Using Physics-Like Interaction Law to perform Active Environment Recognition in Mobile Robotics

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Abstract - In this article, we give some insights of a novel method for active environment recognition in mobile robotics. The basic idea consists on utilizing a Physics-like interaction law to fix a relation between sensors and effectors values at any time. Our main assumption is that the trajectory of the robot in the phase space, which depends uniquely on its environment -when the law and the nature of the robot are fixed- may discriminate environments better than classical Data Analysis Approaches (DAA). In order to test our assumption, we choose to model an analogical robot which light sensor amplitudes and wheels speed are coupled in a set of differential equations. As a result, we show that our Interactionist Approach (IA) is tractable and perform well for discriminating simple environments, comparing to a data analysis (DA) strategy.

Keywords— **Mobile Robotics, Dynamic Systems, Environement Recognition, Physics-like interaction**

I. Introduction

A. Framework

According to the traditional point of view in mobile robotics, sensing is a passive process (i.e. gather data using sensors) whereas moving in the world is an active one. Any task of the robot fulfills the following straight forward schema: sense the world → analyze gathered data → act in the world (see Fig. 1, (a)). The Data Acquisition (DAQ) process relies on a set of sensors that transduct and digitize some environmental variables. The result is called a *set of data*. It feeds in a straightforward manner a DA stage, which aim is to make the data set useful to the experimenter, with respect to a *value function* that embodies the experimenters' needs to understand the physical world. Acting as best as possible (to achieve a precise goal) implies a DA process ruled by an optimal (or suboptimal) decision making policy that leads to an optimal (or suboptimal) action of the robot in the world. The (statistical) precision and reliability of the resulting task depends mainly on the way it has been modeled and on the data analysis process, because the DAQ process is considered to be fixed.

Our general claim supposes that the reliability or the precision of the former results may be enhanced by considering active data acquisition processes. In the case of mobile robotics, that involves considering "small" and "fast" movements of the robot performed during the data acquisition time-lapse. The idea that movement is crucial to gather "good" data is not new. Historically, it is the key point of the *sensorimotor* hypothesis for biological entities [HEL 21], [GIB 79]. Loops including motor neurons and neurons associated with senses have been discovered in the brain. Moreover, it has been shown that eye saccades are necessary in the human recognition process and that active movement may help people to disambiguate artificial scenes [WEX 01]. This precise idea has been exploited in robotics, in the field of active vision [BAL 90], [BAJ 88].

Recently, our team have also done some work on the use of fractal dimension to caracterize the specificity of data gathered by a moving mobile robot [VIG 02]. This work has led to the conclusion that a disconnection between the strategy of movement and the data analysis process may carry poor results.

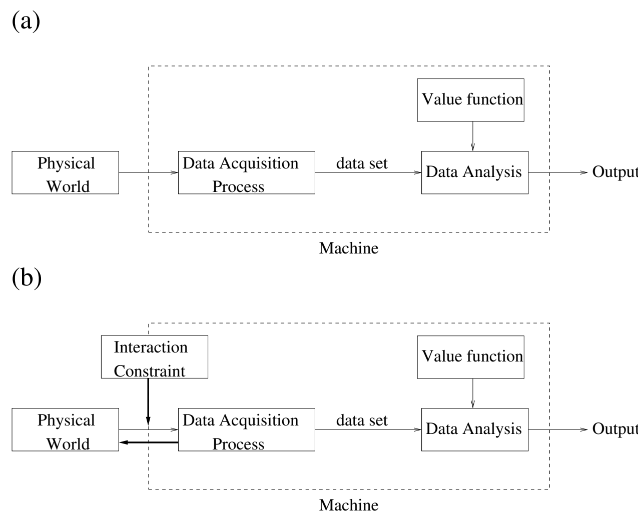

Fig. 1. (a) Classical approach. (b) Interactionist approach.

B. Main assumption

The general idea implies that the acquisition process is made of two interconnected modules: sensing and acting. However, our assumption is much more precise than that. It relies on the existence of a *physics-like interaction law* that links sensors and effectors values (see Fig. 1, (b)). This assumption has immediate consequences: sensory and motor variables are instantly codetermined, with no possibility to orientate that link, e.g. to say that *if* sensor values are changed by a given amount, *then* effectors values will change in a certain way. In the case we depict in this paper, the sensory motor law is modeled by a set of coupled differential equations. The solutions (when then exist) are trajectories in the phase space (combining sensors and effectors variables). The class of solutions may be interpreted as the set of all possible behaviors of the robot facing all possible worlds. A particular trajectory in the phase space is determined *during the experiment*, when the robot is facing a particular world. Thus, two different trajectories (given a certain distance) may be associated to two different environments (see Fig. 2) : this determines the basic principle for an *environment recognition process*.

