requirements.[11] As we have been noting, the first set of requirements has to do with the main tenets of ecological psychology: a cognitive architecture that instantiates the proposed model of ecological resonance will fit in the general ecological framework only if the architecture meets the requirements of avoiding computation and positing mental representations (Raja & Anderson, In Press). These two requirements are necessary because any appeal to computational activities or to mental representations would be inconsistent with the ecological understanding of perceptual processes. In this sense, neither cognitive architectures based on non-ecological notions of resonance, as the *adaptive resonance theory* (Grossberg, 2013), nor cognitive architectures that might be seen as able to accommodate the proposed model of ecological resonance, as the Bayesian architectures based on the *free-energy principle* (Friston, 2010), are suitable to implement ecological resonance in a proper way as they explicitly appeal to notions of computational processing or internal models of the environment (Linson et al. 2017; Ramstead et al. 2019).

The second set of requirements comes from taking ecological resonance to be a kind of informational relationship between two dynamic systems (O-E system and neural system). In this sense, a cognitive architecture able to properly accommodate ecological resonance must

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[10] In this context, a cognitive architecture is understood as the full set of concepts and tools that describe the functioning of cognitive systems or the functioning of parts of cognitive systems (e.g., neural systems) in terms of their fundamental components (e.g., single-neurons, neural networks, biophysical networks), their organization (e.g., modular, holistic), their activities (e.g., computation, phase transitions), and their functions (e.g., building up models of the environments, reducing free energy, and so on).

[11] I have offered the prospects of such an ecological cognitive architecture in Raja (2018).

understand both O-E interactions and neural activities in dynamical terms. There are many architectures that do so, but the dynamic approach itself does not warrant the suitability of a cognitive architecture to instantiate ecological resonance. On the one hand, cognitive architectures that describe neural systems in terms of their dynamics can still hold computational assumptions, as in the case of Izhikevich (2007)[12], or representational assumptions, an in the case *dynamic field theory* (Schöner, Spencer, & the DFT Research Group, 2016).[13] Therefore, these cognitive architectures fall short of meeting the previous ecological requirements. On the other hand, not all dynamic approaches acknowledge the multiscale nature of cognitive systems required by the proposed model of ecological resonance. Van Gelder's *dynamical hypothesis* (1998), for example, consists of taking cognitive systems to be dynamical systems (p., 615) and of promoting a single-scale explanatory strategy based on the use of dynamical models to understand the cognitive performance of the system at its highest relevant level of causal organization (p., 622). In this sense, van Gelder's explanatory strategy is focused on just one scale and, therefore, cannot accommodate ecological resonance at it is a process that intrinsically requires the interaction of (at least) two different scales of the cognitive system.

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[12] Interestingly, along with the idiosyncratic view on the role of dynamics in the computational properties neural systems, Izhikevic and his colleagues have also worked on the notion of resonance at the scale of single-neurons typical of neurophysiological (see Izhikevich et al., 2003; Izhikevich, 2007; see also footnote 6, above). Although it is possible to find a connection between this notion of resonance and ecological resonance (see below), both notions work independently from each other.

[13] For instance, in the context of the neural activity as characterized by dynamic field theory, Schöner (2008) claims: "localized peaks of activation [in neural networks] are units of representation." (p., 109).

Given the previous constraints, I think there are two frameworks that could potentially accommodate ecological resonance and that could be the basis for an ecological cognitive architecture: Warren's *behavioral dynamics* (2006) and different variations of *coordination dynamics* as proposed by Kelso and colleagues (Jirsa, Fusch, & Kelso, 1998; Kelso, 1995; Kelso, Dumas, & Tognoli, 2013; Pillai & Jirsa, 2017; Tognoli & Kelso, 2014). In both frameworks, cognitive systems are described as multiscale dynamic systems without any appeal to notions such as computation or mental representation. In the case of behavioral dynamics, the informational coupling between O-E dynamics and the dynamics of the organisms is described in terms similar to ecological resonance. However, behavioral dynamics provide neither a characterization of the neural scale of cognitive systems nor an account of their sensitivity to perceptual information. Integrating ecological resonance within behavioral dynamics could bridge these theoretical gaps. In the case of coordination dynamics, elegant and detailed characterizations of the scalar relations between behavior and brain activity are provided (e.g., Pillai & Jirsa, 2017 for these relations in the case of rhythmical aiming behavior). However, the models proposed in coordination dynamics do not usually consider the role of perceptual information in the emergence of behavior.[14] Besides, as in the case of behavioral dynamics, coordination dynamics do not provide an account of

