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-predictible affordances as a first step toward agent intersubjectivity.**

***Index Terms*—developmental learning, interactionism, affordance, autonomous mental development, spatial awareness, intersubjectivity.**

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). We build upon our previous work that learned a model of fixed entities and their geometrical properties. The addition into the environment of entities that move according to their own rules makes the learning even more challenging.

This study is situated within the paradigm of artificial constructivist learning [1] and enactive learning [2]. In this paradigm, the learning occurs through the enaction of control loops that implement Piagetian *sensorimotor schemes* [3]. We initialize the agent with a predefined set of control loops called *primitive interactions*. We associate each primitive interaction with a predefined numerical *valence*. We design the agent's software so that the agent seeks to enact interactions that have positive valences, and to avoid enacting interactions that have 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* [5, e.g.]. 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*. There are no human-defined labels attached with perceptions or with categories of entities, no pre-coded ontology of the world, no semantics associated with action data or sensory data.

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In designing agents that autonomously learn to interact with other agents, we pursue the long-term goal of allowing the emergence of collective behaviors within groups of artificial agents. Generating collective behaviors involving other agents 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, which is related to the intersubjectvity problem.

This paper focuses on the resolution of the first problem. It is subdivided as follow: Section II summarizes and formalizes the Radical Interactionism model and the architecture constructing the environment 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 directly detect the state of its environment through perceptual data. The agent's input data is not a percept of the state of the environment but an outcome of a control loop. An RI agent learns and exploits regularities in sequences of the 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, POMDP) 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 goal states or maximize a reward value, but to generate open-ended learning and collective behaviors.

Let I be the set of predefined primitive interactions (pointers to predefined 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 forward for a predefined amount of time while detecting no obstacle. 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 without detecting an obstacle. Otherwise, the tentative enaction of i_t was 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 that have high valences.

To help discovering spatial regularities of the environment, we have proposed the Parallel-RI (PRI) model which allows the simultaneous enaction of multiple interactions. At the end of step t, the agent receives a set $E_t = \{e_{1,t}, ..., e_{k,t}\} \subset I$ of k enacted interactions instead of a single enacted interaction. For example, when the agent is moving, each enacted interaction can reflect the relative displacement of a salient point in the visual field. This allows the computation of optical flow used to infer the agent's displacements.

Previous PRI experiments showed that the agent was able to discover and recognize static objects through the visual interactions that they afforded (relative displacement of salient points). The agent learned to localize distant affordances (possibilities of enacting an interaction, [9]), and to store and keep track of them in an emergent structure that played the role of spatial memory. The agent generated an implicit context in spatial memory, and used it 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 [8]. These models, however, worked poorly with entities that made random movements (other agents), because it was not possible to associate the presence of an observed entity with a specific affordance. The present study addresses this limitation.

III. Integrating Probabilistic Affordances

This section describes and formalizes the mechanisms for defining and recognizing affordances of interactions, called the *signature mechanism*, and its adaptations to probabilistic affordances.

The signature mechanism is based on the assumption that the result of enacting an interaction depends on a limited context of elements in the environment. Such contexts thus relates to the concept of affordances proposed by Gibson and further formalized by Chemero [10] and Stoffregen [**?**]. They consider an affordance as a property emerging from the agent-environment coupling. As a PRI agent can only perceive its environment through enacted interactions, we define the signature S_i of an interaction i as structure, learned through experience, characterizing one (or more) ensemble(s) of interactions $\{j_k\}$ whose enaction (i.e. $\{j_k\} \subset E_t$) can characterize the presence of the element affording i, and thus, the enactability of i.

Formally, a signature is a function $S_i : \mathcal{P}(I) \rightarrow [-1;1]$, where $\mathcal{P}(I)$ is the partition of possible contexts, that gives a numerical value in $[-1, 1]$ that reflects the possibility of successfully enacting i in an interactional context E (1 for an absolute certainty of success and -1 for an absolute certainty of failure). S_i is learned and reinforced when i succeeds or fails to generate accurate predictions.

A signature must be *reversible*: it must be possible to define a function $\hat{S}_i : \{1; -1\} \rightarrow \mathcal{P}(\mathcal{P}(I))$ that can provide *minimum contexts* (i.e. $\nexists E_1, E_2 \in \hat{S}_i(x), x \in \{1; -1\} / E1 \subset E2$) affording i ($\hat{S}_i(1)$) and preventing enaction of i ($\hat{S}_i(-1)$). We note $C_k^{S_i} \in S_i$ such a minimal context affording i.