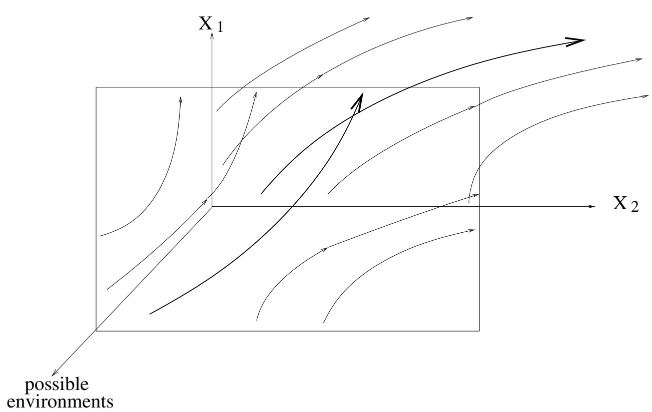

Fig. 2. Different trajectories associated to different environments. X_1 and X_2 are the variables of the phase space. We depict two planes over the environment axis, representing two different environments. The different trajectories in the same plane represent different behaviors of the robot placed in distinct areas of the same environment.

The existence of a physics-like interaction law is a strong constraint because the relation between sensory motor variables must be fulfilled *at any time*. It is based on an action/reaction procedure: the world (which is a priori unknown) acts on the robot by the way of the sensor values and the movement of the robot and, at the same time, the machine reacts to adapt its internal parameters (which are known) in order to follow the interaction law. This action/reaction procedure has already been successfully utilized to design a reinforcement learning algorithm onto which convergence proofs may easily be given [DAV 99], [DAV 04]. One particular advantage consists on the possibility to determine the class of solutions *before the experiment*. In our case, this permits to have an idea about the similarity of the shapes of the possible trajectories. The more two shapes are "different", the easiest it is to discriminate the two associated environments.

C. *Environment recognition - interactionist versus classical approach*

In this article we focus on an environment recognition task in which recognition is made by *gathering data over a fixed time-lapse* d. In a general sense, that means that the robot first evolves locally in a given *target* environment, following some trajectory we will discuss later in this paper. Then, it is presented to a series of k *distractive* environments (i.e. that may or may not correspond to the target environment) where it evolves during d as in the first stage. The aim of this task consists on identifying the target environment among the distractive environments on the basis of the data collected and analyzed during the various experiments.

In the classical approach, called *DA Approach (DAA)*, this implies to put the robot in two given environments, to execute the same trajectory in both cases and to compare the corresponding sensor values. The discrimination between two environments is then given by a distance between two sensor data vectors.

In our approach, called *Interactionist Approach (IA)*, the robot moves in order to fulfill the interaction law. And its motion during the time-lapse d depends on the sensor values, hence the environment. So, one cannot force the robot's trajectory over d, but one may hope that this trajectory is a signature of a local robot/environment interaction. The discrimination between two environments is then given by a distance between two trajectories in the phase space combining sensor and effector variables.

D. *Issues covered by this paper*

We have chosen to model the interaction law with a set of coupled differential equations, which is a particular way of implementing our assumption. In this paper, we detail issues arising from this choice and provide simple examples in which artificial worlds may be discriminated by a simulated robot after using our approach and compared to the classical approach. These results are the beginning of a work leading to an extended comparison, both theoretical and experimental, between the results obtained by the classical approach and ours.

II. MODELIZATION OF OUR ASSUMPTION

A. *General Principle for discriminating environments in the IA approach*

In IA, we impose a local discrimination criterion on the Data Acquisition stage. To make it clearer, we assume that the Data Acquisition step defines a multidimensional phase space that includes both *motor and sensitive* data, in which a state is called X. The interaction of the robot is thus represented in this space by a trajectory $T : t \rightarrow X(t)$. We then suppose that the robot can take two simultaneous different - but "close" - interactive measures, i.e. that it can follow at the same time two different but close trajectories T_1 and T_2 of the phase portrait. We also assume that the interaction is not a completely deterministic process, but that it has a stochastic component. We may then think of two realizations of the same stochastic process, represented by two trajectories T_1 and $T_1^{'}$.

