

Different Forms of Random Motor Activity Scaffold the Formation of Different Habits in a Simulated Robot

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Abstract

A habit is formed through the repeated enactment of sensorimotor regularities created and maintained by means of plastic changes on the mechanism that brings them about. This precarious, self-maintaining sensorimotor organization is known as sensorimotor autonomy. One can imagine how some habits would be better suited to the maintenance of a biological individual. Evolution can bias the parameters of the plastic medium over which sensorimotor autonomy emerge so as to be beneficial to biological autonomy. In this work, we show that varying some parameters that bring about plastic changes in the behavior-generating medium, different sensorimotor individuals emerge. The simulation consists of a simple robot coupled with a habit-based controller with a random-based exploratory phase in a one-dimensional environment. The results show that, varying the parameters of such a phase, qualitative different habits emerge characterized by static, monotonic and oscillatory behaviors. Quantitative variations of the oscillatory behavior are also shown using the frequencies distribution obtained from the motor time series of the formed habits. The results are interpreted in terms of how the sensorimotor habitat could emerge from the random traversing of the sensorimotor environment. Finally, a comparison between this model and the skin brain thesis is presented.

Introduction

The enactive concept of autonomy, defined by concepts of precarious self-maintenance and operational closure, can be used in diverse contexts to identify an “individual”. This concept of autonomy first emerged as a way to identify and delimit biological individuals (autopoiesis) (Maturana and Varela, 1980). It has since been applied in a variety of other contexts, including sensorimotor dynamics, the organs and organization of multicellular life, etc. By applying this method in these different contexts and at different scales, diverse types of precarious individuality emerges. Of particular relevance to the remainder of this paper, is the relationship between an agent’s biological and sensorimotor autonomies, i.e. the relationship between its biological self-maintenance (persistence as an organism) and self-maintaining sensorimotor world interactions. The notion of autonomous sensorimotor dynamics is not one that is widespread, nor is it self-evident, so let us spend a little

bit of time expanding upon what is meant by this concept. It is clear that sensory input influence subsequent actions. The converse is also true: actions influence sensory input. You step forward and the image projected on to your retina changes in rule-like ways, where for instance objects that are closer to you will move more than those that are farther away. It is possible to construct artificial “brains” i.e. media that transform sensory input into motor action, such that (and this is the critical bit) one or more patterns of action maintain the conditions necessary for those patterns of action to persist. In this context, we can identify precarious autonomous sensorimotor individuals¹ — patterns of action that stabilize or otherwise maintain the conditions that are necessary for the mechanism that generates those patterns of action to persist.

A number of investigations have modeled this idea of sensorimotor autonomy (even if they have not always used this word to label it). Studies include (Di Paolo, 2003; Egbert and Barandiaran, 2014; Egbert and Canamero, 2014), and it has been related to Ashby’s notions of ultrastability (Ashby, 1952) and the apparent ultrastability of human perception, exemplified by our ability to adapt to diverse systematic perturbations to our sensory apparatus (e.g. Kohler, inversion of the visual field (Di Paolo, 2003)). The whole idea is the central topic of the recent book by Di Paolo et al. (2017).

The relationship between sensorimotor autonomous individuals and the biological autonomous individual is not one of simple subsumption or hierarchy (Barandiaran, 2008). An organism’s nervous system is part of the medium in which sensorimotor autonomous individuals emerge and persist (or not!). Sensorimotor individuals are thus fundamentally dependent upon the organisms biological body. It is also the case that (most) biological bodies essentially depend upon the nervous-system-mediated sensorimotor activities to persist. Each depends upon the other.

It is interesting, though, that these relationships neither require nor imply that sensorimotor individuals and the biological individual to have compatible norms or viability limits. Nevertheless many habits are beneficial or neutral

¹Other authors might refer to a “sensorimotor autonomy”

with regard to impact upon biological viability (Egbert and Canamero, 2014).. Why? How does this alignment of norms and viability conditions come to exist? How do the sensorimotor individual and the biological individual over which they operate come to cooperate? And just as interestingly: in what conditions does this cooperation fail to emerge/develop?