However, previous implementations fails to integrate probabilistic affordances, as the presence of the affordance may still lead to a failure of the interaction. We thus propose to first separate certainty of presence of affordance and probability of success, and then to differentiate multiple contexts that may lead to a success of the interaction.

A. Separating certainty and probability

When the agent tests an interaction, three cases can be defined from an external observer's perspective:

1) The affordance is present at the right place, and the agent can enact the interaction successfully. (e.g. a prey is in front of the agent, and the agent could grabs the prey).
2) The affordance is present, but the interaction fails. (e.g. a prey is i front of the agent, but the prey moved and the agent missed catching the prey).
3) The affordance is absent, leading to a failure of the interaction. (e.g. there is no prey in front of the agent, leading to a certain failure of catching a prey).

From the agent's perspective, the results of situations 2 and 3 cannot be distinguished, as they have the same result. Moreover, situations 2 prevents the construction of the signature, and thus the possibility to distinguish situations 1 and 2 from situations 3. However, our preliminary tests showed an interesting results: despite remaining negative due to situations 2, the signature responses are slightly higher in case of situations 1-2 than in situations 3. Indeed, the existence of situations 1 influence the signature, allowing the context of interactions corresponding to the affordance to emerge while remaining insufficient to predict a success.

From this observation, we propose to use the average prediction in case of failure ($\overline{S_i^f}$) as a threshold to distinguish situations 2 and 3 after a failure. Then, when the interaction failed in an assumed situation 2 (i.e. $S_i(E_t) > \overline{S_i^f}$), the signature is not reinforced, which limit the influence of situations 2 in preventing the emergence of the signature. This principle is applied when $\overline{S_i^f}$ is lower than a threshold, assuming that the signature started to emerge (we used a threshold of -0.9).

Several interactions can be prevented by the presence of an element (e.g. moving a step forward is expected to success, until an obstacle appears). In such cases, situations 1' are related to the failure of the interaction, and situations 2' and 3' to its success. As situations 2' and 3' are expected to be more frequent than situations 1', the average of predictions will converge to a positive value. We thus used the average of positive predictions $\overline{S_i^s}$ as a threshold to prevent the signature reinforcement in case of success in an assumed situation 2' (i.e. $S_i(E_t) < \overline{S_i^s}$). This principle is applied when $\overline{S_i^s}$ is greater than a threshold (we used a threshold of 0.9).

It is also possible to define the ratio of interaction success when the prediction $S(E_t)$ is greater than the average $\overline{S^f}$ (or interaction failure when $S(E_t)$ is lower than the average $\overline{S^s}$), implying that the agent is in a situation of type 1 or 2 (or 1' or 2'). This ratio thus measures the probability that the presence of the affordance actually affords successfully the interaction.

B. Separating Possible Contexts

The detection of distant affordances (described in Section IV) requires to differentiate the possible contexts affording an interaction, and attribute a probability to each context.

We propose an adaptation of the signature mechanism, based on multiple neurons. Each signature S_i consists of a set of n neurons N_k^i ; the neuron with the strongest output defines the prediction of the signature. 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 k is defined as a set of weights w_l^k (with $Card(\{w_l^k\}) = Card(I)$, with an output defined as:

$$N_i^k(E_t) \; = \; f(\sum_i E_t[i] \times w[i]) \; , \; f(x) = \frac{1}{1+e^{-x}} \qquad (1)$$

where the interactional context E_t takes the form of a vector of size $Card(I)$, with $E_t[k] = 1$ when interaction i_k is enacted as a success and $E_t[k] = 0$ otherwise.

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

$$N_i(E_t) \; = \; max_k(N_i^k(E_t)) \; \times \; 2 \; + \; 1 \qquad (2)$$

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

$$S_i(E_t) \; = \; N_i(E_t) \times W_i \qquad (3)$$

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:

- The enaction result is defined as $R_t = 1$ in case of success and $R_t = -1$ in case of failure.