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[14] For instance, the original formulation of the HKB model (Haken, Kelso, & Bunz, 1985) in which an important part of coordination dynamics is based on does not include a term for perceptual information (see Wilson & Bingham, 2008). Also, Kelso himself acknowledges the necessity of a notion like resonance—which is not developed in his own framework—in order to account for perception and action (e.g., Kelso, 1995, p. 194).

cognitive systems' sensitivity to perceptual information. Again, integrating the proposed model of resonance in the framework of coordination dynamics could bridge these theoretical gaps.[15]

As I see the theoretical environment of ecological psychology and, more generally, of radical embodied cognitive science (see Chemero 2009), behavioral dynamics and coordination dynamics are *general* frameworks in which the *particular* model of ecological resonance could be integrated in order to offer a story about how perceivers are able to integrate ecological information in their own dynamics. In this sense, behavioral dynamics and/or coordination dynamics could be the basis for an ecological cognitive architecture that integrates the notion of ecological resonance as it is characterized here—both having resonance as a foundational notion or having it just as a complement to characterize perceivers' sensitivity to perceptual information. These general frameworks and the proposed model of ecological resonance, however, operate at different explanatory scales and further work is needed for their integration to be completed and, therefore, to have expansive, operational notion of ecological resonance. A further issue must be addressed, nevertheless, before such an operationalization of the ecological notion of resonance can be taken as a general process for detecting information in an ecological way: how do neural systems resonate to non-oscillatory scenes and events? In other words, how do neural systems resonate to non-oscillatory informational patterns? As we have seen, the physical notion of resonance entails an oscillatory driving system that affects the oscillatory behavior of a driven system. In this sense, canonical instances of resonance entail that resonant systems resonate to some form of oscillatory

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[15] Indeed, the combination of these two frameworks along with neural reuse as a principle for the functional structure of the nervous system in terms of the ecological notion of resonance might be the adequate cognitive architecture for a radical embodied cognitive neuroscience (Raja, Under Review; Raja & Anderson, In Press).

force or input (e.g., the body of the guitar resonates to the vibration of the strings). However, the informational patterns that constrain O-E dynamics to which neural dynamics are claimed to resonate in the proposed model are not always oscillatory. For example, the participants' optic flow and its relevant tau value in van der Weel and van der Meer's study (2009) are not oscillatory. Then, how can participants resonate to them?

One possible answer to this question is that, although some informational patterns are not strictly canonical examples of oscillations, they may be described in an oscillatory way. In this sense, those informational patterns would be similar to the periodic pushing activity that makes swings resonate: although a periodic pushing is not a canonical example of oscillation (as it is, for example, the sound of a guitar), its description in oscillatory terms is pretty straight-forward. Such a strategy might work for some informational patterns that entail some kind of rhythmical exploration, for example. However, it is difficult to see how continuous patterns of occlusion in the optic flow, for example, may be described in oscillatory terms. For this reason, perhaps other ways to answer the question may be more fruitful.

Another possible way to address the way neural systems resonate to non-oscillatory informational patterns is to consider that biology capitalizes the oscillatory features needed for the process of resonance. Let me use another musical example to unpack this claim. Flutes and their acoustics are well known (Fletcher & Rossing, 1998; Wolfe, 2018). An interesting aspect of flutes is that, although sound requires an oscillating motion or air flow, they receive non-oscillatory, continuous air flow when flutists blow to the embouchure hole. However, when such a non-oscillatory, continuous air flow gets into the flute, the combined activity of the air jet and the body of the flute produce an oscillatory component of the flow. Once this oscillatory component is produced, some of it is radiated as sound out of the end of the flute and any of its other open holes.

