# Building and exploiting a sensorimotor representation of a naive agent self-interaction

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## I. Introduction

More and more researcher in artificial intelligence are concerned with perception of the environment. Ahead of consideration about objects or task spaces common in developmental robotics, this research is interested in the birth of the principle of space by a naive agent. It is only after having acquired this principle that it is possible to build the higher level paradigms such as the existence of objects or grasping tasks, etc. Indeed space existence is most of the time an *a priori* knowledge about the world which is brought by the engineer with the definition of models such as kinematics models or spatial state parameters.
This work is based on the analysis of the so-called sensorimotor flow, particularly on the study of correlation and invariance in exteroceptive and proprioceptive signals, i.e. sensorimotor contingencies [1]. Such contingencies carry fundamental structural information on the world. Poincaré [2] suggested that information about dimension of the space in which the agent movements are embedded, such as the $3D$ euclidean space of translation or possibly more complex spaces, can be extracted from the study of sensorimotor manifold. Later, studies have been proposed by Philipona et. al [3] then by Laflaquière et. al [4] to extract this specific dimension. More recently, Laflaquière et. al [5] have shown that it was also possible to obtain an internal representation of the agent's movements in a simple environment by the construction of specific motor partitions.
The approach is an extension of the work from Laflaquière et. al [5] with a focus on self-interaction by the agent. Indeed, as pointed out by Frolov [6], self-interaction allows the agent not to make any prior hypothesis on environment stability as any sensation would be caused by the agent itself. From the use of sensory invariance and the construction of kernel sets, an internal, i.e. proprioceptive, representation of the self-touching interaction can be built. A first but incomplete solution have already been proposed in [7] which has been largely completed in [8] and in the present work. In [7], the internal representation is built to geometrically characterize the shape of the body, based on this, [8] proves that it is also possible to use it as an internal representation of movements in space and as a basis for motor planning and particularly sensation reaching. This will allow a totally naive agent, with no knowledge on its structure or on the dimension of the space it is embedded in, to successfully predict self-interaction.

## II. Methods

*Agent and sensorimotor context*

Let's consider, in the vein of Frolov's work [6], a robotic system composed of a tactile body fixed to a robotic multijoint arm controlled by the agent. At the end of the arm, an end-effector is composed of one or two rigid fingers attached together. In order to keep the model simple , the fingers are the only parts that can apply a pressure on the tactile body. This $3D$ body is a $2D$ closed surface with an arbitrary shape extruded along its normal, this forms an artificial skin which is mounted with overlapping deformation sensors. The naive agent controls the arm by generating motor commands $\mathbf{M} \in \mathcal{M}$ where $\mathcal{M}$ is called motor configuration space, supposed compact. Afferent copy of the motor configuration is supposed to be directly available to the agent. The fingers at the end-effector are supposed to form a rigid system whose state $\mathbf{X} \in \chi$ can be characterized by its position and orientation in the $3D$ euclidean space. $\chi$ is called the pose space and $\mathbf{X}$ the pose of the end-effector. Deformation sensors send to the agent a signal $\mathbf{S} \in \mathcal{S}$ in the sensory space. This signal only depends on where the tactile body is touched by the fingers system and thus only depends on the pose $\mathbf{X}$ of the end-effector. Let's call $\phi$ the sensory function such that $\mathbf{S} = \phi(\mathbf{X})$. For the sake of generality, we can assume that $f$ is non-injective and not necessarily continuous. From the arm mechanics there exists a direct kinematic model $f$ linking the motors configurations to the pose of the end-effector system : $\mathbf{X} = f(\mathbf{M})$. $f$ is possibly non-injective: due to the redundancy of the arm, multiple motor configurations can lead to the same end-effector position, but $f$ is necessarily continuous. The sensorimotor law characterizing the sensorimotor flow, called $\Psi$, can be recovered with the composition: $\mathbf{S} = \Psi(\mathbf{M}) = \phi \circ f(\mathbf{M})$.
The objective for the agent is to understand the characteristics, such as topology and space dimension, of the movements of its end-effector $\mathbf{X}$ by analyzing the sensorimotor flow $\mathbf{M}$ and $\mathbf{S}$. The idea is simply to get rid of the sensory function $\phi$ by considering sensory invariants. Indeed, sensory invariants are directly linked to pose invariants because when the agent does not move its end-effector the sensation does not vary. However, a specific sensation can be obtained through different poses of the end-effector, due to non-injectivity of the sensory function $\phi$, therefore the agent has no easy way to separate movements

that doesn't make the sensation vary. However it is possible to put together these kind of movements in a formal way by defining an equivalence relation.