The properties of the nervous system play a key role in influencing which types of sensorimotor autonomous individuals will persist. One possible mechanism through which the biological and sensorimotor norms become aligned is via evolution. Evolution tunes the nervous system so as to produce behaviors that are beneficial to biological viability. This could happen in a variety of different ways. For instance, we can compare among three different possibilities. The first one is the evolution of a set of hard-wired stimulus-response reflexes. If the organism's behavior consisted of nothing but hard-wired responses, then the mechanism that produces the behavior would not depend upon the result of the behavior. That is, the hard-wired reflexes would not participate in maintaining the conditions necessary for such a mechanism to generate them. Therefore, the behavior could not be considered as a sensorimotor individual because these reflexes (and consequently the behaviour) would not cease to operate, unless the organism died. A hard-wired mechanism thus would in fact still depend upon the behavior in terms of biological viability. This behavior would then be part of the precarious biological autonomous individual, not a sensorimotor one.

Another possibility is one where reflexes play a less direct role of scaffolding the formation of sensorimotor individuals. The idea here is that evolution could result in a few hard-wired stimulus responses that influence which patterns of behavior are more likely to occur. Plastic mechanisms in the nervous system then support whichever self-sustaining sensorimotor individual emerge, but the reflexes bias the system to produce sensorimotor individuals that are conducive to biological survival.

No doubt there are hard-wired reflexes that guide some our behavior (and our sensorimotor development). It seems unlikely, though, that more than a few specific stimulus responses could be specified at the genetic level. The last possibility is one where genes can modulate more coarse features of nervous system topology, connectivity and interaction, and random motor babbling enables and biases the formation of different sensorimotor individuals. Plastic changes in the nervous system then support the self-maintaining sensorimotor individual that bring about such changes. This is the idea that we explore using a model in the next section. Specifically, we simulate a simple robot embedded in a 1D world. The robots "controller" is a sensorimotor medium which reinforces previous patterns of sensorimotor behavior. We vary the parameters of the random motor activity that is activated by the controller when it is

in sensorimotor conditions it has not previously experienced and show that just by modulating this basic parameter, it is possible to bias the system to produce particular qualitative behaviors (static, monotonic, oscillatory) and even to vary some of the quantitative aspects of those behaviors (oscillation frequency).

The concept of habit and its models are described in the next section. After that, the model and the experiments are explained. Finally, the results are reported and discussed.

The Concept of Habit

The concept of habit was one of the most important theoretical primitives for the study of mind before being usurped by the notion of mental representation (Barandiaran and Di Paolo, 2014). Currently, with the anti-representationalism trend in cognitive science due to the different embodied approaches to cognition, a reappraisal of the notion of habit has been required. Moreover, habits could be the building blocks for modeling the organization of behavior, and their ecology the core of *Mental Life* (Barandiaran, 2007). A very brief look to the re-definition of habit that inspired this work based is presented so as to compare modeling frameworks below. Di Paolo (2003) argued that habits are dynamic invariants obtained from a circular process between plasticity and behaviour. Habits can be understood as self-sustaining dynamic structures that are challenged when the behaviour is perturbed and adaptation is needed. After that, Barandiaran (2008) detailed the definition of habit as "a self-sustaining pattern of sensorimotor coordination that is formed when the stability of a particular mode of sensorimotor engagement is dynamically coupled with the stability of the mechanism generating it" (p. 281). Finally, Egbert and Barandiaran (2014) added the property of reinforcement by repetition to this concept of habit in order to have a working definition. A habit is then precarious in the sense that, if the sensorimotor patterns of behavior are not continuously re-enacted, the consequently plastic change is produced differently affecting the creation and maintenance of the sensorimotor correlations it contributes to cause.

Simulation models has been used as tools to obtain new insights through the exploration of new theoretical positions and, consequently, a possible conceptual reorganization (Di Paolo et al., 2000). On the one hand, Di Paolo (2003) explored an homeostatic neural controller using an evolutionary robotics approach to propose that true intentionality can be brought about investing a robot with a mechanism for acquiring a way of life: habits. In this case, a habit is grounded on the circular interaction between sensorimotor correlations and neurodynamic patterns, and the plastic reinforcing changes on the habit formation mechanism (Barandiaran, 2017). Barrett (2014) addressed important questions raised when the ecology of habits is presented as a dynamical system (e.g. models with recurrent neural

networks as controllers) challenging the conventional notion of habits and yielding a number of insight that must be treated in the future. Another modelling approach was taken by Egbert and Barandiaran (2014) who instantiated the concept of habit explained above using a novel habit-based controller. In this framework, a habit is formed through the plastic changes resulted by the continuous reenacting of the self-sustaining sensorimotor state trajectory emerging from the sensorimotor coupling between the robot and the environment. One important different between the two controllers is the scale in which they are modeled: the former is modeled in the neuro-dynamic level and the latter is modeled at the level of the sensorimotor dynamic.