This example shows the way flutes produce oscillatory patterns of flow out of non-oscillatory ones just due to the physical properties of its material constitution. The structural aspects of the continuous air flow (e.g., the strength of blowing, the pattern of blowing, etc.) that gets into the flute are preserved but just transformed into an oscillatory flow. In a similar flavor, the biophysical properties of neural systems may be responsible for transforming non-oscillatory informational patterns into oscillatory informational patterns neural systems can resonate to while maintaining the structural (i.e., informational) properties of the former. For example, as part of the peripheral nervous system, the activity of sensory receptors while registering the environmental energy flows (e.g., the optic flow) is intrinsically oscillatory. In this sense, sensory receptors may play in neural systems the same role the air jet plays in flutes: transforming the input flow in a way the system can resonate to it. In the specific case of neural systems, such a role consists of transforming non-oscillatory environmental energy flows and the informational patterns found in them into oscillatory flows that maintain the same—or equivalent—structural properties and, therefore, the same—or equivalent—informational patterns.

Understanding the way neural systems resonate to non-oscillatory informational patterns as capitalized by their biophysical properties has two interesting consequences. First, it avoids the need for re-describing informational patterns and energy flows in terms of oscillations. We can have non-oscillatory informational patterns—like the ones in van der Weel and van der Meer’s experiment (2009), for example—that are registered by sensory receptors in an oscillatory fashion due to their intrinsic biophysical constraints. And second, it might serve as a framework to provide an integrative notion of resonance in which the activity of neural systems may be accounted for in terms of resonant systems at different scales: from resonance at the physiological scale of the sensory receptors of neural systems, in terms of single-neuron resonance (Hutcheson & Yarom, 2000; Kasevich & LaBerge, 2011), to different resonant processes at the scale of neural networks (e.g., *resonance frequency shift*, see Roach et al., 2018; *coherence resonance*, see Yu et al., 2018; *network resonance*, see Helfrich, Breska, & Knight, 2019; or *stochastic resonance*, see Ikemoto et al., 2018) and the ecological notion of resonance as the fundamental process for the detection of ecological information.

Of course, the success of the proposal just sketched, in which biology capitalizes the way neural systems resonate to non-oscillatory informational patterns, requires further theoretical and empirical research to take resonance as the general process to detect information in an ecological way. However, for what matters for the theoretical model presented in this paper, I take such a biological capitalization to be the most promising avenue for future research (for more on this, see section 4.3).

Having the previous caveat in mind and acknowledging that further work is needed to understand the way neural systems resonate to non-oscillatory informational patterns, the conclusion of this section is that resonance may be a promising candidate to answer the first question posited at the end of the previous one: How is the skier able to *detect* the variable(s) that specifies the position and the approaching speed of gates in her visual field (direct perception)? The answer is that the skier's perceptual system resonates to that information in the way just proposed. However, the question of direct learning is still open. So far, resonance explains the way perceptual systems detect perceptual information, but not the way they are able to switch from one perceptual variable to another one when perceivers need it to achieve their goals in a given task. Thus, the question is: Is a resonant system able to account for such a switching? In the next section, I explore several properties of resonant systems that may answer it.

4. Resonance and Direct Learning

An important difference between direct perception and direct learning has to do with the kind changes they highlight. Although change is central for ecological psychologists and direct perception is possible due to the changes (or transformations) in the ambient energy arrays perceivers provoke by acting in their environments, direct perception does not include, in principle, the notion of change that is fundamental for direct learning. Direct perception entails changes in the detection of variables of perceptual information when perceptual tasks change. However, direct learning entails changes in the detection of variables of perceptual information within the same perceptual task; and, actually, those changes constitute the process of learning. Given this, a resonant system capable to exhibit direct learning must be able to account for its idiosyncratic form of change regarding the detection of perceptual information.

