Discovering, recognizing, and localizing dynamic affordances to adapt to unknown agents

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***Abstract*—We present an architecture for self-motivated and environmentally-agnostic agents to integrate non-predictible elements in their emerging model of their environment. This approach aims designing agents that construct their own model of their environment through experience, rather than exploiting pre-coded knowledge. Over time, the agent learns the relation between its perception of objects and the interactions that they afford, in the form of data structures, called signatures of interaction. These signatures are used to recognize and localize objects (or affordances) in surrounding environment, that are stored and tracked in a spatial memory, and used to generate behaviors satisfying agent's motivational principles. A long term objective of this approach is to study the interaction between multiple agents and the emergence of collaborative or competitive behaviors. Emergence of such behaviors requires the possibility to integrate other agents in the environment model and predict possible actions of these agents. In this paper, we propose a novel architecture of signature of interaction that can define, recognize and localize non-predictable affordances.**

***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 enaction of control loops that implement Piagetian *sensorimotor schemes* [3], and called *interactions*. The agent starts with a predefined set of uninterpreted *interactions* associated with predefined numerical *valences*, and seeks to enact interactions with positive valences and avoids interactions with negative valences. Such software endows the agent with a kind of self motivation that we have called *interactional motivation* [4]. This view on self motivation relates to the notion of *intrinsic motivation* of artificial agents for *developmental learning* [e.g., 5]. For a complete description, we refer the reader to our previous papers in which we have called this approach *Radical Interactionism* (RI) [6] and *artificial interactionism* [7]. Overall, the learning is *unsupervised*. The agent has no *a priori* knowledge on its perception nor on its environment.

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Through this integration of mobile entities, we pursue the long-term goal of allowing the emergence of social interactions within groups of artificial agents [e.g., 8]. Generating such collective behaviors requires overcoming two main problems:

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

2) inferring the intentions of these 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 Interactionism (RI) Model

In contrast with most machine learning approaches, an RI agent cannot access states of its environment: its input data is not a percept of a state but an outcome of a control loop, called *interaction*. The agent learns and exploits regularities in sequences of interactions 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 construction of emergent models of the environment, and generate open-ended learning and behaviors.

Let I be the set of predefined primitive interactions (control loops), and $\nu_i \in \mathbb{R}$ the predefined valence of primitive interaction $i \in I$. At the beginning of step t, the agent selects an *intended interaction* $i_t \in I$. An example consists in moving a step forward. At the end of step t, the agent is informed of the *enacted interaction* $e_t \in I$ that was actually enacted. If $i_t = e_t$ then the enaction is a success. The agent *did* move forward. Otherwise, the enaction of i_t 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 with high valences.

To help discovering spatial regularities of the environment, we have proposed 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 to 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 $E_t = \{e_{1,t}, ..., e_{k,t}\} \subset I$, containing a primary interaction and a set of secondary interactions associated to this primary interaction.

Previous PRI experiments showed that the agent was able to define, recognize and localize 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 consecutive interactions [11]. These models, however, could not integrate entities moving randomly (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 more) ensemble(s) of interactions $\{j_k\}$ whose enaction (i.e. $\{j_k\} \in E_t$) can characterize the presence of an element affording i for next step $t+1$.

Defining objects by learning affordances they provide is abundant in literature (e.g. [12][13][14]). Most of these approaches define affordances from perception, which limit 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 $S_i : \mathcal{P}(I) \rightarrow [-1; 1]$, where $\mathcal{P}(I)$ is the partition of I, i.e., the set of all possible contexts. $S_i(E_t) \in [-1, 1]$ gives the certainty of successfully enacting interaction i at step $t+1$: 1 for certainty of success, -1 for certainty of failure. To improve estimations, the agent adjusts S_i each time i succeeds or fails.

Signatures must be *reversible*: they allow defining a reverse function $\hat{S}_i : \{-1; 1\} \rightarrow \mathcal{P}(\mathcal{P}(I))$ such that $\hat{S}_i(1)$ gives the set of minimal contexts C_l^i in which i_t 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 propose to separate the estimation of the presence of an affordance from the probability of success of enacting the interaction.

A. Separating Affordances from Certainty of Success

From an observer's perspective, three types of situations can happen when the agent tries 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 pray 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 propose to use the average prediction in case of failure $\overline{S_i^f}$ as a threshold to distinguish between situations 2 and 3. When the interaction fails in an assumed situation 2 (i.e., $S_i(E_t) > \overline{S_i^f}$), the signature is not reinforced, which limits the influence of situations 2 in signature construction.

