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Identifying and localizing dynamic affordances to improve interactions with other agents

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Abstract—Allowing robots to learn by themselves to coordinate their actions and cooperate requires that they be able to recognize each other and be capable of intersubjectivity. To comply with artificial developmental learning and self motivation, we follow the radical interactionism hypothesis, in which an agent has no a priori knowledge on its environment (not even that the environment is 2D), and does not receive rewards defined as a direct function of the environment’s state. We aim at designing agents that learn to efficiently interact with other entities that may be static or may make irregular moves following their own motivation. This paper presents new mechanisms to identify and localize such mobile entities. The agent has to learn the relation that they afford. These relations are recorded under the form of data structures, called signatures of interaction, that characterize entities in the agent’s point of view, and whose properties are exploited to interact with distant entities. These mechanisms were tested in a simulated prey-predator environment. The obtained signatures showed that the predator successfully learned to identify mobile preys and their probabilistic moves, and to efficiently target distant preys in the 2D environment.

Index Terms—Developmental learning, interactionism, affordance, autonomous mental development, spatial awareness.

I. INTRODUCTION

We address the problem of how an artificial agent that learns an emergent model of its environment through interaction can acquire knowledge about mobile entities that move freely in the environment (e.g., other agents).

This study is situated within the framework of artificial constructivist learning [e.g., 1] and enactive learning [e.g., 2]. In this framework, the learning occurs through the enactment of control loops that implement Piagetian sensorimotor schemes [3], which we call interactions. This framework also relates to the notion of intrinsic motivation of artificial agents for developmental learning [e.g., 4].

More precisely, we investigate a modeling hypothesis called Radical Interactionism (RI) [5] and artificial interactionism [6]. We implement a kind of self motivation called interactional motivation [7]. The agent starts with a predefined set of uninterpreted interactions associated with predefined numerical valences, and seeks to enact interactions of positive valence and to avoid interactions of negative valence. Overall, the learning is unsupervised. There are no human-defined labels attached with perceptions, actions, or categories of entities, not even spatial localization of percepts.

Through the learning of interaction with other mobile entities, we pursue the long-term goal of allowing the emergence of social behaviors within groups of artificial agents [e.g., 8], for example collective hunting. Generating such behaviors requires overcoming two main problems:

1) learning to define, recognize and localize other agents that make self-motivated movements in the environment,

2) inferring the intentions of other agents based on their own environmental contexts.

This paper focuses on the resolution of the first problem. It is subdivided as follows: Section II summarizes and formalizes the Radical Interactionism model, Section III presents a model for defining and recognizing probabilistic affordances, and Section IV presents a mechanism to recognize and localize distant probabilistic affordances in space. Finally, Section V encompasses some conclusive remarks and future development of the intersubjectivity problem.

II. THE RADICAL INTERACTIONIST (RI) HYPOTHESIS

In contrast with most machine learning approaches, an RI agent cannot directly access the state of its environment: its input data is outcome of control loops rather than percepts of the environment’s state. The agent learns and exploits regularities in sequences of control loops offered by its coupling with its environment. The learning mechanism differs from reinforcement learning (e.g., as it is typically implemented in a Partially Observable Markov Decision Process) by the fact that RI agents have no reward defined as a function of the system’s state. Our goal is not to design agents that reach predefined goals or maximize a reward value, but to study the open-ended learning of emergent models of the environment, and to generate social behaviors.

Let \( \mathcal{I} \) be the set of predefined primitive interactions (control loops). At the beginning of step \( t \), the agent selects an intended interaction \( i_k \in \mathcal{I} \). An example consists in moving forward for a predefined duration. At the end of step \( t \), the agent receives the enacted interaction \( e_t \in \mathcal{I} \) that was actually enacted. If \( i_k = e_t \) then the enactment is a success. The agent did move forward. Otherwise, the enactment of \( i_k \) is a failure. For example, the agent actually enacted another interaction consisting in bumping into an obstacle, which may have a negative valence.
An RI agent learns to anticipate the results of its interactions, and tries to enact interactions of high valence.