In the relevant literature, the changes in the detection of perceptual information typical of direct learning encompass the information generated both in the successful performance of a task and in the patterns of error while performing a task. For example, when a skier misses gates in a slalom, the perceptual information generated in such missing is specific of the adjustment needed for her to detect the adequate informational variable: as perceptual information depends on the movements of the perceiver in her environment, different movements generate different information to be detected. According to direct learning, changes in performance and environmental exploration needed to successfully perform a task are specified in the information-for-learning generated in performance and in performance errors.

The adjustment of the detection of perceptual information may be characterized, complementarily, in terms of the modulation of the constraints that perceptual information imposes in perceptual systems. Such an explanation is the one that can be pictured in terms of resonance.

Concretely, the adjustment in the detection of perceptual information due to learning may be depicted as a modulation in the relation between perceptual information (the driving aspect of the resonant process), the intrinsic "resonant" frequencies of perceptual systems (the driven aspect of the resonant process), and the different ways both can be coupled (e.g., in terms of different dominant frequencies or harmonics). Put simply, as resonant systems able to learn, perceptual systems must be able to resonate to a variable and, afterward, to equally self-modulate or being modulated to resonate to a different (and better) one. Of course, such a capability of modulation—or being modulated—requires resonant systems to exhibit a set of features. Minimally, first, resonant systems must be able to *spontaneous* self-modulation: they must exhibit intrinsic activity and change. Second, resonant systems must be sensitive to perceptual information in a *complex* manner: at different scales, at different times, and so on, and such complexity may be a way to trigger modulation. Third, resonant systems must be *flexible* enough as to be able to resonate to some variables of perceptual information but to not to get trapped in those resonant states. And finally, resonant systems must be able to be sensitive to *subtle changes* in the perceiver-environment relation and modulate themselves—in addition to being externally modulated—with regard to them. Importantly, these features do not undermine or substitute the importance of the new patterns of environmental exploration in direct learning but complement their importance by describing how perceptual systems can adapt the detection of information to them.

In the following, I consider two of the resources that may be found in the ecological literature to help develop a resonance-based account of direct learning that aims to meet the previous four requirements: non-linear resonance and metastability. After that, I consider ecological and biophysical notions of resonance in an integrated fashion.

4.1 Non-Linear Resonance

So far, I have presented a very simple phenomenon of resonance: it occurs when the dynamics of a driving system affect the dynamics of a driven system at concrete frequencies. Pushing a swing, a couple of tuning forks, or a guitar when just one string is played are examples of this simple kind of resonance. However, resonance can be very complex in the real world. The dynamics of driving and driven systems are not always smooth and steady but changing, noisy, or chaotic. And usually many different systems affect each other in different ways at the same time. The complexity in the interaction dynamics of resonant systems makes them exhibit a set of important common properties: spontaneous oscillation, entrainment, and non-linear resonance (Large 1994, 2008, 2010).[16] The importance of these properties of complex interactions of resonant systems is that they display several interesting behaviors: they are able to resonate to different frequencies given the same stimulation; when they act as driven systems are able to anticipate the dynamics of the driving ones; and they can act as filters for some resonant frequencies.

Edward Large (2008) developed a model of neural oscillators to study the way these properties allow people to perceive musical rhythms.[17] In general, neural oscillators—both real neurons and the components of Large's model—spontaneously oscillate at different frequencies and instantiate different degrees of coupling to the systems they interact with. Moreover, they exhibit intrinsic nonlinear dynamics and resonance. Neural oscillators support the plausibility of describing the role of the neural aspects of perceptual systems as a kind of (nonlinear) resonator and, as such, may help to enrich the ecological notion of resonance to support direct learning.

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[16] Sometimes also referred to as "high order resonance" (e.g., Large 2008, 203 & ff.).

[17] In case mathematical details of the model are of interest for the reader, Edward Large's work is very complete in that regard (Large 1994, 2008, 2010; Large et al. 2016).