Symmetrically, some interactions may fail due to the presence 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 $\overline{S_i^s}$ is used as a threshold to prevent the signature reinforcement in case of success in an assumed situation 2 (i.e. $S_i(E_t) < \overline{S_i^s}$).

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

B. Implementation of Signatures

We propose a signature architecture extending Gay *et al*'s implementation [9], based on multiple neurons, and illustrated in Fig. 1. Each signature S_i consists of m neurons N_i^1 to N_i^m ; 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 reinforce 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 $Card(\{w_k^n\}) = Card(I)$, and an output defined as:

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

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}. The enaction result of i is defined as $R_t = 1$ in case of success ($i_t \in E_t$) and $R_t = -1$ in case of failure ($i_t \notin E_t$).

- The weight W_i is updated as follows:
$W_i \;\Leftarrow\; W_i + \Delta_i.(\alpha * N_i - \alpha/2)$, with $\Delta_i = R_t - S_i(E_{t-1})$ and α the learning rate.

- In case of a success, only the neuron with higher output is reinforced, all neurons are reinforced in case of failure:
$w_k^n \;\Leftarrow\; w_k^n + \alpha.\Delta_i^n.N_i^n$, with $\Delta_i^n = (R_t.W_i + 1)/2 - N_i^n$

A consequence of this implementation is that high weights of neurons characterize contexts affording i. Weights of neurons can be gathered 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 $S_i(E_{t-1}) < \overline{S_i^s}$.

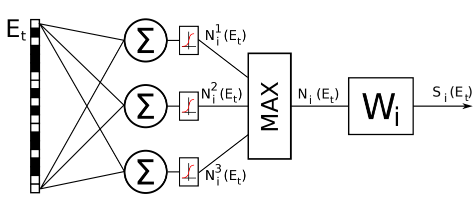

Fig. 1. Signature architecture based on multiple neurons. As the signature output relies on the neuron with the greatest output, neurons are in competitions, leading to a specialization of each neuron for a specific context. The last function remaps the output to range $[-1; 1]$ and uses a global weight W_i, that can inverse the signature result, allowing the representation of contexts preventing the enaction of an interaction.

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:

- ▷ *move forward* by one step,
- ▶ *bump* in a solid element, - ⌓ *turn left* by 90°,
- ▶ *eat* something edible, - ⌔ *turn right* by 90°,

Interactions *move forward*, *bump* and *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 *seeing* a red, green or blue element at a certain (but unknown) position in egocentric space, while enacting a primary interaction. Interaction *bump* does not generate visual interactions (no movement). We discretize the visual field as a regular grid of 15 × 8 positions in front of the agents that matches the environment's grid. We thus define 4 × 3 × 15 × 8 = 1440 secondary interactions. Signatures are implemented as 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, it can stay immobile, or move left, right, up or down, with a probability of 20% for each possibility. 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.

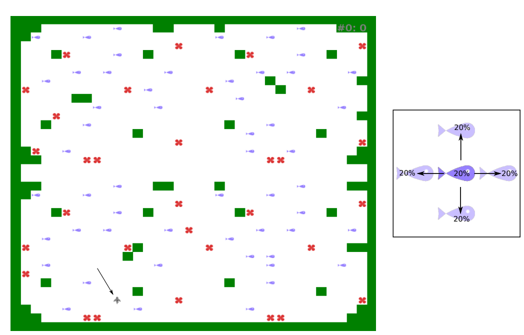

Fig. 2. Test environment. The agent is represented as a grey shark (bottom left), wall as green blocks, algae as red leafs and mobile preys as blue fishes. At each simulation step, the fish has 20% of remaining at current position or to move up, down, left and right.

We then let the agent behaves in its environment, driven by the signature learning mechanism. Signature of bump (Fig. 3) emerges and stabilizes within 5000 simulation steps.

The signature is similar to signature obtained in previous environments [9][11], and associates the success of bump to the presence of 'seeing a green element in the position 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 through they come from different sensory modalities.