Model

The robot controller proposed by Egbert and Barandiaran (2014) is a dynamical construct called the Iterant Deformable Sensorimotor Medium (IDSM). The IDSM coupled to robot sensors and motors influences the rate of change of the motors as a function of the current sensorimotor state, the rate of sensorimotor state change, and the current state of mapping as time passes (see Equation 6). The influence can then be understood as a "continuous transfer function that can be depicted as a multidimensional vector space (the dimension been the sensory and motor variables)" (Barandiaran, 2017, p. 421). The controller was designed such that current sensorimotor patterns of activity increases the likelihood of repeating similar sensorimotor patterns in the future. Broadly, as a robot embedded with an IDSM moves through sensorimotor state trajectories, a set of records of the sensorimotor dynamics, known as nodes, are created and modified. Formally, each node is a tuple of two vectors and a scalar in a normalized sensorimotor space, $N = \langle N_{\mathbf{p}}, N_{\mathbf{v}}, N_{\omega} \rangle$, where the elements indicate the sensorimotor state associated with the node or "position", the rate of sensorimotor change or "velocity", and the "weight" of the node, respectively. The normalized sensorimotor space is defined such that the range of all sensor and motor values are linearly scaled to lie in $[0, 1]$. A new node is created when the weighted density of nodes, $\phi(\mathbf{x})$, near the current sensorimotor state, \mathbf{x} , meets the condition expressed by Equation 1. This density function can be understood as a measure of how similar the current sensorimotor state is to the set of nodes created previously. It is calculated using the distance from every node to the current sensorimotor state bounded by the sigmoidal function in Equation 3, and whose result is scaled by the sigmoidal function of the weights defined in Equation 2.

$$\phi(\mathbf{x}) = \sum_N \omega(N_w) \cdot d(N_{\mathbf{p}}, \mathbf{x}) < k_t \quad (1)$$

$$\omega(N_w) = \frac{2}{1 + \exp(-k_w N_w)} \quad (2)$$

$$d(N_{\mathbf{p}}, \mathbf{x}) = \frac{2}{1 + \exp(k_d \|N_{\mathbf{p}} - \mathbf{x}\|^2)} \quad (3)$$

A weight represents the overall influence of the node in the rate of change of the motor output. After a node is created, its weight changes according to Equation 4. k_{dec} is a decay term which allows a steady decrease of the influence of the node when sensorimotor trajectories near that node are not re-enacted by the robot. k_{reinf} is a reinforcing term which allows the increase of the influence of the node when its position is closed to the current sensorimotor state.

$$\frac{dN_w}{dt} = -k_{dec} + k_{reinf} d(N_{\mathbf{p}}, \mathbf{x}) \quad (4)$$

A node is activated t_{act} units of time after creation, that is, the IDSM output is not influenced by the node during such a time, although its weight is updated. Equations 6 and 6 describes the so-called "influence" of the IDSM which in previous works has been the mapping function from the current sensorimotor state to a rate of motor change. The influence is composed by an "velocity" factor and a "attraction" factor. The former is the motor components of $N_{\mathbf{v}}$, and the latter is a force that cause the system to visit regions of the sensorimotor space with a higher density of nodes so that changes in the environment and perturbations can be compensated. Note that only the motor component of the "attraction" factor is used. The velocity factor pushes the sensorimotor dynamic away from the node while the attraction factor draws the sensorimotor dynamic toward the node (see Egbert and Barandiaran (2014) for more details). As can be seen, both factors are scaled by the distance function and the weight function defined by Equation 3 and 2, respectively. Once summed and scaled, the result is also scaled by the density of the nodes at the current sensorimotor state defined by Equation 1.

$$\mathbf{I} = \frac{1}{\phi(\mathbf{x})} \sum_N \omega(N_w) \cdot d(N_{\mathbf{p}}, \mathbf{x}) \cdot (Vel + Att)^\mu \quad (5)$$

Vel : $N_{\mathbf{v}}$
Att : $A(N_{\mathbf{p}} - \mathbf{x}, N_{\mathbf{v}})$

$$A(\mathbf{a}, N_{\mathbf{v}}) = \mathbf{a} - \left(\mathbf{a} \bullet \frac{N_{\mathbf{v}}}{\|N_{\mathbf{v}}\|} \right) \frac{N_{\mathbf{v}}}{\|N_{\mathbf{v}}\|} \quad (6)$$

The controller was originally designed such that $\frac{d\mu}{dt} = \mathbf{I}$, where μ represents when motor components are only used, but the Equation 7 presents another alternative. As stated by Egbert (2018), the motor output is determined either by the influence function of the IDSM (\mathbf{I}) or by a random process (\mathbf{R}). The sigmoidal function, $s(\psi)$, is defined by the Equation 8 where ψ determines the local density of the nodes.