To help the agent discover that its environment has a spatial structure (2D in our experiments), we designed the Parallel-RI (PRI) model [9] which allows the simultaneous enaction of multiple interactions. The PRI considers additional stimuli that cannot be separated from the movement that produced them. The optical flow is an example of such stimuli, that must be associated with a movement to characterize a position in space. Thus, the PRI model considers primary interactions as control loops (action,result), and secondary interactions as a couple (interaction, stimulus). At the end of step \( t \), the agent receives, not one, but a set of \( k \) enacted interactions \( E_t = \{e_1, ..., e_k\} \subset I \), containing a primary interaction and a set of secondary interactions associated with this primary interaction.

Previous PRI experiments showed that the agent was able to identify and localize static affordances (possibilities of enacting an interaction [10]), and to store and keep track of them in an emergent structure, called Space Memory [9]. This memory generates an implicit context of affordances that the agent can exploit to generate behaviors in accordance with its interactional motivation. A subsequent model also showed the possibility to identify objects that moved in a straight line, by considering sequences of interactions [11]. These models, however, could not integrate entities moving irregularly (other agents). The present study addresses this limitation.

### III. Integrating Mobile Affordances

This section explains the signature mechanism [9] by which the agent estimates the possibility of enacting interactions in a given context. This mechanism is based on the assumption that the enaction result of an interaction \( i \) depends on a limited context of elements in the environment, defining the affordance of \( i \). As a PRI agent can only perceive its environment through enacted interactions, we define the signature \( S_i \) of an interaction \( i \) as an emerging structure characterizing one or several sets of interactions (i.e. \( \{j_k \in E_i\} \)) whose enaction can characterize the presence of an element affording \( i \) for next step \( t + 1 \).

Defining objects by learning the affordances they provide is abundant in literature, e.g., [12]–[14]. Most of these approaches define affordances from perception, which limits the detection to next action, or requires prior knowledge on environment and space [e.g., 15] to detect distant affordances. Signatures cope with this limitation by using interactions instead of perception, allowing to exploit spatial properties implicitly encoded in interactions to detect distant affordances.

Formally, a signature of interaction is a function \( S_i : P(I) \rightarrow [-1; 1] \), where \( P(I) \) is the partition of \( I \), i.e., the set of all possible contexts. \( S_i(E_t) \in [-1, 1] \) gives the prediction of successfully enacting interaction \( i \) at step \( t + 1 \): 1 for certainty of success, -1 for certainty of failure. The agent adjusts the parameters of \( S_i \) each time \( i \) succeeds or fails.

Signatures must be reversible by defining a pseudo-reverse function \( \hat{S}_i : \{-1;1\} \rightarrow P(P(I)) \) such that \( \hat{S}_i(1) \) gives the set of minimal contexts \( C^i_l \) in which \( i \) is possible, i.e. contexts that afford \( i \), and \( \hat{S}_i(-1) \) gives the set of minimal contexts in which the enaction of \( i \) is impossible.

However, when interacting with mobile entities, the presence of an affordance at the end of step \( t \) does not guaranty that the interaction can be enacted during step \( t + 1 \) because the entity may move in the meantime. We thus must separate the estimation of the presence of an affordance from the prediction of success of enacting the interaction.

#### A. Separating affordances from prediction of success

From an observer’s perspective, three types of situations can happen when the agent is interacting with a mobile entity:

1) The affordance is present at the right place, and the agent enacts the interaction successfully (e.g., a prey is in front of the agent, and the agent catches the prey).

2) The affordance is present, but the interaction fails (e.g., a prey is in front of the agent, but the prey moves and the agent fails to catch it).

3) The affordance is absent, leading to a failure of the interaction (e.g., there is not prey in front of the agent, but the agent tries to catch one and fails).

From the agent’s perspective, situations 2 and 3 cannot be distinguished, as they have the same result. Situations 2 distorts the learning of signatures, as situations 1 and 2 can occur in the same context \( E \), causing the prediction \( S_i(E) \) to remain negative even though the affordance is present.

However, our preliminary tests showed that, despite remaining negative, signature predictions are slightly higher in case of situations 1-2 than in situations 3. Indeed, situations 1 allow contexts of interactions designating the affordance to emerge, while remaining insufficient to predict with a positive value.