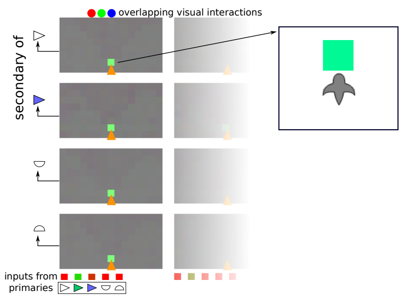

Fig. 3. Signatures of interaction *bump*, recorded after 100 000 simulation steps. A signature is characterized by the weights of 6 formal neurons, each neuron being represented by a column. As the signature identified a unique context, we only represent weights of one neuron. As external observers, we can 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 interaction are grouped according to their primary interaction, 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 interaction 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 correspond, for an external observer, to the presence of a wall in front of the agent. Bump is also related to the success of bump, as it can bump repeatedly.

Signatures of secondary interactions related to static elements (seeing red and seeing green) progressively stabilize, depending on they frequency of occurrence. After 50 000 simulation steps, most of these signatures stabilized. These signatures are also similar to signatures obtained with static entities [9][11]. They designate elements of the same color but on a different position in space. From an external point of view, the spatial offset between the visual interaction and the element designated by its signature matches the movement performed by the enaction of its associated primary interaction. This property is used for distant affordance detection [9] (details in Section IV).

Signatures of interactions related to mobile elements require more steps, as they relate to a larger variety of contexts to identify: at least 45 000 steps are required to identify contexts affording *move forward* and *eat*. Signature of interaction eat (Fig. 5) characterizes five contexts corresponding to the five positions of fish that can lead to a success of eat. Note that the position under the agent does not appear in contexts of interactions associated to move forward, as this situation is not possible. The signature of move forward (Fig. 4) has a negative weight W. The signature thus shows the affordance that prevents this interaction. The signature designates five contexts associated to the presence of a fish, and one context associated to the presence of a wall in front of the agent.

Signatures of secondary interactions consisting in seeing blue (Fig. 6) elements designate five contexts, corresponding to the five positions leading to a success of these interactions, with an offset (from an external point of view) corresponding to the movement of the associated primary interaction.

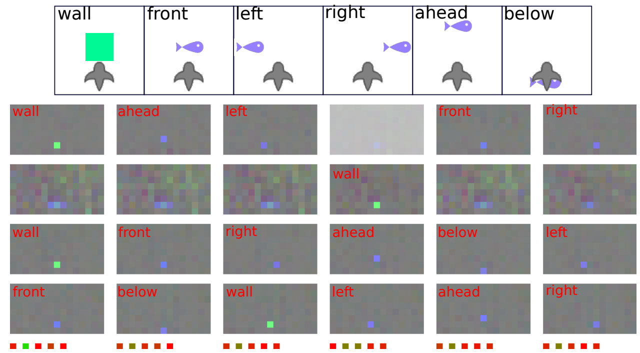

Fig. 4. Signature of *move forward*, recorded after 100 000 simulation steps. Each column represents a neuron of the signature. The weight W is negative: the signature thus represents contexts *preventing* moving forward. The signature identifies six contexts, represented (from an external point of view) 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 fishes are close to 20%, which correspond to the probability that the fish move 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 I
AVERAGE RATIOS OF SUCCESS WHEN PREDICT A SUCCESS IN CONTEXTS WALL, FISH IN FRONT AND FISH IN OTHER POSITIONS (SURROUNDING)

interaction	***wall***	***front***	***surround.***
forward	0.96	0.25	0.19
bump	0.97	/	/
eat	/	0.24	0.19
seeing blue (Fig. 6)	/	0.24	0.18

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 $\{j_k\} \in \hat{S}_i(1)$ 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

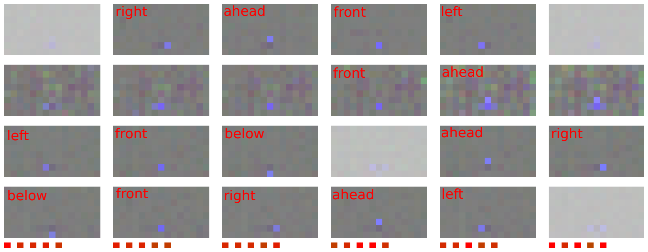

Fig. 5. Signature of eat. The weight W is positive. The signature identifies 5 configurations of fish (front, ahead, left, right, below), 4 in the case of a move forward (as below context cannot be observed). In contexts with fish around front position, we can observe the absence of a green or red element (dark blob) in front of the agent, as this would prevent the prey from moving to this position.