As they exhibit spontaneous oscillations, the relation between the dynamics of neural oscillators' intrinsic frequencies and the rhythms of their stimulation differ depending on the intrinsic frequencies of the former (Guckenheimer & Kuznetsov, 2007). However, as soon as both systems interact, they affect each other. This is the phenomenon of entrainment described by Large. When entrainment occurs, the coupling between two systems (e.g., perceiver-environment system and perceptual system) is perfect when their frequencies are similar. However, when the frequency of the driven system (e.g., perceptual systems' neural components) is greater than the one of the driving systems (e.g., perceiver-environment systems' perceptual information), the dynamics of the driven system anticipate the dynamics of the driving one (Large 2008: 203, Fig. 6.5B).[18] Also, when complex interactions of systems exhibit nonlinear resonance, driving and driven systems are coupled to each other in different patterns: in terms of their main frequencies, in terms of the harmonics of those frequencies, etc. In other words, they are nonlinear resonators because their patterns of resonance are not always linearly related to the main frequency of the stimulation. Although driven systems have a tendency to resonate to frequencies near to their own resonant frequency, they also resonate to the harmonics of the main frequency. Moreover, the harmonics of the driven systems also resonate to the harmonics of the driving ones. And, even more, driven systems remain coupled to those harmonics even when driving systems are not acting as stimulation anymore (Large 2008, 203-204, Fig. 6.5C): they resonate to absent dynamics of driving systems (e.g., to absent perceptual information).

The just sketched features of neural oscillators make resonance an interesting candidate to account for the activity of the CNS as part of perceptual systems not only in direct perception but

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[18] Such kind of anticipation is often referred to as strong anticipation in the ecological literature (Stepp and Turvey 2010; Stepp, Turvey, and Chemero 2010).

also in direct learning. Entrainment, anticipation, and nonlinear resonance make perceptual systems able to exhibit the plasticity in their relationship with perceptual information that is needed for perceptual learning (the first and second requirements described above). These properties are the product of the complexity of the relations between neural oscillators and perceptual information and, at the same time, allow for the modulation of the activity of perceptual systems with respect to such information.[19] They make perceptual systems able to resonate to main aspects of perceptual information (the "main frequency" of the input) or to other aspects of it (the "harmonics" of the input), and also sensitive to different informational variables or to different transformations of the same informational variable while the perceiver is performing the same task. Importantly, Large's model of neural oscillators offers a concrete understanding and a concrete measuring of how such modulation may occur when new rhythms are presented to perceivers. Rhythms are parts of available perceptual information and, as it is shown by the characteristics captured by Large's model, perceivers relate to them in different ways: detecting different aspects of such parts of available perceptual information, being able to follow the rhythm, being able to generate compatible rhythms, etc. In other words, perceivers are able to *learn* new rhythms and to behave accordingly by resonating to them.

The properties of nonlinear resonators enrich the ecological notion of resonance to the extent that it fits better with an ecological account of perceptual learning. Nonlinear resonance may be the way perceptual systems self-modulate and are modulated in their relation to perceptual

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[19] Notice that, crucially, these properties are the product of the intrinsic complexity of the systems involved in perception and learning and not the product of an internal, mediatory mechanism for perception or learning. In this sense, this description of perceptual systems and the role of the CNS in them is still compatible with ecological psychology (Raja, 2018; Raja & Anderson, forthcoming).

information, thus being able to exhibit changes in the detection of such information. However, nonlinear resonance by itself does not explain the patterns of stable and unstable detection of informational variables that perceivers show in their learning paths. In their path to become experts, perceivers sometimes detect one information variable and stay on that state for a while before they get to detect a better one. In this sense, perceivers show a metastable regime in their relation to perceptual information, in which periods of consistent detection of informational variables alternate with periods of change in the informational variable detected.