We thus use the average prediction in case of failure \( \hat{S}^i_l \) as a threshold to distinguish between situations 2 and 3. When the interaction fails in an assumed situation 2 (i.e., \( S_i(E_t) > \hat{S}^i_l \)), the signature is not reinforced, which limits the influence of situations 2 in signature construction.

Symmetrically, some interactions may fail due to the presence of an entity in a specific location (e.g., trying to move forward will succeeds unless an obstacle appears). As success of such interactions are expected to be more frequent than failures, the average of predictions will converge to a positive value. In this case, the average of positive predictions \( \bar{S}^i_l \) is used as a threshold to prevent the signature reinforcement in case of success in an assumed situation 2 (i.e. \( S_i(E_t) < \bar{S}^i_l \)).

It is then possible to define the ratio of success when the prediction \( S_i(E_t) > \hat{S}^i_l \) (or failure when \( S_i(E_t) < \hat{S}^i_l \)), implying that the agent is in a situation of type 1 or 2. A ratio \( p^i_{C} \) is thus defined for each context \( C^i_l \in \hat{S}_i(1) \) measuring the probability that the interaction will succeed in the presence of an affordance containing a mobile entity.

#### B. Implementation of Signatures

We extend Gay et al’s signature architecture [9] using multiple neurons as illustrated in Fig. 1. Each signature \( S_i \) consists of \( m \) neurons \( N^i_k \) to \( N^i_{km} \); the neuron with the
strongest output defines the prediction of $S_i$. In case of success, the neuron with the strongest output is reinforced, while a failure reinforces all neurons. This competition leads to a specialization of each neuron for a specific context, while they are desensitized from other contexts. Thus, with a sufficient number of neurons, a signature can identify contexts affording its interaction independently.

Formally, a neuron $N_i^n$ is defined as a set of weights $\{w_k^n\}$, with $\text{Card}(\{w_k^n\}) = \text{Card}(1)$, and an output defined as:

$$N_i^n(E_t) = f(\sum_k E_t[k] \times w_k^n), \quad f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

where $E_t[k] = 1$ when $i_k \in E_t$ and $E_t[k] = 0$ otherwise.

Then, the response of the group is defined as the maximum output, and remapped to a range in $[-1; 1]$:

$$N_i(E_t) = \max_n(N_i^n(E_t)) \times 2 - 1 \tag{2}$$

In order to consider interactions that are afforded by the absence of an entity instead of its presence, we added an output weight $W_i$ defining the output of the signature:

$$S_i(E_t) = N_i(E_t) \times W_i \tag{3}$$

The weight $W_i$ is restrained in the interval $[-1, 1]$, allowing to inverse the result of the prediction, which makes neurons able to integrate contexts preventing the enaction of $i$.

The learning process uses a classical gradient descent and prediction values obtained with $E_{t-1}$.

A consequence of this implementation is that high weights of neurons characterize contexts affording $i$. Weights of neurons can be grouped by primary interaction, each group containing a weight related to a primary interaction and weights related to its associated secondary interaction. Thus, a signature $S_i$ can be subdivided into minimal contexts $C_{j,n}^i$, associated with a primary interaction $j$ and a neuron $n$. It is then possible to define the ratio of success $p_{j,n}^i$ of each context $C_{j,n}^i$ by updating it when $j \in E_{t-1}$ and neuron $n$ has the highest activity, and $S_i(E_{t-1}) < S_i^\alpha$.

$$p_{j,n}^i = \text{if } S_i(E_{t-1}) < S_i^\alpha \text{ then } p_{j,n}^i 
C. Test Environment
This signature mechanism was tested on an artificial agent moving in the 2-dimensional discrete environment shown in Fig. 2. The sensorimotor possibilities of the agent define the following five primary interactions:

- \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde}~ \text{move forward} by one step,
- \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde}~ \text{bump} in a solid element,
- \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde}~ \text{turn left} by 90°
- \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde}~ \text{eat} something edible,
- \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde} \text{\textasciitilde}~ \text{turn right} by 90°

Interactions \text{move forward}, \text{bump} and \text{eat} are considered as mutually alternative: intending one of these interactions may lead to the enaction of one of the two others instead.