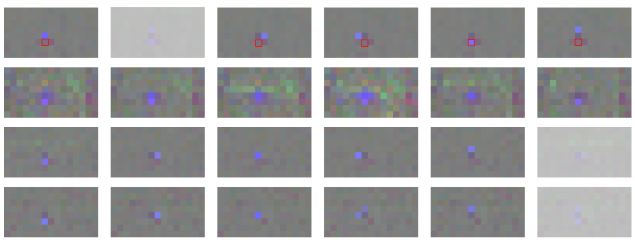

Fig. 6. Signature of secondary interaction seeing a blue element at the position identified with a red square, while moving forward. The weight W is positive. The signature identifies 5 configurations of fish. The signature also indicates the absence of an element that would prevent the fish from moving on the right place, but also elements that could hide the fish (dark blobs).

these signatures S_{j_k}, a set of contexts, called *predecessor* $\hat{S}_i^{[j]}$, that, after enacting j, afford i. The *backmove* principle consists in defining the initial predecessor $\hat{S}_i^{\sigma_0} = \hat{S}_i(1)$, with $\sigma_0 = [\,]$. Then, recursively project the predecessor $\hat{S}_i^{\sigma_a}$ with: $\hat{S}_i^{\sigma_{a+1}} = \bigcup_{\forall C_l^i \in \hat{S}_i^{\sigma_a} / j \in C_l^i} \{E \in \mathcal{P}(I) / \forall j_k \in C_l^i, S_{j_k}(E) > 0\}$, with $\sigma_{a+1} = [j, \sigma_a]$ and $C_l^i = \{j_k\}$ contexts of interactions associated to the same primary interaction j. A predecessor $\hat{S}_i^{\sigma}$ characterizes a set of contexts that are expected to afford i after enacting sequence σ. Then, when a context $C_l^j \in \hat{S}_i^{\sigma}$ is observed in E_t, a distant affordance of i is assumed to be present at *position* σ, 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 σ. 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 σ.

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_i^{σ}. A projection sequence ξ is a structure characterized by:

- a sequence σ of primary interactions, characterizing the movement required to reach the affordance,

- a sequence λ 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_i, a first set of sequence $([\,], [j_k], p_0)$ is generated for each interaction j_k designated by S_i, where $\sigma = [\,]$ (empty backmove sequence), $\lambda = [j_k]$, and p is the success ratio of the context C_l^i containing j_k. Note that this set characterizes S_i under the form of projection sequences.

Then, the set of sequences is recursively backmoved. A sequence $(\sigma, \lambda, \eta, p)$ 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 $S_{\lambda[0]}$, a set of sequences $([j, \sigma], [j_k, \lambda], [n, \eta], p * p_{S_{\lambda[0]}^{j,n}})$ is generated, for each interaction j_k designated by $S_{\lambda[0]}$.

A sequence ξ_1 is removed from the list if it exists another sequence ξ_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. $\exists k / \lambda_{\xi_1}[k] \in C_l^i, \lambda_{\xi_2}[k] \in C_m^i, C_l^i \neq C_m^i$), implying that σ_{ξ_1} and σ_{ξ_2} are related to two exclusive future position of the affordance.

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

B. Detection of Distant Affordances

A projection sequence of a signature S_i 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 ξ_k^i of signature S_i whose last element is enacted, defining *candidate* affordances of i. Each candidate ξ_k^i gathers a set $\Theta_{\xi_k^i} = \{\xi_l^i \; / \; \sigma_l = \sigma_k \wedge \lambda_l[0] \in E_t\}$ of sequences, sharing the same σ and whose last element $\lambda[0]$ is enacted.

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

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 $w^{global} = W_S \times w_k$. Then each backmove through a weight w_k of a signature S, the global weight of the new sequence is updated as $w^{global} = w^{global} \times W_S \times w_k$. The filter mechanism then compare values $p \times w^{global}$ instead of p alone, offering a good compromise between probability and pertinence of sequences.

The agent is presented 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 fishes and an alga. Sequences localizing static objects (walls) allows moving toward them. Sequences localizing fishes does 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. Alga is ignored, as it has the same property as 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 similarly than in a static environment.

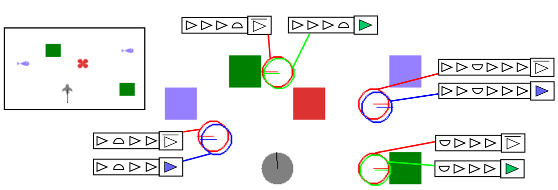

Fig. 7. Distant affordances are detected and localized through sequences of interactions allowing to reach them. Circles show the position and orientation associated to these sequences (red: not moving forward, blue: eat, green: bump). We can notice that the agent ignore the alga, as it as the same interactional property than an empty space.