We state that *the robot is able to discriminate locally between sensorimotor trajectories* if we can exhibit a distance function operating on trajectories $(T_1, T_2) \rightarrow \langle T_1, T_2 \rangle$, such that the following constraint C_1 if fulfilled:

$$\boxed{C_1 : \langle T_1, T_2 \rangle > \langle T_1, T_1^{'} \rangle}$$

Roughly, it means that two trajectories (produced by the interaction with two environments) must be more different (in the sense of a distance to be defined) than two realizations of the same trajectory (produced by the interaction with one environment). The issue is that the robot have to interact *at the same time* along two different trajectories. To comply with this requirement, while avoiding to interrupt the interaction, we imagine to make the DAQ stage both able to:

- apply a discontinuous perturbation at some given instant of its interaction along trajectory T_1.
- predict the lacking semi-trajectories that would have occurred if no perturbation had happened.

Fig. 3 illustrates this idea. Note that we thus constrain the notion of locality, both in the spatial sense (proximity between sensorimotor trajectories in the phase space, according to a distance) and temporal sense (time span required to make two trajectories out of one). Locality extends to the distance functions, since we don't define a global distance, but instead functions that locally verify the constraint (C_1).

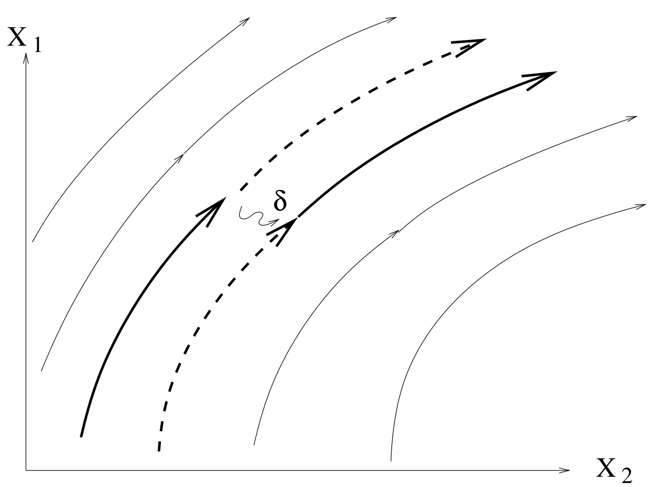

Fig. 3. Perturbation and prediction to make two trajectories out of one. Thick lines are measured interactions, dashed lines are predicted ones. Zigzag curve marked with δ is the perturbation. Other curves form the phase portrait in the sensorimotor phase space (X_1, X_2).

B. Model of the robot's interaction with its environment

First, we discuss the formalism in which to express the interaction of the robot in its environment. Because we need a balanced representation that takes into account sensitive and motor values at the same time, in a deterministic fashion, we favor the Theory of Dynamical Systems as our main theoretical framework. The physical variables that determine the robot's behavior submit to a system of differential equations that involve the internal variables of the robot X_i (value returned by the sensors, current that feeds the motors, rotation speed of the wheels) and the external variables X_e (position in the environment). This system is coupled to another one that links the absolute position of the robot in the environment to the value returned by its sensors. As an example, we present the coupling dynamics

$$\dot{X}_i = AX_i + f(X_e) \quad (1)$$
$$\dot{X}_e = g(X_e, X_i) \quad (2)$$

When it exists, we note $T : t \rightarrow (X_i(t), X_e(t))$ a solution of this system. The trajectories T_1 and T_2 are projections of such solution in the space of internal variables. Indeed, we impose that the robot ignores the value of the external variables to which it has no access. The internal variables are the only one it can be aware of. Hence, the mentioned trajectories are the projections $T_i : t \rightarrow X_i(t)$ of the general solutions on the space of internal variables, and will be used by both DAA and IA.
The DAQ step generally needs sensors to be chosen -that fit specific physical variables- and placed in such a way that meaningful measures (in the sense of the experimenter) can be taken. This may include an appropriate setting of the position and speed of the sensors in the 3D space. For that purpose, the robot is equipped with effectors that enable it to move across the environment. The DA step often performs a discretization (i.e. sampling and quantization) and some projection from the temporal domain to the frequential one (e.g. Fourier transform, wavelet analysis). Both participate to the creation of a phase space, associated with some *ad hoc* function endowed with the properties of a distance. The aim of this space is to give a "complete description" of the observed environment; which means that any two environments that the experimenter can distinguish are separate in the metric phase space.

Let's sum up the main steps performed during DA and DAQ stages:

- choice of physical continuous variables measured by sensors, including their respective positions and speeds.
- choice of a phase space via discretization, projection and filtering.
- choice of a distance on the phase space.