- The weight W_i is updated as follow:

$W_i \; \Leftarrow \; W_i + \Delta^i.(\alpha * N_i - \alpha/2)$, with $\Delta^i = R_t - S_i(E_t)$ 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:

$W_k^i \; \Leftarrow \; W_k^i + \alpha.\Delta_k^i.N_k^i$, with $\Delta_k^i = (R_t.W_i + 1)/2 - N_k^i$

To increase the specialization of neurons, in case of a success, weights of the most active neuron connected to failed interaction can be reduced (desensitizing this neuron from other contexts than the current one) and reducing weights of other neurons that are related to successful interactions (desensitizing other neurons from the current context).

A consequence of this implementation is that high weights of neurons characterize contexts affording an interaction. It is also possible to consider weighs of a neuron 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 $C_{j,n}^{S_i}$, associated to a primary interaction j and a neuron n. It is then possible to define the ratio of success $p_{j,n}^{s,i}$ and of failure $p_{j,n}^{f,i}$ of each context individually by updating them when primary interaction j is enacted and neuron n has the highest activity, and $S_i(E_t) < \overline{S_i^s}$ or $S_i(E_t) > \overline{S_i^f}$.

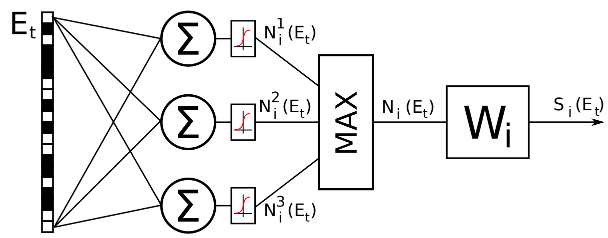

Fig. 1. Signature architecture based on multiple neurons. As the signature output relies on the neuron with greatest output, neurons are in competitions with each other, leading to a specialisation of each neuron for a specific context. The last function remaps the output to range $[-1; 1]$ and uses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

C. Implementation

This signature mechanism was tested on an artificial agent moving in a 2-dimensional discrete environment. The sensorimotor possibilities of the agent define a list of five primary interactions, listed below:

- ▷ move forward by one step
- ▶ bump in a solid element
- ▶ eat something edible
- ◡ turn right by 90°
- ◠ turn left 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 among red,green, blue, and measure distances. Secondary (visual) interactions consist in seeing a red, green or blue element while enacting a primary interaction, at a certain (but initially unknown) position of space. The interaction bump, that does not produce movement, does not generate visual interactions. We discretize the visual field as a regular grid of 15×8 positions centered on the agents that matches the grid of the environment. We thus define $4 \times 3 \times 15 \times 8 = 1440$ possible secondary interactions. Signatures are implemented as set of 6 neurons.

As we only study the emergence of signatures, we define a unique learning mechanism that foster interactions with low certitude of success or failure. Note that a secondary interaction can be candidate if its associated primary interaction is predicted as a success with a high certitude.

The environment is populated by 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 agent's sensorimotor system:

- wall (green), affording bump
- algae (red), that are walkthroughable (and thus useless in the agent's perspective).
- fishes (blue), affording eat.

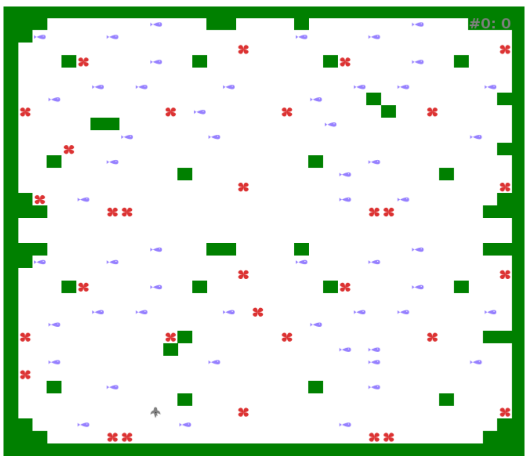

Fig. 2. Test environment. The agent is represented as a grey shark (bottom left), wall as green blocks, algae as red leafs and mobile preys as blue fishes.

The fishes move randomly in the environment: at each simulation step, a fish can move in one of these five directions, with a probability of 20%: immobile, left, right, top, bottom. If the fish cannot move in the selected direction because of an obstacle (wall, alga or other fish), the fish remains at its current position, making the immobile situation probability slightly higher than other directions. This random movement simulates agents with unknown behavior. All object are opaques: the agent cannot perceive an element behind another one.