Therefore, if the robot visits unfamiliar sensorimotor states, the motor activity is to be random. 100 times per unit of time, \mathbf{R} has a p chance of being set to a random vector drawn from a Normal Distribution with mean 0 and variance r , that is, $\mathcal{N}(\mu = 0, \sigma^2 = r)$.

$$\frac{d\mu}{dt} = (1 - s)\mathbf{I} + s\mathbf{R} \quad (7)$$

$$s(\psi) = \frac{1}{1 + \exp(k_s\psi - k_s)}; \psi = \sum_N d(N\mathbf{p}, \mathbf{x}) \quad (8)$$

The IDSM can be used to train functional habits. Egbert and Barandiaran (2014) presented a two-phase experiment: (1) in the training phase, a robot executes a task using a Braitenberg vehicle-inspired controller, whilst the IDSM tracks the sensorimotor state trajectories; (2) in the free-action phase, the motor activity is only determined by the influence of the IDSM. If the robot is trained from different initial conditions, the robot continues performing similar patterns of behavior after training regardless the initial conditions.

Recently, Egbert (2018) investigated agency and norm-driven behavior using the IDSM as a framework to model a sensorimotor individual. The experiment consisted of a robot coupled with an IDSM with a random-based exploratory phase, that is, the motor activity was determined by Equation 7 in order to perform a task. In this case, neither a training phase nor a random initialization of the IDSM was needed but a good tuning of the parameters.

A remarkable difference between these approaches is that, whilst Egbert and Barandiaran (2014) used the IDSM to “exploit” the regularities among the sensorimotor contingencies, body and environment, Egbert (2018) used an augmented controller to also “explore” the sensorimotor space. Therefore, whilst only the re-enacting of sensorimotor trajectories is needed in the former for habit formation, random behavior is also needed in the latter for the emergence of precarious but stable sensorimotor patterns of behavior.

Other efforts have been recently done to understand how the habits formed using a simplification of the IDSM is biased by the number of nodes, nodes position and velocity (Woolford and Egbert, 2019). In the current work, an experiment is performed to show how different forms of the random motor activity (\mathbf{R}) employed in unfamiliar sensorimotor states bias the formation of habits so as to take different qualitative forms with different quantitative properties. The details are described in the next section.

Experiment

The experiment consists of varying the parameters of the random process, that is: p (i.e. the probability of setting a new random vector R in every time unit) and r (i.e.

the variance of the normal distribution from where R is drawn), such that $p \in \{0.0, 0.01, 0.02, \dots, 0.39, 0.40\}$ and $r \in \{0, 1, 2, \dots, 9, 10\}$. For each condition in $r \times p$, the formation of self-organized habits is allowed 100 times, randomizing the robot initial conditions in each run. We simulate an IDSM with a random-based exploratory phase coupled with a simple robot situated in a one-dimensional periodic environment. The robot has one motor which determines its velocity $m = \frac{dx}{dt}$, where x is the robot position, and the sensor activity is activated according to $\frac{1}{1+x^2}$. The motor activity is bounded such that $m \in [-1, 1]$, and the environment dimension is 4, so that the periodic variable $x \in [-2, 2]$. Table 1 lists the value of the controller parameters used during the experiment.

k_t	k_ω	k_d	k_{dec}	k_{ref}	k_s	t_{act}
1	0.0025	1000	-1	10	20	1

Table 1: Values of the controller parameters.

Each run lasts 200 units of time. Habit formation is allowed during all the time such that the position and velocity of each created node are recorded. Motor activity, robot position, and sensorimotor trajectory are only recorded from time 100 onward. The frequency and amplitude of the motor time series is then computed using the Fast Fourier Transform. Motor activity mean and standard deviation are also calculated. The processed data is used to train a Decision Tree Classifier with 2255 self-organized habits classified by hand. The model is trained splitting the data into two data sets whose elements are randomly chosen. The training data set constituted by 90% of the data, and the testing data set constituted by 10% of the data. The accuracy of the Decision Tree classifier is 0.9956.