4.2 Metastability

The metastable relation between perceivers and perceptual information during learning processes is due, on the one hand, to the exploratory activity of the former. As noted before, perceivers' errors in their intended actions provide the necessary information-for-learning for them to know the kind of change in performance they need to detect the right informational variable for their task goals. Therefore, changes in perceivers' exploratory activities are a way to account for periods of stability and instability in the detection of different variables of perceptual information. On the other hand, as in the case of their modulation, it is possible to complement the story regarding perceivers' exploratory activities with a story about the resonant properties of perceptual systems that allow them and their neural components to maintain the metastable regime.

In the ecological-friendly literature on brain dynamics, metastability is understood as the capacity to smoothly get into different synchronization patterns—which may be understood as a form of resonance—without being completely locked (i.e., fully determined, strongly stabilized) in any of them (Kelso & Engstrøm, 2006; Kelso & Tognoli, 2007; Kelso, 2012; Tognoli & Kelso, 2014). In other words, metastable systems are soft-assembled and able to get out of a given assembly in favor of a different one. According to Kelso and Tognoli (2007), metastability is one of the main features of the dynamics of the CNS and, therefore, may be taken to be a property of perceptual systems in general (see figure 3). As they claim, "[m]etastable coordination dynamics reconciles the well-known tendencies of specialized brain regions to express their autonomy, with the tendencies for those regions to work together as a synergy." (p., 40).

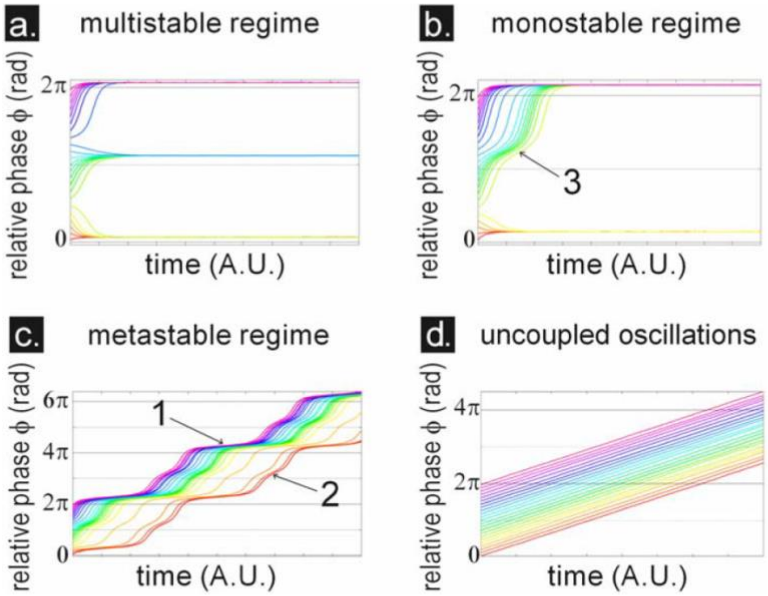

Figure 3. Examples of different coordination/coupling regimes of oscillators (colored lines). (A) A multistable regime. Given the interactions between oscillators, the whole system may get to different stable patterns of relative frequencies (horizontal trends). (B) A monostable regime. Given the interactions between oscillators, the whole system may get to one stable pattern of relative frequencies. (C) A metastable regime. Given the interactions between oscillators, the whole system combines both stable and unstable periods (non-horizontal trends) of relative frequencies. (D) Uncoupled oscillators. No synchronization between oscillators. (From Kelso & Tognoli, 2007, figure 2).

A metastable resonant system offers important advantages to understand the patterns of detection of perceptual information during learning events. On the one hand, it accounts for the metastable relation between perceivers and perceptual information and does so without proposing any ad-hoc explanation or mechanism. As Kelso and Tognoli show, metastability just follows from the intrinsic dynamics of neural systems as combinations of different oscillators—which is also what makes neural systems good candidates to be resonant systems (see 4.1). Thus, as neural systems are components of perceptual systems, it is fair to understand perceptual systems and their activity of detection of perceptual information as metastable. Moreover, metastable regimes are regimes able to be coupled to different variables of perceptual information without being fully locked to any of them (third requirement) and are able to undergo through qualitative changes in their dynamics when they face subtle changes in their driving stimulation (fourth requirement). On the other hand, the analysis of the multiple stable periods of the dynamics space of metastable systems and the different trends between stabilities may be a source of information to understand the path of learning both at the perceiver-environment and at the neural scales. The stable dynamics of metastable regimes may correspond to stages of learning and the trends between stabilities to the changes suffered by perceptual systems during the processes of learning. In this sense, metastability is both an important concept and an interesting tool to understand learning processes in terms of resonance.