We then let the agent behaves in its environment, driven by the signature learning mechanism. Signature of bump emerges and stabilizes in nearly 5000 simulation step. The signature is similar to signature obtained in static environments [ ], 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 gathered these interactions, even through they are associated to different primary interactions.

Signatures of secondary interactions related to static elements (seeing red and seeing green) progressively stabilize,

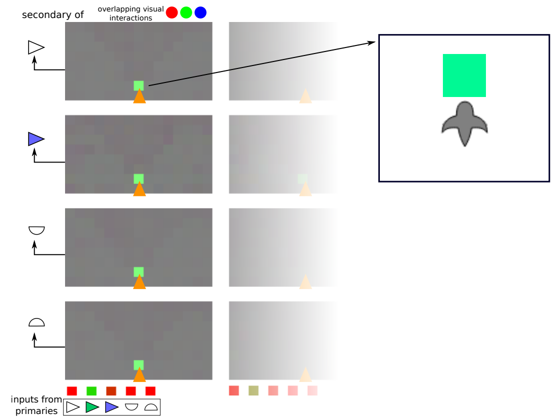

Fig. 3. Signatures of interaction *bump*, recorded after 100 000 simulation steps. A signature is characterized by the weights of 6 formal neurons, each neuron being represented by a column. As the signature identified a unique context, we only represent weights of one neuron. As external observers, 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, from an external observer perspective, to the presence of a wall in front of the agent. Bump is also related to the success of bump: indeed, the agent can bump repeatedly. The signature thus gathered every interaction allowing to detect the presence of a wall in front of the agent.

depending of they frequency of occurrence. After 50 000 simulation steps, most of these signatures stabilized. These signatures are also similar to signatures obtained in static environments [ ]. 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 secondary interaction and the element designated by its signature matches the movement performed by the enation of its associated primary interaction. This property is used for signature projection and distant affordance detection [ ] (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 eat and move forward. Signature of interaction eat 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 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 elements designate five contexts, corresponding to the five positions leading to a success of these interactions.

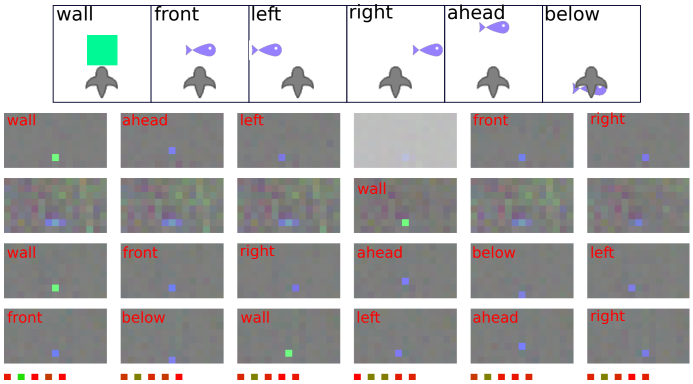

Fig. 4. Signature of *move forward*, recorded after 100 000 simulation steps. Each column represents a neuron of the signature. The weight W is negative: the signature thus represents contexts *preventing* moving forward. The signature identifies six contexts, represented (from an external point of view) 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, although context related to the wall context is already formed on fourth neuron.

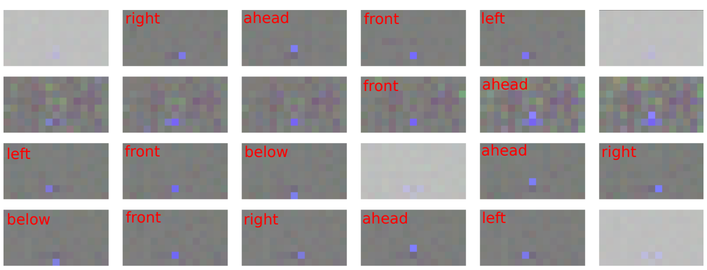

Fig. 5. Signature of eat. The weight W is positive: the signature thus represents contexts affording eat. The signature identifies 5 configurations of fish (front, ahead, left, right, below), 4 in the case of a move forward (as below context cannot be observed). In contexts with fish around front position, 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.