Results

The self-reinforcing sensorimotor patterns can be distinguished by the sensorimotor trajectories in the sensorimotor space which produce qualitatively different behaviors in the environment. We have chosen to classify habits into three categories based on the similarities among their sensorimotor trajectories and the patterns generated in the environment. To understand the qualitative features, some examples are presented.

Examples

The figures of the following examples were created choosing arbitrary values for p and r . Each Figure consists of the sensorimotor space, the time series of the motor activity and robot position. Blue circles depict node position and white arrows show the direction of node velocity. The color intensity represents the value of the node weight, i.e. the bluer the node, the higher its weight. Gray dots are plotted when

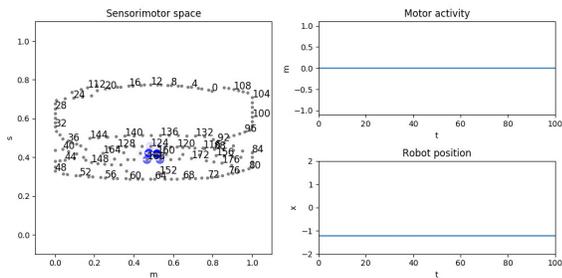


Figure 1: Example of a Static behavior obtained using $p = 0.1$ and $r = 3$.

weights have been degraded so that those nodes are imperceptible. The numbers located beside some nodes are useful to visualize node creation over time.

Static Behavior: This behavior is characterized by a point-like sensorimotor trajectory and zero motor activity. This stationary sensorimotor trajectory is usually formed after randomly driven changes in motor activity. Figure 1 shows how those changes ends up in this kind of behavior. The initial possible sensorimotor trajectory runs from node 0 to 108. New nodes were created after the random-based exploratory phase was applied and the current sensorimotor state was different enough from the ones previously experienced such that the condition in Equation 1 was met. For instance, nodes 116 and 132. Over time, these nodes formed new narrow sensorimotor trajectories. The weights of distant nodes from such new trajectories were degraded such that the motor activity was determined by the influence of the newest nodes. At some time, the robot reaches an equilibrium when the velocities of the latest created nodes were opposite as can be seen for the directions of the white arrows.

Monotonic Behavior: This behavior is characterized by a linear sensorimotor trajectory whose motor value is constant, either -1 or 1 , and sensor value varies along the sensor range. Figure 2 depicts how this kind of behavior emerged after large random changes in motor activity. Many nodes were created over time, but the nodes located around the sensorimotor trajectory were reinforced sufficiently to overcome other possible trajectories (for example, the sensorimotor trajectory possibly defined by the nodes around $m = 1$). As can be seen, the nodes influencing the sensorimotor trajectory were not generated successively but they were created and reinforced in different moments.

This type of behavior also emerged due to other reasons. Figure 3a shows that this sensorimotor pattern can emerge when the random vector is drawn from normal distribution with variance 0 such that the motor-components of the terms *Velocity* and *Attraction* in Equation 6 are always zero. Here, we have a first examples of how the parameters of the random motor process can bias habit formation. As we shall

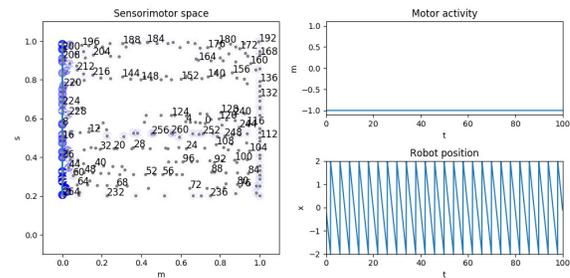


Figure 2: Example of a monotonic behavior obtained using $p = 0.38$ and $r = 9$.

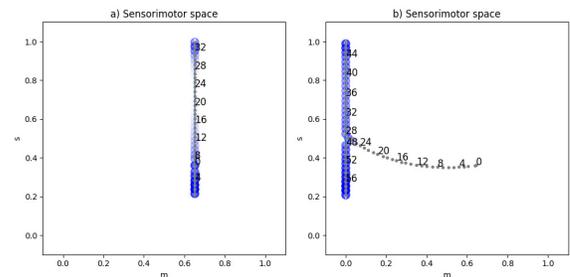


Figure 3: Examples of a monotonic behavior obtained using a) $p = 0.01$ and $r = 0$, and b) $p = 0.0$ and $r = 1$

see below this bias does not only hold for $p = 0$, but also for small values of p . Therefore, the randomly-set initial condition of the motor value remains constant over time. Figure 3b shows that this behavior can also emerge when the probability of changing vector \mathbf{R} is zero such that either the highest or the lowest motor value is reached. Therefore, new nodes are created and reinforced along the sensor range.