We add a set of secondary interactions provided by the agent’s visual system, that can detect colors and measure distances, with a field of view of 180°. Secondary interactions consist in \text{seeing} the displacement of a red, green or blue entity at a certain (but unknown) position in egocentric space, while enacting a primary interaction. Interaction \text{bump} does not generate visual interactions (no movement). We discretize the visual field as a grid of $15 \times 8$ positions in front of the agents that matches the environment’s grid. We thus define $4 \times 3 \times 15 \times 8 = 1440$ secondary interactions. Signatures are implemented using sets of $m = 6$ neurons. The signature learning process is driven by a learning mechanism that foster interactions with low certainty of success or failure (low $|S_i(E_t)|$).

The environment contains three types of objects offering spatial regularities that the agent can discover by interacting with them, and characterized by a color that makes them recognizable through its sensorimotor system: 1) wall (green), affording bump, 2) algae (red), that are walkthroughable (and thus useless in the agent’s perspective), and 3) fish (blue), affording eat. The fish move randomly: at each simulation step, they can stay immobile, or move left, right, up, or down, with a probability of 20% each. If the fish cannot move in the selected direction because of an obstacle (wall, alga or other fish), it remains immobile, making the immobile situation slightly more probable than other directions. This random movement simulates agents with unknown behavior.
The signature is similar to signatures obtained in previous environments [9][11]. It associates the success of bump with the presence of seeing a green element moving right in front of the agent, and of a previously enacted bump. The signature thus gathered every interaction allowing to detect the presence of a wall in front of the agent, even though they come from different sensory modalities.

Fig. 3. Signatures of interaction bump after 100 000 steps. It is characterized by the weights of 6 formal neurons, each neuron being represented by a column. As the signature identified a unique context, we only represent weights of one neuron. As an external observer, knowing that the environment is 2D, we organize weights of a neuron to make signatures more readable: first, weights associated with primary interactions are represented with five squares below (green for a positive weight, red for a negative weight). Weights associated with secondary interactions are grouped according to their primary interactions, forming the four groups (from top to bottom: forward, eat, turn left, turn right; bump does not produce visual interactions). Each group is organized to place visual interactions with their associated position in space, relative to the agent (orange triangle). Colors associated with visual interactions are overlapped to generate signatures under the form of a RGB image. Signature of bump identified a context that consist of seeing a green element in front of the agent, which corresponds to the presence of a wall in front of the agent. Bump is also related to the success of previous bumps, since the agent can bump repeatedly.

Fig. 4. Signature of move forward, recorded after 100 000 simulation steps. Each column represents a neuron of the signature. The weight W is negative: the signature thus represents contexts preventing moving forward. The signature identifies six contexts, represented (from an external point of view) above. As a fish cannot be below the agent after forward or eat, only 5 contexts are related to forward primary interaction (greyed context has low weights and is thus unused by the signature). As eat interaction is rarely enacted, contexts related to this primary interaction (second line) are still constructing.

We also analyze the ratio of successful enaction after a prediction of success. The ratios obtained in contexts implying static objects (such as walls) are close to 1 indicating that the presence of this type of affordance implies the success of the interaction. Ratios obtained with mobile fish are close to 20%, which correspond to the probability that the fish moves in the right direction when the agent tries to eat it. The contexts with a fish in front of the agent is however slightly greater. This can be explained by the fact a prey cannot move to a different position when blocked by a wall or an alga, increasing the probability of eating the fish when in front of the agent. These ratios, summarized in table I, show that signatures can integrate and encode stochastic properties of the environment.

<table>
<thead>
<tr>
<th>interaction</th>
<th>wall</th>
<th>front</th>
<th>surround</th>
</tr>
</thead>
<tbody>
<tr>
<td>forward</td>
<td>0.96</td>
<td>0.25</td>
<td>0.19</td>
</tr>
<tr>
<td>bump</td>
<td>0.97</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td>eat</td>
<td>/</td>
<td>0.23</td>
<td>0.19</td>
</tr>
<tr>
<td>seeing blue (Fig. 6)</td>
<td>/</td>
<td>0.23</td>
<td>0.18</td>
</tr>
</tbody>
</table>