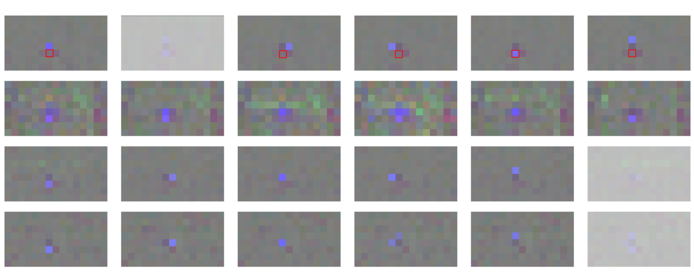

Fig. 6. Signature of secondary interaction seeing a blue element at the position identified with a red square, while moving forward. The weight W is positive. The signature identifies 5 configurations of fish. The signature also indicates the absence of an element that would prevent the fish from moving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

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: this indicates that the presence of this type of affordance implies the success of the interaction. Ratios obtained in contexts implying mobile fishes are close to 20%, which correspond to the probability that the fish move in the right direction allowing the agent 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 a a different position when blocked by a wall or an alga, increasing the probability of eating the fish when in front of the agent.

TABLE I
AVERAGE RATIOS OF SUCCESS WHEN PREDICT A SUCCESS AND FAILURE WHEN PREDICT A FAILURE IN EACH TYPE OF CONTEXT (WALL, FISH IN FRONT, FISH IN OTHER POSITIONS (SURROUNDING)

interaction	***ratio of success***	***ratio of failure***
forward (wall)	0.96	0.999
forward (front)	0.25	0.999
forward ('surrounding')	0.19	0.999
bump (wall)	0.97	0.999
eat (front)	0.24	0.999
eat ('surrounding')	0.19	0.999
seeing blue (Fig. 6) (middle)	0.24	0.999
seeing blue (Fig. 6) ('surround.')	0.18	0.999

These signatures can thus be projected to detect distant affordances. The probability of each context is also used to define the probability of future enaction of interactions.

IV. Localizing Distant Affordances

The detection of distant affordances relies on a property of signatures as defined in a RI model: a signature of an interaction designates an affordance under the form of sets of interactions $\{j_k\} \in \hat{S}_i(1)$ allowing to define the presence of this affordance. However, each interaction j_k can have its own signature, and each context $C_l = \{j_k\}$ affording i is composed of interactions j_k related to the same primary interaction j. The backmove principle thus propose to *project* a signature S_i through a primary interaction j using the following procedure: we note $\hat{S}_i^{\sigma_0} = \hat{S}_i(1)$, where σ_0 is an empty sequence of interactions, and construct: $\hat{S}_i^{[j,\sigma_0]} = \bigcup_{\forall C_l \in \hat{S}_i^{\sigma_0} / j \in C_l} \{E \in \mathcal{P}(I) / \forall j_k \in C_l, S_{j_k}(E) > 0\}$, which characterizes contexts that can afford i after enacting j.

As this process can be repeated by considering $\sigma_{a+1} = [j, \sigma_a]$, it is possible to *backmove* a signature S_i by a sequence of interactions σ, to obtain a *predecessor* of i, noted S_i^{σ}. A predecessor S_i^{σ}. characterizes a set of contexts $\hat{S}_i^{\sigma}$ that, if *moved* through the enaction of the sequence of interactions σ, affords i. Then, when a predecessor $\hat{S}_i^{\sigma}$ is observed in the context E_t, a distant affordance of i is assumed to be present at a position characterized by sequence σ, in egocentric reference.

A. Backmoving a probabilistic affordance

Applying the backmove principle to a signature of a probabilistic affordances would generate a set of predecessor that cover all the possible future positions of this affordance after enacting a given sequence σ. A unique mobile element of the environment would thus be detected a set of different positions. However, this localization through multiple position cannot be exploited by the space memory architecture, as requires to consider affordances with unique positions in space. We thus propose to only consider predecessors that have the greatest probability, defining a unique position of an affordance in surrounding space.

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. The predecessors can then be reconstructed by gathering projection sequences that have the same properties.

A projection sequence 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 sequence η, indicating the contexts that interactions of λ belong to.

- a probability p characterizing the probability of enacting i from the partial affordance characterized by the projection sequence.