The value function evoked in section II, imposed by the experimenter, has to maintain an analogical link between the complexity of the DA step -in an algorithmic sense- and the discriminability of two environments for the experimenter. To give an intuitive feeling of this idea, let's imagine a couple of environments E_1 and E_2 that are obviously distinct in the experimenter's perception, and another couple E_3 and E_4 that are almost the same in the same sense. Then the DA step needed to distinguish the two environments of the first couple must be less complex than in the second case, algorithmically speaking. Note that DAA and IA share this analogical constraint as a value function.

Now let's focus on the instantiation of the Interaction constraint acting on the DAQ stage evoked in subsection II-A. (C_1) is verified if and only if there exists a distance function operating on trajectories $(T_1, T_2) \rightarrow \langle T_1, T_2 \rangle$, such that $\langle T_1, T_2 \rangle > \langle T_1, T_1^{'} \rangle$. To be able to verify it, the robot must compute $\langle T_1, T_1' \rangle$ and $\langle T_1, T_2 \rangle$. The first one requires the system to interact twice along the same sensorimotor trajectory, while the second needs two neighboring trajectories, with respect to a given distance. As we already stated, we introduce a twofold procedural mechanism, named Local Discrimination Criterion that enforces these conditions without interrupting the interaction: on one hand, we apply a cyclic discontinuous perturbation on the system's dynamics so as to leap from one trajectory to another. On the other hand, we assume that the system is endowed with a model of its own interaction with the environment that allows it to give predictions on future or past trajectories. Consequently, after the perturbation has occurred, the interaction goes on and finally the robot gets two half-trajectories. At this point, it uses its predictor to extrapolate the future trajectory, that would have took place if no perturbation had occurred, as well as the past of the actual trajectory, if time could reverse. Note first, that this mechanism can also be used to estimate a realization $T_1^{'}$ of an ongoing trajectory, given its initial condition. Fig. 4 summarizes these ideas. Secondly we remark that unlike the robot/environment interaction where each part influences *instantly* the other in a *symmetric* way, the nature of the influence of the perturbating mechanism on the dynamics is sequential: first, the perturbation takes places while the robot/environment interaction goes on, then the corresponding recorded data is processed to check the validity of (C_1).

Finally, we suggest that the perturbation δX itself may be applied incrementally: if, once triggered, it doesn't allow criterion (C_1) to be verified, then the intensity of the perturbation is increased next time, and so on until either (C_1) is verified, or a threshold is reached, which allows the robot to conclude that (C_1) can't be verified in that configuration (both of the robot, the environment, and the system of differential equations modeling the interaction).

C. Implementation

In this part we discuss more technically a possible implementation of the mobile robot that illustrates the measurement process seen in the beginning of this section, and applied to the context of robotics as in section II-B, before instantiating the recognition algorithm in the compared cases.

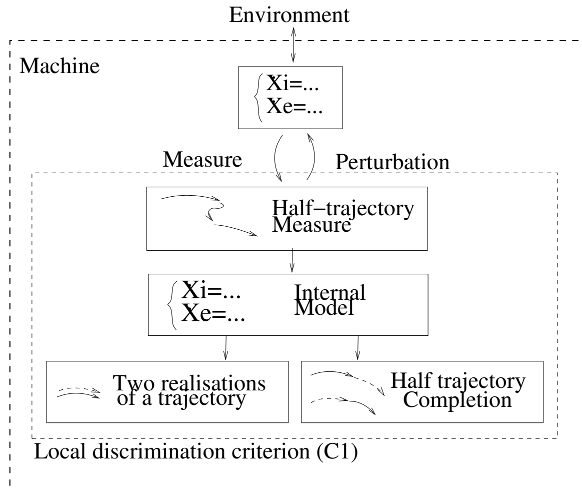

Fig. 4. Inner structure of the machine, where the local discrimination criterion (C_1) influences the machine/environment interaction.

C.1 Analogical modelization of the robot

All the experiments conducted in this article are simulated because, mainly, we consider an analogical robot which active sensors do not exist in reality. The manipulated differential equation systems, will be solved numerically with LSODE [1].

The environment is assimilated to a light-emitting curve whose shape is a circle. In every point $M(x, y)$ of the physical space, one can then measure the intensity of incoming light radiations. The function $I(x, y)$ plotted in figure 5 depicts that intensity landscape.

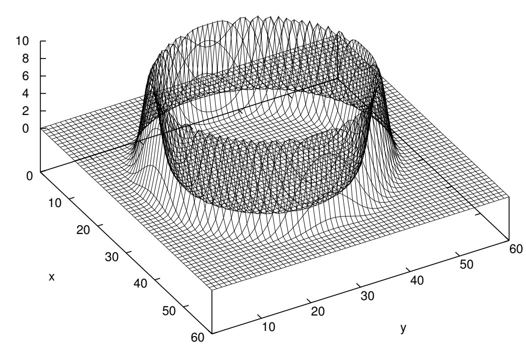

Fig. 5. Voltage returned by light sensors as a function of (x, y).