IV. LOCALIZING DISTANT AFFORDANCES

The detection of distant affordances relies on a property of signatures: a signature of an interaction designates an affordance as sets of interactions \( \{j_k\} \in S_i(1) \) allowing to detect the presence of this affordance. However, each interaction \( j_k \) can have its own signature. It is thus possible to define, from
these signatures $S_{jk_i}$, a set of contexts, called predecessor $\hat{S}_{t_i}^{(j)}$, that, after enacting $j$, afford $i$. The backmove principle [9] consists in defining the initial predecessor $\hat{S}_{t_i}^{(\sigma_0)} = \hat{S}_{t_i}(1)$, with $\sigma_0 = \{\}$ (empty sequence). Then, recursively project the predecessor $\hat{S}_{t_i}^{(\sigma_0)}$ with: $\hat{S}_{t_i}^{(\sigma_i+1)} = \bigcup_{\forall C_i^j \in \hat{S}_{t_i}^{(\sigma_0)}} \{ E \in \mathcal{P}(I)/\forall j_k \in C_i^j, S_{t_k}(E) > 0 \}$, with $\sigma_{i+1} = (j_i, \sigma_i)$ and $C_i^j = \{j_k\}$ contexts of interactions associated with the same primary interaction $j$. A predecessor $\hat{S}_{t_i}^{(\sigma_i)}$ characterizes a set of contexts that are expected to afford $i$ after enacting sequence $\sigma$. Then, when a context $C_i^j \in \hat{S}_{t_i}^{(\sigma_i)}$ is observed in $E_t$, a distant affordance of $i$ is assumed to be present at position $\sigma$, in egocentric reference.

A. Backmoving a Probabilistic Affordance

Applying the backmove principle to a signature of a probabilistic affordance would generate a set of predecessor covering all possible future positions of this affordance after enacting a sequence $\sigma$. This would lead to a detection of an affordance through multiple positions, which cannot be exploited by a Space Memory. We thus propose to only consider most probable predicted position of an affordance after enacting a sequence $\sigma$.

The proposed backmove method introduces a new structure called projection sequence. The idea is to split predecessors into individual interactions: for each backmove, each sequence considers a unique interaction of $S_{t_i}^{(\sigma_i)}$. A projection sequence $\xi$ is a tuple $(\sigma, \lambda, p)$ characterized by:

- a sequence $\sigma$ of primary interactions, characterizing the movement required to reach the affordance,
- a sequence $\lambda$ of primary or secondary interactions, that characterize the successive projections from an interaction to an interaction of its signature (principle of backmove).
- a probability $p$ characterizing the probability of enacting $i$ from the partial affordance characterized by the sequence.

The set of projection sequence is constructed as follows: from a signature $S_t$, a first set of sequences $\xi_k = (\sigma, \lambda, p)$ is generated for each interaction $j_k \in C_i^j$ (and for each $C_i^j \in \hat{S}_{t_i}(1)$), where $\sigma_0 = \{\}$, $\lambda_0 = \{j_k\}$, and $p_0$ is the success ratio of the context $C_i^j$ containing $j_k$. Note that this set characterizes $S_t$ under the form of projection sequences.

Then, the set of sequences is recursively backmoved. A sequence $(\sigma, \lambda, p)$ leads to interaction $\lambda[0]$. This sequence is backmoved by primitive interaction $j$ associated to $\lambda[0]$ (or by $\lambda[0]$ if primary): from signature $S_{t_0}$, a set of sequences $\{j_i, \sigma_i, j_k, \lambda, p + p_{C_{j_k}[0]}\}$ is generated, for each interaction $j_k \in C_{\lambda[0]}$ designated by $S_{t_0}$ (i.e. $C_{\lambda[0]} \in \hat{S}_{t_0}(1)$).

A sequence $\xi_1$ is removed from the list if it exists another sequence $\xi_2$ with $p_{\xi_2} > p_{\xi_1}$ that have similar properties:
- same backmove sequence $(\sigma_{\xi_1} = \sigma_{\xi_2})$
- same final interaction $\lambda_{\xi_1}[0] = \lambda_{\xi_2}[0]$
- divergence comes from different contexts (i.e. $\exists k / \lambda_{\xi_2}[k] \in C_i[1], \lambda_{\xi_1}[k] \in C_i[0], C_i[1] \neq C_i[0]$), implying that $\sigma_{\xi_1}$ and $\sigma_{\xi_2}$ are related to two exclusive future position of the affordance.