V. Conclusion and Future Work

This work proposes a new mechanism to enable an environmentally agnostic agent to consider mobile and non-predictable entities in its emergent model of the environment. Results obtained in a simulated environment showed that the agent can still localize distant affordances without the notion of space, and define these position in a similar way than in static environment, allowing the use of a Space Memory [9].

Future work will study how the space memory can be used in such a stochastic environment, and how intrinsically motivated decisional mechanism can integrate probabilities of presence of affordance into consideration.

We will also implement these mechanisms in multi-agent contexts, to study the mutual integration of agents in their own environmental model, and how these models can be exploited for generating behaviors solving collaborative tasks, such as coordinate hunting of large preys. We also plan to study the possibility of predicting other agent's intentions through observation of its own context, as a previous implementation of the space memory demonstrated the possibility for reference change, opening intersubjectivity possibilities between agents.

References

[1] K. R. Thorisson, "A new constructivist ai: From manual methods to self-constructive systems," in *Theoretical Foundations of Artificial General Intelligence*, P. Wang and B. Goertzel, Eds., vol. 4, pp. 145–171. Atlantis Press, 2012, Series Title: Atlantis Thinking Machines.

[2] T. Froese and T. Ziemke, "Enactive artificial intelligence: Investigating the systemic organization of life and mind," *Artificial Intelligence*, vol. 173, no. 3–4, pp. 466–500, 2009.

[3] J. Piaget, *The construction of reality in the child*, New York: Basic Books, 1954.

[4] O. L. Georgeon, J. B. Marshall, and S. Gay, "Interactional motivation in artificial systems: Between extrinsic and intrinsic motivation," in *IEEE International Conference on Development and Learning and Epigenetic Robotics (ICDL)*. 2012, pp. 1–2, IEEE.

[5] F. Kaplan P.-Y. Oudeyer and V. Hafner, "Intrinsic motivation systems for autonomous mental development," *IEEE Trans. Evol. Computat.*, vol. 11, no. 2, pp. 265–286, 2007.

[6] O. L. Georgeon and D. Aha, "The radical interactionism conceptual commitment," *Journal of Artificial General Intelligence*, vol. 4, pp. 31–36, 12 2013.

[7] M. Guillermin and O. L. Georgeon, "Artificial interactionism: Avoiding isolating perception from cognition in ai," *Frontiers in Artificial Intelligence*, vol. 5, 2022.

[8] A. Netanyahu, T. Shu, B. Katz, A. Barbu, and J." Tenenbaum, "Phase: Physically-grounded abstract social events for machine social perception.," in *The Thirty-Fifth AAAI Conference on Artificial Intelligence (AAAI)*, 2021.

[9] O. L. Georgeon S. L. Gay, A. Mille and A. Dutech, "Autonomous construction and exploitation of a spatial memory by a self-motivated agent," *Cognitive Systems Research*, vol. 41, pp. 1–35, 08 2016.

[10] J. J. Gibson, "The theory of affordances," *Perceiving, Acting, and Knowing: Toward an Ecological Psychology, Hilldale, USA*, vol. 1, no. 2, pp. 67–82, 1977.

[11] S. L. Gay and S. Hassas, "Autonomous object modeling based on affordances in a dynamic environment," in *Conference on Biologically Inspired Cognitive Architectures*, 2015, vol. 71, pp. 150–156.

[12] L. S. Katrin R. Subramanian A. Paola, P. Èric and P. P. A. Ronald, "Building affordance relations for robotic agents - a review," in *International Joint Conference on Artificial Intelligence*, Zhi-Hua Zhou, Ed. 8 2021, pp. 4302–4311, International Joint Conferences on Artificial Intelligence Organization, Survey Track.

[13] P. Santana J. Baleia and J. Barata, "On exploiting haptic cues for self-supervised learning of depth-based robot navigation affordances," *Journal of Intelligent and Robotic Systems*, vol. 80, 02 2015.

[14] E. Uğur and E. Şahin, "Traversability: A case study for learning and perceiving affordances in robots," *Adaptive Behavior*, vol. 18, no. 3-4, pp. 258–284, 2010.

[15] S. M. Nguyen A. Manoury and C. Buche, "Hierarchical affordance discovery using intrinsic motivation," in *International Conference on Human-Agent Interaction*, New York, NY, USA, 2019, HAI '19, pp. 186–193, Association for Computing Machinery.