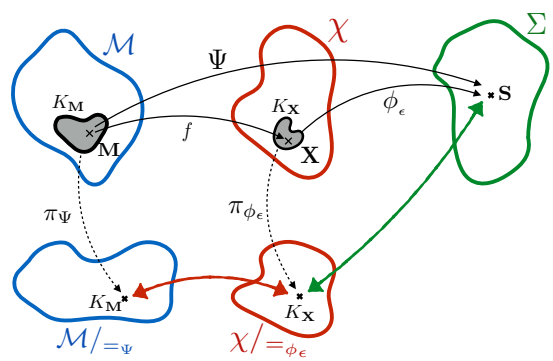
*Sensory invariants and equivalence relations*

The definition of sensory invariants gives way to the definition of equivalence relation in topology. Let's call $=_\phi$ the equivalence relation which characterize the equivalence between two poses $\mathbf{X}_1$ and $\mathbf{X}_2$ if and only if $\phi(\mathbf{X}_1) = \phi(\mathbf{X}_2) = \mathbf{S}$. Two different end-effector poses can result in a same sensation, as an example: the same tactile area is touched by different fingers. Likewise, let's call $=_\Psi$ the equivalence relation between two motor configurations $\mathbf{M}_1$ and $\mathbf{M}_2$ such that $\Psi(\mathbf{M}_1) = \Psi(\mathbf{M}_2) = \mathbf{S}$. The former equivalence relation, in addition of taking account of non-injectivity of $\phi$ also includes the non-injectivy, or redundancy, of the direct kinematic model $f$. As an example: several different motor configurations of the arm will lead to the same pose $\mathbf{X}$ of the end-effector which naturally lead to a single sensation.

*Quotient spaces*

The equivalence relations $=_\phi$ and $=_\Psi$ make it possible to define new spaces called quotient spaces, which respectively are $\mathcal{X}/_{=_\phi}$ the pose quotient space and $\mathcal{M}/_{=_\Psi}$ the motor configuration quotient space. In these new spaces, each point is defined as a set of poses $\mathbf{X}$ for $\chi/_{=_\phi}$ or a set of motor configurations $\mathbf{M}$ for $\mathcal{M}/_{=_\Psi}$ which all lead to a single sensation. Therefore, for each reachable sensation $\mathbf{S}$, its possible to find a pre-image in $\chi/_{=_\phi}$ or in $\mathcal{M}/_{=_\Psi}$. In other words, any trajectory in $\chi/_{=_\phi}$ or in $\mathcal{M}/_{=_\Psi}$ will give a sensation variation, which is not the case in $\chi$ or $\mathcal{M}$.
An important property arises by adding the hypothesis that the space $\chi/_{=_\phi}$ is Hausdorff, i.e. any point can be separated from another by disjoint neighborhoods. Then it is possible to find a continuous and bijective function linking $\mathcal{M}/_{=_\Psi}$ to $\chi/_{=_\phi}$ as shown in Figure 1. . This property, that has been detailed in [8] where a mathematical proof is provided, allows the space $\mathcal{M}/_{=_\Psi}$ to be a representative of the space $\chi/_{=_\phi}$, i.e. the agent will be able to identify any continuous trajectory of the end-effector in $\chi/_{=_\phi}$ by another continuous trajectory in $\mathcal{M}/_{=_\Psi}$. In this way, trajectory planning can be performed internally without any prior knowledge on the structure of the agent.

Fig. 1. Relations between motor configuration space $\mathcal{M}$, pose space $\chi$, sensory space $\mathcal{S}$ and the quotient spaces $\mathcal{M}/_{=_\psi}$ and $\chi/_{=_\phi}$. Double-headed arrows represent bijections.




All these methods are rather theoretical but can be applied on a simple simulated agent. The transition from the theory to the simulation is described in the following part with few technical details.

## III. Simulation set up

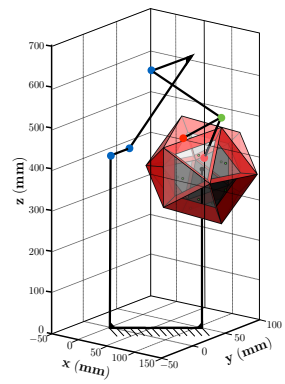
*Simulated agent*

The simulated agent is composed of a body containing 20 to 200 overlapping tactile sensors, thus the sensory input can be seen as high dimensional. The robotic arm is composed of 3 revolute joint in a series with a spheroidal joint playing the role of a wrist on which the end-effector with one or two fingers is fixed as shown in Figure 2. This gives a 6 degrees of freedom serial arm. Auto-collisions of rigid arm parts are not taken in consideration, apart from these resulting from fingers touching the tactile body. To validate the generality of the approach, bodies with different shapes and topologies have been considered: hollow cubes and spheres, torus...

*Random sampling*

At the beginning the agent is totally naive and has no choice but to use random walk trajectories to roam its motor configuration space. The motor configurations that led to non-null sensation are stored (the sensation signal being null when no finger touches the body). One can note that the non-null subset of end-effector poses that lead to non-null sensation forms a

Fig. 2. Robotic arm and spherical tactile body. Blue dots represent revolute joints, green dot indicates spheroidal joint and red dots represent fingertips of the end-effector.




manifold in the pose space. If the number of samples goes to infinity, this manifold should contains all the possible interaction state of the fingers with the tactile body. In the simulations, the number of stored samples have been limited to one million.