[1] Livermore Solver for Ordinary Differential Equations http://www.netlib.org/odepack/opkd-sum

The robot is equipped with two continuous current motors on the left and right, fed by currents i_l and i_r. Two light sensitive diodes (FLEDs) are connected to an intermediary level that couples the two sides of the robot in a way such that the voltages and currents feeding both motors depend on the voltage produced by both diodes. Fig. 6 summarizes those facts. The motors are linked to wheels whose angular velocity are noted (ω_l, ω_r), and that enable the robot to move on a planar surface.

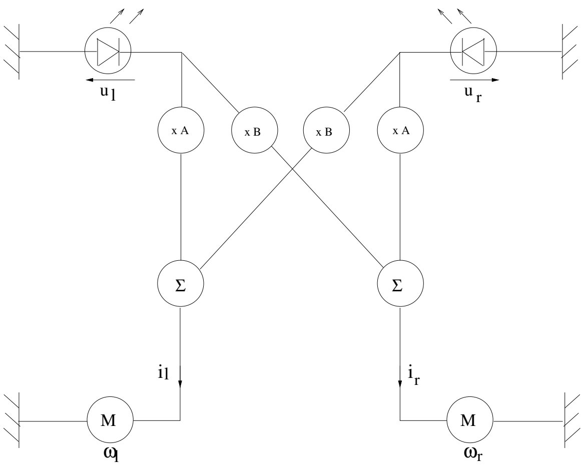

Fig. 6. Electrical circuit governing the robot's behavior

We do not exhibit precisely the modeling process leading to the equations shown in section II-B that account for the robot/environment interaction. We will develop them below. First notice than $X_i = [w_l, i_l, w_r, i_r]^T$ while $X_e = [x, y, \theta]^T$, where x and y stand for the absolute position of the center of the robot, while θ stands for its orientation with respect to some fixed direction. Now equations 1 in a developed form may be written as follows:

$$
\left\{
\begin{array}{ll}
\dot{X}_i & = A X_i + f(X_e) \\
f(X_e) & = [0 \; u_l \; 0 \; u_r \;]^T \\
u_l & = U_0 + \alpha v_l + \beta v_r \\
u_r & = U_0 + \beta v_r + \alpha v_l \\
v_{l/r} & = V_0 \left(e^{-\left(\frac{r_{l/r} - r_o}{\sigma}\right)^2} \right) \\
r_{l/r} & = \sqrt{x_{l/r}^2 + y_{l/r}^2} \\
x_{l/r} & = x + e\cos(\theta \mp \pi/2) \\
y_{l/r} & = y + e\sin(\theta \mp \pi/2)
\end{array}
\right.
$$

Similarly, we develop equation 2

$$
\left\{
\begin{array}{l}
\dot{x} = d/2 \; (\omega_l \cos\theta + \omega_r \cos\theta) \\
\dot{y} = d/2 \; (\omega_l \sin\theta + \omega_r \sin\theta) \\
\dot{\theta} = \frac{d}{2e}(-\omega_l + \omega_r)
\end{array}
\right.
$$

Note that both f and g in equations 1 and 2 are highly nonlinear, what makes it hard to find an analytic solution to the system.

We then focus on the predictor we proposed in subsection II-B. Remember it is necessary to extrapolate interrupted trajectories in the future and in the past. We could choose a classical time-series method relying for example on Kalman filtering but instead we endow the machine with an inner numerical integration method, as well as an approximate differential equation system. Doing so, giving the initial condition X_i^O allows the system to predict a full trajectory in the future of in the past.

C.2 Recognition Algorithm

So far we've described the robot, the environment, and their interaction law. However we lack a precise formalization of the environment recognition algorithm itself. In both classical or interactive perspective, each comparison needs two experiments, with the same mobile robot but different environments, in addition to an identity operator.

In the classical case, the robot is placed in the environment and moves in it. For the sake of comparison, we focus on the discrete sequence of internal variables $T : t_k \rightarrow X_i(t_k)$ obtained with the interactionist method. The outputs O_1 and O_2 thus produced are two matrices T_1 and T_2. One has to build a distance $\langle ., . \rangle$ on the space of such matrices, as well as a threshold ε. Classically any couple of environments which corresponding matrices verify $\langle T_1, T_2 \rangle \leq \varepsilon$ will be considered identical. This algorithm is illustrated by Fig. 7 (a).