Oscillatory Behavior: This behavior is characterized by a closed sensorimotor trajectory. This trajectory produces an oscillatory motor activity and, therefore, an oscillatory robot displacement as can be seen in Figures 4 and 5. Both figures were produced with the same values of p and r but different random seed. The nodes defining the sensorimotor trajectory in Figure 4 were created almost successively over time, while the latest created nodes in Figure 5 constrained the formation of other possible trajectories due to the opposite directions of nodes velocities (see nodes 132 – 184). The random motor activity biased the final sensorimotor pattern either defining slightly changes in motor activity (for instance, nodes 99 – 108 in Figure 4) or driving the node creation to specific regions of the sensorimotor space (for instance, nodes 84 – 88 in Figure 5).

The class of some trajectories could not be so clear. For example, a sensorimotor trajectory could be formed with most of the nodes located around either $m = -1$ or $m = 1$, and just a few nodes around another motor value whose

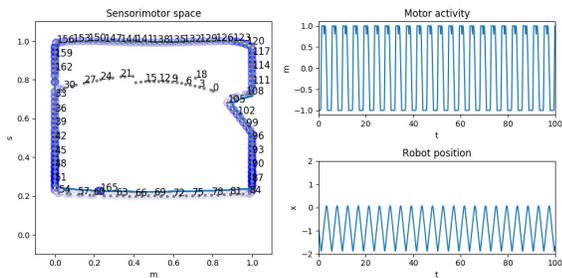


Figure 4: Example of an oscillatory behavior obtained using $p = 0.02$ and $r = 2$.

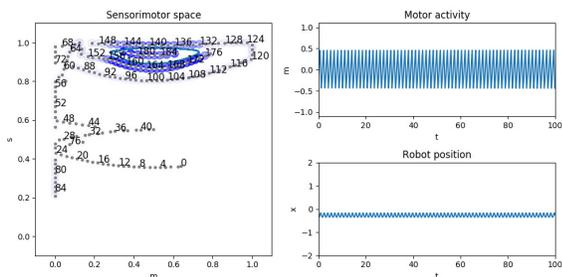


Figure 5: Example of an oscillatory behavior obtained using $p = 0.02$ and $r = 2$.

weights influence the motor activity. This behavior might be wrongly classified as an oscillatory behavior if only the sensorimotor trajectory is used as the reference. However, the robot would be performing a monotonic behavior because the influence of the smaller set of nodes is usually only enough to slightly increase or decrease robot speed.

The values of p of r used to generate the figures do not entail that qualitatively similar behaviors are more likely to emerge under these conditions. We present the results of modulating both parameters in order to know what kind of behaviors emerge regardless robot initial conditions.

Statistical Results

Static Behaviors: Figure 6 shows that static behaviors can emerge neither when $r = 0$ and p varies nor when r varies and $p = 0.0$. Note that the higher the value of p and the lower the value of r , the more likely is the emergence of these kinds of habits. Therefore, continuous changes of the components of \mathbf{R} drawn from a normal distribution with a small standard deviation, σ , result in fast small steps in the sensorimotor space that avoids the formation of wide sensorimotor trajectories.

Monotonic Behaviors: Figure 7 shows that only monotonic behaviors emerge when $r = 0$ and p varies, and when r varies and $p = 0.0$. In the first case, $r = 0$ implies that R is a vector constituted by zeros. The random-based exploratory

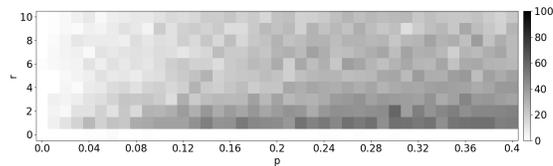


Figure 6: Grayscale representation of the number of static behaviors emerged per each couple of p and r .