The set of projection sequences of a signature $S_t$ provides, for each interaction $i \in I$, a set of the most probable sequences of interactions linking interactions from a context $E_t$ with entities designated by $S_t$. It is then possible to gather sequences $\xi_m$ with the same $\sigma$ and $\lambda_m[0] \in E_t$, and to reconstruct contexts $\{\lambda_m[k]\}$ for each step $k$ of $\sigma$, allowing predicting the most probable evolution of an affordance position.

B. Detection of Distant Affordances

A projection sequence of a signature $S_t$ detects a potential affordance of $i$ when its last interaction $\lambda[0]$ is enacted. However, a sequence only characterizes a part of the affordance; a larger part of the context must be evaluated to confirm the presence of the whole affordance. The detection of distant affordances of an interaction $i$ starts by selecting projection sequences $\xi_i$ of signature $S_t$ whose last element is enacted, defining candidate affordances of $i$. Each candidate $\xi_i$ gathers a set $\Theta_{\xi_i} = \{\xi_i, \lambda_i[0] \in E_t\}$ of sequences, sharing the same $\sigma$ and whose last element $\lambda[0]$ is enacted.

The set $E_{\xi_i}^{\alpha} = \{\lambda_i[0] / \xi_i \in \Theta_{\xi_i}\}$ of last interaction of sequences of $\Theta_{\xi_i}$ represents a set $E_{\xi_i}^{\alpha} \subset E_t$ gathering interactions that can intervene in the detection of the affordance of $i$ at position $\sigma_{\xi_i}$. From a context $E_{\xi_i}^{\alpha}$, the following recursive procedure is applied: a candidate context is defined as $C_{\xi_i}^{\alpha+1} = \{\lambda_{\xi_i}[a + 1], \lambda_i \in \Theta_{\xi_i}\}$. Then, each element $j_k \in C_{\xi_i}^{\alpha+1}$ is evaluated with $S_{j_k}(E_{\xi_i}^{\alpha})$. Interactions predicted as a failure are removed from $C_{\xi_i}^{\alpha+1}$, and their projection sequences, removed from $\Theta_{\xi_i}$. Remaining interactions define context $E_{\xi_i}^{\alpha+1}$. The process is repeated until sequence $\sigma_{\xi_i}$
is completed (or until $\Theta_{i_k}$ is empty). Interaction $i$ is then predicted using $S_i(E_i)$. If the signature predicts a success, the affordance of $i$ is confirmed at position $\sigma_{i_k}$.

C. Test Environments

The affordance detection mechanism was tested with signatures recorded after 200 000 simulation steps. The projection mechanism generates projection sequences with a maximum length up to 7 interactions.

The projection sequence construction mechanism was adapted for a signature implementation based on neurons. First, we only project interactions designated by a signature with a weight with an absolute value that is greater than a threshold, eliminating non-significant weights. Then, we added a new property to projection sequences, the global weight, characterizing the pertinence of the sequence to represent the affordance. This global weight is computed as follows: first sequences have a global weight defined as $w^\text{global}_S = W_S \times w_k$. Then each backmove through a weight $w_k$ of a signature $S$, the global weight of the new sequence is updated as $w^\text{global} = w^\text{global} \times W_S \times w_k$. The filter mechanism then compare values $p \times w^\text{global}_i$ instead of $p$ alone, offering a good compromise between probability and pertinence of sequences.

The agent is presented to different environment configurations. An enaction cycle is performed to let the agent perceive its environment, and sequences of detected affordances are analyzed. Fig. 7 shows the detection in a context containing two wall blocks, two fish and an alga. Sequences localizing static objects (walls) allows moving toward them. Sequences localizing fish do not reach the position of the prey, but a position just next to it. Indeed, as the agent can eat a fish on its side, the resulting sequence is a compromise between probability and length of the sequence. The alga is ignored since it has the same property as an empty space. Thus, the affordance detection mechanism can still detect and localize distant affordances under the form of sequences of interactions, which can be stored and exploited by the space memory similar in a static environment.

![Fig. 7. Distant affordances are detected and localized through sequences of interactions, which can be stored and exploited by the space memory similar in a static environment.](image)

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