*Construction of the intern representation*

To build the quotient spaces one should now define discrete sensory invariants. Indeed in a discrete sampling process, it is not possible to obtain strictly identical sensations. Consequently, a vector quantization step in the sensory space should be performed first. This quantization can be simply done performing k-means and voronoi cells. Sensory centroids obtained by k-means are called target sensations. More target sensations there is, more precise is the internal representation but it requires a higher number of samples. During the simulations a maximum number of one thousand target sensations where computed, each containing a maximum of one thousand sampled motor configurations. For each cluster of sensations there is a set of motor configurations that produce "close" sensations, these sets are called motor kernel sets. Each motor kernel set corresponds to a single point in the representation space $\mathcal{M}/_{=_\psi}$. Indeed, each point of the internal representation corresponds to a set of different end-effector poses that generates little variation around the target sensation.
To exploit the representation it is mandatory to define a relation between points.

*Motor planning*

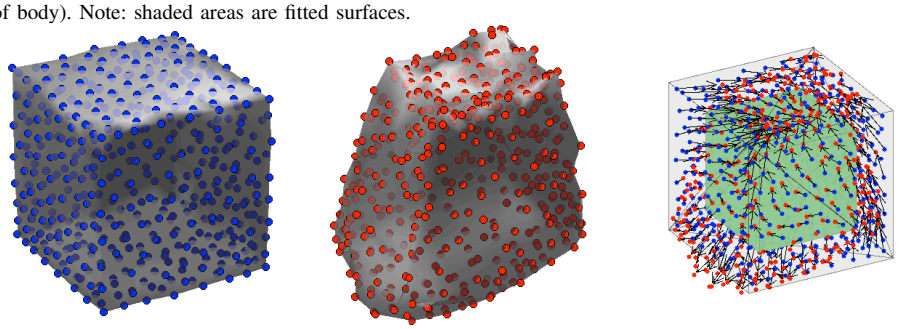
Links between points are topological relations. Note that by defining these links, one fixes the topology of the internal representation space. Let's first build a fully connected graph where each node is a point of the internal representation and is linked with any other points by a weighted edge. The weight of the edge being the distance between the points. The points themselves being sets, the distance should be defined between sets in the motor configuration space and should be derived from quotient metrics. In this way, the agent is able to proceed from any point to another along a path computed in the graph.

## IV. Simulation results

Results from the building of the internal representation are shown in this section.

*Topology of the representation and body shape*

Fig. 3. Left: original body cubic shape, middle: recovered body cubic shape, right: two representations compared and superposed on the tactile body (gray: tactile skin, green: inside of body). Note: shaded areas are fitted surfaces.



In the case where the agent touches its own body with only one finger it is a point-contact, the quotient pose space is equivalent to the space of contact points on the tactile body. Therefore the internal representation is equivalent, in topology,

to a $3D$ discrete shape of the body. It is possible to recover the body shape as shown in Figure 3.
When contact occurs with the 2 fingers end-effector, the topology of the quotient pose space is much more complicated and can not be easily visualized in $3D$.
In both cases, the internal representation can also be used to compute a motor trajectory that links any pair of sensations.

*Sensation trajectory planning*

Thanks to the graph structure of the representation and graph theory, it is possible to compute a path between two target sensations. Using this computed path, a continuous trajectory can be interpolated between successive motor configuration kernels, thus generating new commands. Such a trajectory can also be optimized using a cost function on the graph to assure a smooth trajectory of the end-effector. A result of this optimization is shown in Figure 4.

Fig. 4. Exemple of a smooth trajectory linking the green and blue poses of the 2 fingers end-effector for cubic and spherical bodies. The agent is naturally bypassing the inside of the body where no sensation was generated. Red crosses show known end-effector poses and blue dotted line show interpolated poses along the continuous motor trajectory.

## V. Conclusions

In this work, a method for the construction of an internal representation of a naive agent self-interaction has been proposed where theoretical properties can be exploited to perform smooth end-effector trajectory planning by the agent. All this is rooted in the sensorimotor paradigm that avoids making use of *a priori* knowledge on the agent structure and thus being more flexible than traditional approaches. A simulated example is proposed with a tactile creature adapted from the work of Frolov detailing the topological characteristics of the internal representation and showing some trajectory generation.
By now, this work has only been tested on very simple simulated agents, future works are needed to show that this paradigm can be successfully applied on more complex agents with multiple bodies and different end-effectors but also on real robots. As an example self-collisions, that has been avoided here, should bring strong additional structural information about the self-interaction space.
The authors consider the self-interaction representation to be one of the first steps towards the perception of space. Such an internal representation should also prove to be useful when characterizing distal perception in the environment and particularly in visuo-tactile or audio-tactile binding.

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