4.3 From Metaphor to Theory

So far, I have analyzed the way the operationalized notion of resonance may be used to understand the role of neural systems in learning events and the specific features resonant neural systems should have in order to be able to contribute to direct learning: *spontaneous* dynamics, *complex* and *flexible* resonant profiles, and sensitivity to *subtle changes* in resonance conditions. Such a notion of resonance—the informationally constrained coupling of organism-environment and neural dynamics—along with well-known properties of non-linear neural systems (nonlinear resonance and metastability) suggest those are plausible features of neural systems and support the possibility for resonance to be a central neural process in direct learning.

Moving from the metaphor of resonance to a theory of resonance in perceptual learning, however, requires some more concrete steps. First, the role of resonance as the principle that establishes the harmony (or informational coupling) of the dynamics of the multiple scales of analysis of direct learning is worth being further explored. And second, a concrete account of the relevance the theory could have in experimental research on direct learning is worth pursuing.

Following the Gibsonian notion of resonance, the proposed theoretical model operates at a specific level of abstraction: the dynamics of the organism-environment and neural scales. In this sense, the model is easily depicted in terms of dynamical systems theory and resonance can be straightforwardly related to informational coupling; namely, we can understand resonance to capture the informational constraint organism-environment dynamics impose on neural dynamics and their consequent coupling. More concretely, the model allows us to understand neural dynamics in terms of oscillatory assemblies of neurons that are coupled (exhibiting the relevant features already noted) to the informational variables that constrain the dynamics at the organism-environment scale. However, using ecological resonance as the principle of informational coupling at this level of description does not entail a process (or mechanism) of biophysical resonance at a lower level of analysis. Why is resonance the principle that accounts for informational coupling and not computation or feature detection, for example? In other words, why are single neurons and neural networks *resonating* and not carrying out a different process?

Although a foundational answer to these questions requires further research, it is important to point out that processes of biophysical resonance that could account for informational coupling have been described at the neurophysiological scale of neural systems. Lau & Zochowski (2011), for example, have shown that intrinsic resonant properties of single neurons are of chief importance in the oscillatory patterns neural networks are able to exhibit. Concretely, the variations of subthreshold oscillations that are ubiquitous in the brain lead to *resonance frequency shifts* in single neurons—i.e., neurons have a flexible resonance profile depending on subthreshold oscillations—that, in terms of neural networks, entail complex patterns of coupling between such neural networks and their input flows. Similar resonance frequency shifts have been shown to be directly triggered by network input flows themselves (Shtraman & Zochowski, 2015) and have been related to processes of structural and functional coupling between neural networks during learning events both in neural models and in vivo neural tissues (Roach et al., 2018).

Such low-level, biophysical notions of resonance and resonance frequency shift are compatible with the features of spontaneity, complexity, flexibility, and subtle input sensibility—this one reinforced by another process of biophysical resonance named *stochastic resonance* (Ikemoto et al., 2018)—a neural system must exhibit for a theory of resonance to account for direct learning. Neural networks consisting of single-neurons that change their own resonance profiles due to other network variables and the network input and that, in doing so, entail dynamic changes in the network's coupling patterns seem to be good candidates to exhibit nonlinear resonance and metastability. In this sense, the biophysical process of resonance is, at least, a good candidate to be the principle for the informational coupling entailed by the resonance-based theoretical model.