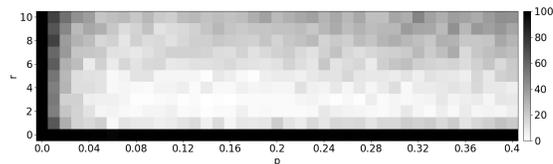


Figure 7: Grayscale representation of the number of monotonic behaviors emerged per each couple of p and r .

phase tries to influence motor activity at the beginning of the time because $s(\phi) \approx 1$ and then $\frac{d\mu}{dt} = \mathbf{R}$. The motor activity is constant with the same value of the initial condition. At some time, $s(\phi) \approx 0$ and then $\frac{d\mu}{dt} = \mathbf{I}$; however, the motor-components of $N_{\mathbf{V}}$ are zero because those components of the created nodes are zero too. Therefore, motor activity remains constant. New nodes could be created along the sensor value range but the IDSM do not take over motor activity at any time (see Figure 3a). On the other hand, in the second case, $p = 0.0$ implies that R is constant over time, although was defined randomly. Therefore, the only possible sensorimotor trajectory is formed when the motor value reaches one limit of the motor range after a transient (see Figure 3b). Notice that behaviors formed when $r = 0$ and p keeps fixed motor state over time, whilst behaviors formed when r varies and $p = 0.0$ maximize motor state during a transient. Finally, monotonic behaviors are also considerably likely when continuous changes of the components of \mathbf{R} drawn from a normal distribution with a high standard deviation result in fast large steps in the sensorimotor space that allows the reinforcing of the nodes in the limits of the sensorimotor space.

Oscillatory Behaviors: Figure 8 shows that this behavior is highly probable to emerge for any couple of parameters, except when $r = 0$ and p varies or when r varies and $p = 0.0$. However, oscillatory behaviors are more likely when sporadic changes (small values of p ; see from 0.02 to 0.12, for instance) of the components of \mathbf{R} drawn from a normal distribution, whose variance can be chosen along the set but zero, are performed. These changes result in slow small steps in the sensorimotor space allowing the formation of closed sensorimotor trajectories. As can be seen in Figure 9, outliers or not-formed habits, usually characterized by

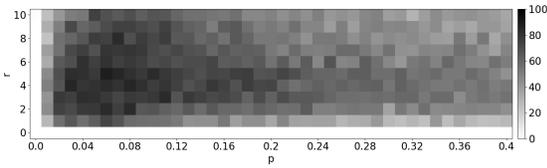


Figure 8: Grayscale representation of the number of oscillatory behaviors emerged per each couple of p and r .

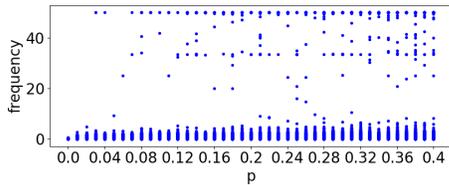


Figure 9: Frequencies distribution considering all the values of r per each value of p .

high frequencies, are less likely for small values of p .

Discussion

We have shown how simply by changing the parameters of the random motor activity that is engaged when the sensorimotor state is unfamiliar, it is possible to bias qualitative and quantitative properties of the patterns of sensorimotor activity that become ingrained as habits in the IDSM. For low values of p , monotonic behaviors, where motor values are maximized, are the most likely to emerge. When $r = 0$, other monotonic behaviors are the most likely, now where a random motor velocity is maintained. Other values of p and r produce more subtle variations in the types of emergent habits, with regions that are more likely to produce oscillatory behaviors. These behaviors produce motor activities at different frequencies. Outliers and not-formed habits characterized commonly by high frequencies are more likely for high values of p . The random-based exploratory phase produces changes such that the final behavior could be driven to a specific region of the sensorimotor space, or it could contribute directly to the shape of the such a behavior. For instance, the behaviors depicted in Figure 4 and Figure 5, respectively.

We can interpret this model in term of how random motor babbling makes certain kind of sensorimotor organization available for the agent. First, notice that sensorimotor contingencies can be described as lawful regularities of sensory stimulation, internal activity, and motor activity. However, according to Buhrmann et al. (2013), defining formally this concept has resulted problematic due to the range of useful interpretations. They introduced the operational definition of four kinds of sensorimotor contingencies by consid-

ering how the sensorimotor flow changes in relation to the body and environment, internal activity, functional behavior, and normative dimension. The four distinct notions are briefly summarized (Buhrmann et al., 2013): (1) Sensorimotor environment: the set of all possible sensor states obtained as function of given motor command varying freely, i.e. without considering internal activity, for a particular embodiment and external environment. (2) Sensorimotor habitat: the set of all actual sensorimotor trajectories that can be generated considering internal activity, i.e. closing the loop, given a range of boundary conditions and parameters (3) Sensorimotor coordination: any reliable sensorimotor pattern (e.g. stable trajectories, transients) that contribute functionally to the goals of an agent. (4) Sensorimotor strategies: organization of sensorimotor coordination patterns regularly used by the agent because it has been previously chosen as consequence of having been normatively evaluated.