The output, returned by the corresponding set of experiments in the interactionist case, is a little more intricate. It first includes the discretized internal trajectories $T : t_k \rightarrow X_i(t_k)$. Remind that we perturbate the interaction in a cyclic manner. This process naturally delimitates segments of the internal variables trajectories. Secondly, each segment comes with a -possibly empty- set of distances $\{\langle ., . \rangle_i\}_{i=1..n}$ that verify the Local Discrimination Criterion. Let us focus on this local level: for each segment, we compare the sets of C_1-complying distance functions, corresponding respectively to the first and second experiments. If for a given couple of corresponding [2] segments $(S_{1,k}, S_{2,k})$, the C_1-complying distance set is nonempty, we can compare those distances. If we can find the same distance in both sets, we call this distance a *compatible* one. If, according to that distance, the (C_1) criterion is verified (i.e. $\langle S_{1,k}, S_{2,k} \rangle > \langle S_{1,k}, S'_{1,k} \rangle$), then the segments are distinct, and so are the two global trajectories. If for all segments k, we find a nonempty distance set, among which we exhibit a compatible distance, according to which the segments are undiscriminable, then the trajectories are identical. This is summarized in Fig. 7 (b).

[2] that notion of correspondence -in a discrete framework- implies that the perturbation frequency as well as the sampling frequency are identical in both experiments

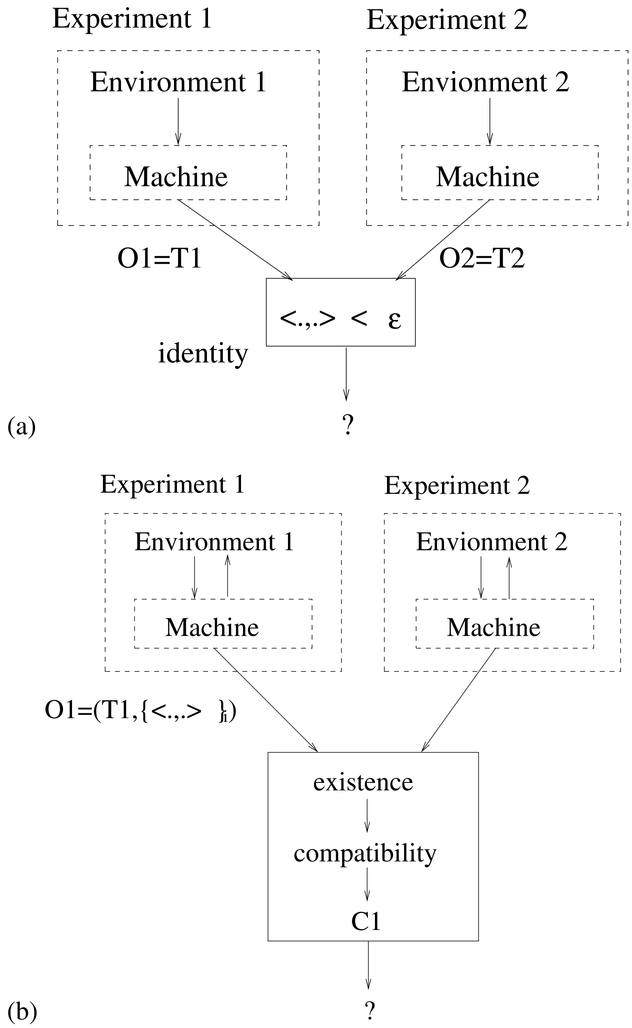

Fig. 7. Environment recognition in a classical (a) and interactive (b) perspective.

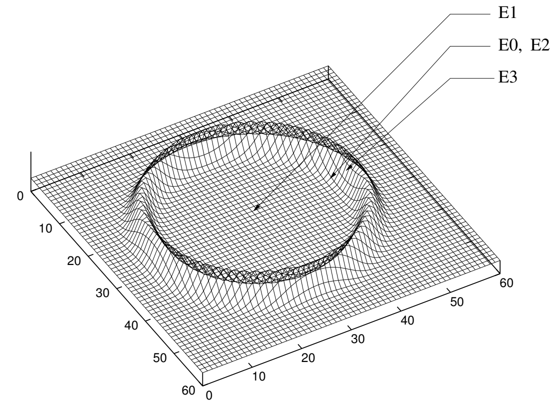

Fig. 8. Environments (E_0, E_1, E_2, E_3).