The set of projection sequence is constructed as follow: from a signature S_i, a first set of sequence $([\,],[j_k],[n],p_0)$ is generated for each interaction j_k designated by S_i, where $\sigma=[\,]$ the initial (empty) backmove sequence, $\lambda=[j_k]$, n is the index of the context containing j_k and p is the success ratio of the context 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 (σ,λ,η,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 $([j,\sigma],[j_k,\lambda],[n,\eta],p*p_{S^{j,n}_{\lambda[0]}})$ is generated, for each interaction j_k designated by $S_{\lambda[0]}$.

Sequence filter is applied during the sequence construction process. A sequence is removed from the list if it exists another sequence with $p_2>p_1$ that have similar properties:

- same backmove sequence ($\sigma_1=\sigma_2$)

- same final interaction ($\lambda_1[0]=\lambda_2[0]$)

- divergence comes from different contexts ($\exists k, \lambda_1[k+1]=\lambda_2[k+1]\wedge\lambda_1[k]\neq\lambda_2[k]\wedge\eta[k]\neq\eta[k]$). This property implies that the two sequences are related to two possible, exclusive, future position of the affordance instead of the same context.

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. These sequences can then be used to detect and confirm the presence of an affordance at position characterized by σ.

B. *Detection of distant affordances*

The position of an affordance in space are defined as sequences of primary interactions whose enaction would allow to enact the interaction associated to this interaction. The sequence is considered regardless of its enactability: the position of an affordance is considered independently from its accessibility.

Projection sequences can be used to detect potential affordances: if the projection sequence of a signature S_i has its last interaction enacted (i.e. $\lambda[0]\in E_t$), then a part of the context affording i is present at position σ. However, the sequence only characterize a part of the affordance, that may be incomplete. It is thus required to evaluate a larger part of the current context to confirm the presence of the affordance.

It is not possible to simply simulate the evolution of the context by recursively evaluating the certitude of secondary interactions associated to interactions of σ: as several objects can move, multiple possibilities of future contexts can emerge, with multiple combination in case of multiple mobile elements.

The projection sequences solve this problem, as they only consider the most probable evolution of positions. The detection of distant affordances of an interaction i starts by selecting projection sequences of signature S_i whose last element is enacted ($\lambda[0]\in E_t$), electing a set of couples $(\lambda[0],\sigma)$ as candidate affordances. Each candidate gathers a set of sequences with same properties ($\lambda[0]=j$ and $\sigma=\sigma$) that are active ($\lambda[0]\in E_t$). The set of last interaction of sequences of such an ensemble represents an ensemble $E^0\in E_t$ gathering interactions that can intervene in the presence of the affordance.

From the context E^0 of a candidate affordance, the following recursive procedure is applied: elements $\lambda[1]$ of sequences are gathered into a candidate context C^1 (duplicate interactions are removed). Then, each element of C^1 is evaluated with its signature on context E^0. Interactions predicted as a failure are removed from C^1, and their projection sequences, removed from the set. Remaining interactions of C^1 define context E^1. The process is repeated with C^{l+1}, until sequence σ is completed (or until the set of projection sequence 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 σ.

Confirmed affordances of the same interaction can then be gathered if they are characterized by the same elements of the context. the different sequences σ thus indicate the different way to reach this affordance. Note that the space memory only considers shortest sequences to characterize the position of an affordance.

C. *Test Environments*

The affordance detection mechanism was tested with signatures recorded after 150 000 simulation steps in the environment described in Section III-2. The projection mechanism is added to the architecture, and used to generate projection sequences, with a maximum length up to 7 interactions.

As we implemented signature with neurons, we had to adapt the projection sequence construction mechanism. 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 had to cope with low weights that generate sequences with higher probability than weights with higher (and thus more representative of the affordance). 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 follow: 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 then presented different environment configurations, and an enaction cycle is performed to let the agent perceive its environment through enacted interactions. The sequences of detected affordances are then analyzed.

RESULTATS : QUELS SERAIENT LES MEILLEURS CONTEXTES ?

V. Conclusion and Future Work

This work propose a new mechanism to enable an environmentally agnostic agent to consider mobile and non-predictable elements in its emergent model of the environment. Results obtained in a simulated environment showed that the agent can still detect position of 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.

Future work will study how the space memory can be used in such a stochastic environment, and how intrinsically motivated decisionnal 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.

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