Now, consider what kind of sensorimotor contingencies are available for the agent when the sensorimotor trajectories are formed. In the random, exploratory phase, the available sensorimotor contingencies can be described as the immediate sensory consequences of random motor changes (comparable to the sensorimotor-environment as described by Buhrmann et al. (2013)). Thus, the agent is randomly “navigating” the sensorimotor environment to generating a history of sensorimotor states that bias the formation of the possible sensorimotor trajectories due to the history-dependent plasticity of the behavior-generating medium. In the non-stochastic phase, the sensorimotor dynamics and thus the experienced sensorimotor contingencies are available only through specific patterns of agent-environment interaction driven by the influence of the controller. Therefore, the results shown in Figure 6, 7 and 8 could be considered as the sensorimotor habitat since they depict the actual sensorimotor trajectories generated by the closed-loop system for a range of two relevant initial parameters: p and r . Notice, then, that the model can be seen as capturing the development of a sensorimotor habitat from the random traversing of the sensorimotor environment.

In this preliminary model, even though we did not include any simulation of biological autonomy—no biological essential variables or viability limits—it is easy to imagine how some of these behaviors would be better suited to the survival of the biological individual. As example, consider the skin brain thesis which states that the early nervous system and sensorimotor organization of the organisms emerge from the evolution of a transverse net organization extended across the body that produced coordinated patterns of contraction and extension (Keijzer, 2015). This thesis first considers a contractile tissue extended across the body of the organisms. This surface is an excitable medium across which excitatory and inhibitory activity can produce self-organized patterns of contraction-extension. These patterns are produced by means of a multicellular organization

composed by cells with neural-like features (synaptic signaling to neighboring cells and, later in evolution, to non-neighboring cells) and external individual sensitivity with internal local feedback. The morphology of a multicellular body allows the organism to be sensitive to spatiotemporal dynamics of its own body and, therefore, to spatiotemporal structures of an environment. Consequently, functional patterns of contraction-extension can emerge due to a close organizational loop “that is sensitive to the ongoing dynamical contraction changes across this body and influencing the processes that generate and maintain these same patterns of behavior” (Keijzer, 2015, p. 325). Notice that, even though patterns of contraction and extension are not random as in the IDSM, the thesis stresses the internal spontaneous activity which, firstly, allows the organism to generate patterns of contraction-extension. These patterns enable the organization of an early nervous system which in turn generates them. This self-induced movement generates specific patterns in the sensory surface which in turn influences the early nervous system organization and, thus, the pattern generation such that the organism can cope with external disturbances.

We can compare the skin brain thesis and the model described in this work. In both cases there are many possible sensorimotor individuals that could inhabit a given sensorimotor environment. In the case of an organism with the organization described by the skin brain thesis, a sensorimotor individual thus would emerge from the reenactment of the sensorimotor contingencies generated first by the self-initiated motility, and later by the nervous system dynamic (which depends upon the sensorimotor contingencies it brings about). Notice that any sensorimotor trajectory is biased by the preliminary self-induced motility of the organism that allows the “navigation” of the sensorimotor environment. Similarly, in our experiments, a sensorimotor individual results from the reenactment of the sensorimotor contingencies generated by the random and the node-driven motor activity (the latter depends upon the history-dependent plasticity that the own activity brings about). The formation of any sensorimotor trajectory is biased by the random traversing of the sensorimotor environment. Even though the three qualitative categories of behaviour (static, monotonic and oscillatory) described in the results can be considered trivial, the results shed light on how evolution can bias the parameters of a plastic medium over which sensorimotor individuals emerge, so as to encourage the formation of sensorimotor individuals that are conducive or beneficial to biological survival. This form of evolutionary coupling of biological individual and sensorimotor individual norms underdetermines the patterns of behavior that emerge — unlike hardwired, purely reflexive behavior, the patterns of behavior in the sensorimotor individual remain precarious autonomous entities.

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