III. Results

In the previous section, we've detailed the comparison protocol between DAA and IA. Now we present some results for the environment recognition process. As we already said, we place the robot in a target environment E_0 where it obeys the aforementioned interaction process. Then we place it in three other environments E_1, E_2, E_3 where $E_2 = E_0$, and all the others are distinct as shown by Fig. 8. The associated local trajectories in a projection space made of internal variables only are presented in Fig. 9 (we note that T_0 and T_2 are not superposed, because of the stochastic nature of the interaction).

A. The IA case

In that case, we obtain both a trajectory T_0 in the space of internal variables X_i, and a set of distances $\{\langle .,. \rangle\}_0$ that verify criterion (C_1). Then we start again in k distractive environments and we similarly obtain k trajectories $T_{i=1...k}$. Each trajectory also comes with a potentially empty set of distance functions $\{\langle .,. \rangle\}_i$. Here, if we note T_i and T_j two trajectory matrices, the possible distances we use are associated with the built-in norms in Octave [3] :

- $\langle T_i, T_j \rangle_1$: the largest column sum of the absolute values of $T_i - T_j$.
- $\langle T_i, T_j \rangle_2$: largest singular value of $T_i - T_j$.
- $\langle T_i, T_j \rangle_3$: infinity norm, the largest row sum of the absolute values of $T_i - T_j$.
- $\langle T_i, T_j \rangle_4$: Frobenius norm of $T_i - T_j$, i.e. $\sqrt{(}\sum(diag((T_i - T_j)' * (T_i - T_j))))$.

Then, according to the method previously exposed, we begin by verifying that all trajectory come with a nonempty set of C_1-complying distance functions. Table I shows that trajectories T_0, T_2, T_3 satisfy that constraint (which is marked by an 'x'). Furthermore, we remark that the concerned distances are all compatible. Hence, we can compare T_0 with T_2 and T_3 with distances $\langle .,. \rangle_{k=1,2,3,4}$. The last step is to verify -only for environments that passed the previous test- the (C_1) criterion, i.e. $\langle T_i, T_j \rangle_k < \langle T_i, T_i' \rangle_k$, which means that T_i and T_j can't be distinguished from the point of view of $\langle .,. \rangle_k$. Table II gives, for each couple E_i, E_j and for each distance $\langle .,. \rangle_k$, the result under the form a/b where $a = \langle T_i, T_j \rangle_k$ and $b = \langle T_i, T_i' \rangle_k$. The result is highlighted when $a < b$, i.e. when the corresponding environments can't be distinguished with the associated distance. We observe that T_0 and T_3 are distinct for all distances, consequently E_0 and E_3 are different from an interactionist point of view. However, T_0 and T_2 are equal for distances $\langle .,. \rangle_1$, $\langle .,. \rangle_3$, $\langle .,. \rangle_4$. As a result we can state that this method has succeeded in identifying E_0 and E_2, while the others were discarded.

[3] GNU Octave is a numerical computation language, available under GNU General Public License (GPL) http://www.octave.org/

TABLE I
C_1-COMPLYING DISTANCES FOR EACH ENVIRONMENT

Environment	Distances			
	$\langle .,. \rangle_1$	$\langle .,. \rangle_2$	$\langle .,. \rangle_3$	$\langle .,. \rangle_4$
E_0	x	x	x	x
E_1	-	-	-	-
E_2	x	x	x	x
E_3	x	x	x	x

TABLE II
TRAJECTORY COMPARISON IN IA

Trajectory	Distances			
	$\langle .,. \rangle_1$	$\langle .,. \rangle_2$	$\langle .,. \rangle_3$	$\langle .,. \rangle_4$
(T_0, T_2)	**93/104**	4/3	**0.3/0.9**	**4/8**
(T_0, T_3)	5381/104	284/3	29/0.9	284/8

B. The DAA case

In this case, we only obtain a trajectory T_0 in the internal variables space, as well as k trajectories $T_{i=1\ldots k}$ corresponding to the distractive environments. Table III presents values of $\langle T_i, T_j \rangle_k$ for the different distances depicted above. Unless we fix a threshold for each distance this table is useless. Once it is fixed, one may state that, for a given distance, T_i and T_j are equivalent and consequently E_i and E_j are equivalent too.
For example, if we impose the same threshold $\varepsilon = 3.5$ for all distances, T_0 and T_1 are equal according to distance $\langle .,. \rangle_3$ -although they were generated by interactions in different places- as well as T_0 and T_2, while T_0 and T_3 are different for all distances. We could also impose a distance-depending threshold $\varepsilon = [\varepsilon_1\ \varepsilon_2\ \varepsilon_3\ \varepsilon_4]$, but the arbitrary nature of this choice remains the same.