It is important to note that the biophysical notion of resonance is independent of the Gibsonian notion. They are compatible but to some extent autonomous. It is possible for the theoretical model based on ecological resonance to hold without the need for a parallel process of biophysical resonance (and vice versa). However, the integration of biophysical considerations in the model makes the theory of resonance a broader framework to understand direct perception and direct learning without appealing to robust notions of computation or feature detection. Moreover, it helps to envision a broader and more ambitious research program.

A research program in direct learning based on the theory of resonance just sketched would encompass the joint forces of different disciplines at different scales of analysis. Imagine, following the example of section 3, that Satoshi wants to learn how to avoid approaching objects in an efficient, successful fashion (because he plays a sport in which such ability is required, for example). A research program based on resonance would start with the ecological analysis of perceptual information and the different variables Satoshi uses to guide his avoiding behavior during the learning path. In this sense, the starting point would be current research on direct learning. Then, based on the operationalized model of ecological resonance, the aim of the research would be to find ways in which perceptual information constrains neural dynamics and, concurrently, to find the signatures of nonlinear resonance and metastability in those dynamics. At this scale, the works of Large and others with nonlinear oscillators (Large, 2008, 2010) and of Kelso and others in coordination dynamics (Kelso, 2012; Tognoli & Kelso, 2014) might provide experimental and analytical tools. Finally, the model based on ecological resonance could be complemented with the study of the biophysical underpinnings of the detection of perceptual information for avoiding approaching objects during learning events through a process of resonance frequency shift (e.g., by analyzing what kind of changes in environmental exploration changes the input flow in a way relevant for the frequency profiles of neurons and for the coupling patterns of neural networks). This scale of analysis would complement the dynamical study and would offer a more robust, integrative, and general account of Satoshi's learning process based on resonance.

5. Conclusion

Inspired by the conceptual revolution in AI carried out by Rodney Brooks with behavioral robotics, I have contended that resonance may be a promising principle to understand the way perceptual systems detect perceptual information and switch from some informational variables to different ones during processes of perceptual learning. An important remark regarding my project in this paper is that, unlike Brooks' works, I am consciously providing a theoretical framework and not an empirical program. In this sense, some of the aspects of my proposal at this stage are necessarily abstract. I have tried to set the foundations for a cognitive architecture built upon the ecological concept of resonance that can accommodate the role of perceptual systems and its neural parts in the overall theoretical and empirical space of direct learning. To do so, I have provided a theoretical model inspired by Gibson's notion of resonance that can be further developed by also considering the role of biophysical resonance in perceptual learning. In any case, the role of resonance in perceptual learning does not aim to substitute direct learning. On the contrary, the aim of my project is to complement the existing research on perceptual learning—that successfully investigates the process of learning in terms of perceiver-environment interactions and perceptual information—with a story regarding the way perceptual systems—a component of whole perceiver-environment interactions—are able to detect such information and to undergo through the changes in detection occurred during learning processes.

After considering the underpinnings of perceptual systems and their neural components as resonant systems, I have explored the ecological literature and pointed out two different concepts and their associated tools—nonlinear resonance and metastability—to enrich the resonant cognitive architecture as to better grasp the singularities of direct learning with regard to direct perception. As presented in this work, the relations between simple resonance, nonlinear resonance, and metastability are also abstract relations of compatibility. As a way to picture such compatibility in resonant terms, I have explored the suitability of a resonant mechanism (resonance frequency shift) as the fundamental process of resonant networks that might exhibit those properties. Of course, further empirical work is needed to fully flesh out those relations and their potential. The fact that there are different models and proofs of concept for all of them both in the ecological and the neuroscientific literature offers good prospects for this kind of research.

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About the Author

Vicente Raja is a postdoctoral fellow at the Rotman Institute of Philosophy (Western University, Canada). His main fields of research are cognitive science, its philosophy, and theoretical neuroscience. He pays special attention to embodied approaches to perception, action, and cognition, and to the relation between brain activity and behavior. Other philosophical interests include history and philosophy of psychology and philosophy of technology. His experimental work encompasses nonlinear analyses of both human and plant behavior.