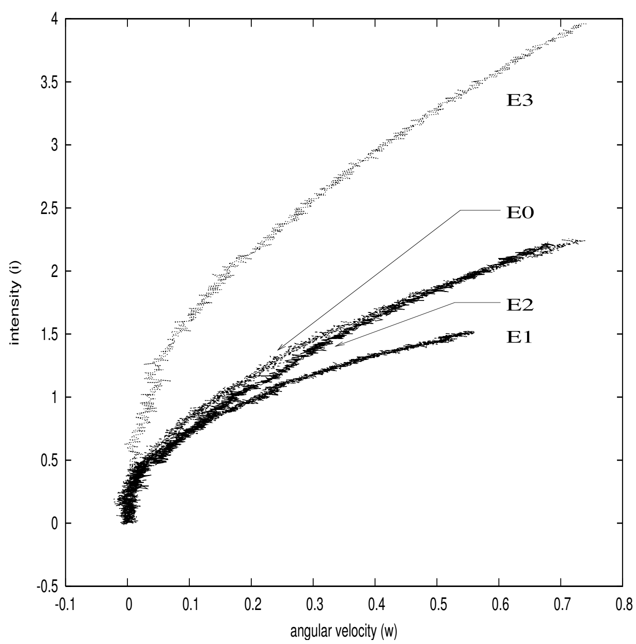

Fig. 9. Internal trajectory $t \rightarrow (w_r(t), i_r(t))$ in different environments (E_0, E_1, E_2, E_3).

TABLE III
TRAJECTORY COMPARISON IN DAA

Trajectory	Distances			
	$\langle .,. \rangle_1$	$\langle .,. \rangle_2$	$\langle .,. \rangle_3$	$\langle .,. \rangle_4$
(T_0, T_1)	389	22	3	22
(T_0, T_2)	93	4	0.3	4
(T_0, T_3)	5381	284	29	284

C. Conclusion

In DAA, one may compute several distances between trajectories, but has to fix a threshold in order to conclude to the indiscriminability of two environments given a performed trajectory. As we saw, the mere choice of this threshold, be it differentiated with respect to the considered distance, yields the recognition result.
On the opposite, the interactionist approach returns a set of (C_1) relevant distances for every trajectory. If none is provided, no comparison is possible, thus discrimination is impossible. If not, two trajectories may be compared with respect to that distance that has a local discrimination capability.
We can't deny that the IA approach makes specific assumptions, namely that discrimination is conditionned by the compliance towards criterion (C_1). Furthermore, we create *a priori* the set of possible distance functions, the trajectory duration, the sampling frequency as well as the composition of the phase space, but these are not distinctive features of the IA method and are intrinsic drawbacks when simulating a physical phneomenon on a digital computer. *All things considered, it seems to us that criterion (C_1) is less arbitrary than imposing both the distance and the threshold.*

IV. CONCLUSION AND FUTURE WORK

In this article, our aim was to confront a balanced conception of robot/environment interaction, with the passive way in which a robot classically performs discrimination and recognition tasks. To ensure a Physics-like interaction between sensors and effectors values at any time, we've adopted the theoretical framework of the Dynamical Systems Theory so as to model an analogical robot which sensors and motors values are coupled via a set of differential equations. Furthermore, adding a discrimination constraint on the robot/environment interaction, and focusing on sensorimotor trajectories rather on sensory data only, we show that our method makes it possible both to know whether the robot can discriminate or not, then to actually discriminate several types on interaction if discrimination has a sense. Finally we show that this can be used to recognize an environment if the interaction is performed in the same conditions, in a way comparable to the classical approach, where one can discriminate sensory or motor trajectories, given some metric constraints and the choice of a threshold.

Let us now consider the perspectives opened by this work.

1) developping this framework could be achieved in several ways:

- verifying the invariance of recognition towards spatial transformation.
- implementing a real analog robot instead of simulating it.
- implementing an analog architecture of the Local Discrimination Criterion since the current version is based on a discrete method. Reasons for this choice are discussed in the field of epistemology by [BAI 04].

2) criticizing this framework draws the following topics to be questionned:

- why describing the discrimination capability in a metric framework, even if the distance can be changed during the experiment ?
- why keeping the robot, its interaction law and the environnement unchangeable ? Exploring their possible codetermination needs to make them deformable (e.g. non-rigid robot morphology, non-rigid environment, "deformable" differential equation system).
- why choosing the Dynamical Systems Theory framewok that lacks that idea of deformable phase space ?

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