# Can Representation be Liberated from Symbolism: Modeling Robot Actions with Roboticles

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**Abstract.**
Since its origins, Artificial Intelligence has been faced with the challenge to control robot operations through the so called *deliberative thinking* paradigm. Robot actions are governed by a reasoning process which needs robots to acquire information from the environment to update their internal world model causing the failure to generate an useful action in a finite amount of time. The framework of *roboticles*, appearing in this paper and borrowed from the theory of complex dynamical system, is a tool to deal with quantities like *energy* or *effort*, to symbolize the amount of sensor information a robot is fed with, later dissipated by the action of its effectors. The dynamical law works as a triggering mechanism which controls the flow of energy between sensors and effectors so that its current value can be interpreted, in some sense, as the internal world model handled by the agent. Environment changing, detected through sensor signals, results in moving the representation point of the system on the energy surface. Moreover, actions issued by robot effectors dissipate energy in a way to maintain the working point of the system in a *stationary state* where the energy supplied by sensor signals is balanced by the effort delivered to the effectors.

## 1 INTRODUCTION

The symbol system hypothesis has been dominating Artificial Intelligence for so a long time that the problem of knowledge representation has often been cast in what it's generally known as *deliberative thinking* paradigm. Every intelligent activity is implemented as a reasoning process which operates on a symbolic internal model resulting in the *sense-think-act* cycle when it is applied to autonomous robots. Though the behaviour-based approach has been proved successful for many tasks involving real autonomous agents working in complex dynamical environments, the problem of where to store and how to handle acquired sensor information for future uses, it has remained quite almost unsolved.

Within the *behaviour-based* paradigm, originated from the pioneristic work of Brooks [5], many authors such as Connell[6], Maes [11], Arkin [2], Donath [1], Pfeifer [16], D'Angelo [7], Kaelbling [10] have devised several innovative architectures which have borrowed from cybernetics the idea that situated agents must be embodied within their environment. A number of theoretical problems, such as the issues on *non-monotonic reasoning* and the *frame problem*, simply disappear as a consequence of the *symbol grounding* between internal model and external world.

However, the dilemma of an internal representation of the world remains quite unsolved even if minimalism doesn't recognize the need of any form of representation which, on the other hand, plays a crucial rôle when a group of autonomous agents are expected to execute a common goal. But information handling, as Artificial Intelligence seems to suggest, cannot be discarded in principle even if agents should be provided with more effective handling of their world models.

For example, let us suppose a teammate is trying to participate to a collective action where the displacement of the group inside the environment is a very important feature. In this case there is no explicit goal to satisfy but a somewhat persistent pattern to be fed by individual actions which act as cue-based communication, termed *stigmergic* in biological literature. So, the detection of the pattern, the group is trying to enforce, can be considered as a form of implicit communication ([13], [12], [14], [15]) with the effect of triggering agent behaviours (*implicit coordination*) in a way to make emerging the observed collective behaviour.

But how can a teammate be aware that a pattern must be enforced if it's not a part of a world model, shared with the others teammates, he's dealing with? The problem stems from the fact that communication implies an information exchange process among the involved agents and, at this point, the choice of a symbol system, carrying all necessary information, seems to be the best solution. But the agent world models must agree each others and, moreover, they must be compliant with the environment features which are relevant for the group activity.

A possible way to fulfill this condition, avoiding both the frame-problem and non-monotonic reasoning troubles, is the requirement that also exchanged information must be situated and embodied. This means that not only information contents should be considered but also its carrier (medium) which works as symbol grounding for that information. Within this perspective there is no need to separate information *contents* from its *form*, so that agents can act directly on sensor signals generated by the interaction of its sensor devices with the environment.

The rest of the paper is organized as fallow. In sect. 2 we use some terminology from dynamical system theory applied to wheel driven vehicles and we generalize the well-known concept of energy. In sect. 3 we introduce the roboticle paradigm whereas in sect. 4 some properties are derived and discussed. Finally, sect. 5 considers an example adapted from Breitenberg's vehicle one.

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## 2 VEHICLE CONTROL AND ENERGY

The idea of a non-symbolic representation is not new in literature. For example, Steels [18] has exploited analogical representation as a tool to implement sensorimotor coordination. In the last decade, however, several authors have been faced with the problem of finding out a different paradigm to acquire and use knowledge from the environment.

Many of them can be much more appreciated if they are cast in the language of complex dynamical system theory. In fact, features ascribed to the behaviour-based approach, like the *direct coupling of perception to action* and the *dynamic interaction with the environment* are an attempt to deal with dynamical systems using a symbolic framework.

Thus, if robots are dynamical systems which receive a stream of input sensor signals from and generates a stream of output actions to the environment, then it means that we can describe them giving a set of *state variables* **x** and a *dynamical law* $\Phi$ which tells how the values of the state variables change over time. In the continuous-time case the dynamical law takes the form of a set of differential equations referred to as a *vector field* on the state space. The interested reader is referred to Hale and Koçak [8].

The same framework has been used with slight different purposes. For example, Beer [3] uses complex dynamical systems to model the behaviour of a neural network with the aim to gain insights on learning mechanisms. From another point of view, Jäger [9] tries to understand behaviour arbitration as interaction among behaviours, introducing what he terms the *dual dynamic* as an attempt to separate the proper dynamics of a behaviour (*target dynamics*) from that responsible to trigger the behaviour itself (*activation dynamics*).

However, the most promising results which are expected within this framework, should concern a different way to deal with robot sensor data and actions. Thus, our investigation has been focused on wheel driven autonomous vehicles moving on plain surfaces. If we assume the cartesian coordinates *x* and *y* as state variables, the continuous non linear system

$$\dot{x} = u(x, y, \lambda) \qquad \dot{y} = v(x, y, \lambda) \tag{1}$$

with control parameter $\lambda$, defines the governor unit of such a vehicle. The action of the dynamical law (1) is twofold. It generates the set of points covered by the vehicle from the *initial point* $< x_0, y_0 >$ and, moreover, it defines how that trajectory is covered, depending on sensor information about the state of the vehicle with respect to the environment.

The implicit description of the trajectory can be easily obtained from (1) as differential form

$$v(x, y, \lambda)dx - u(x, y, \lambda)dy = 0 \tag{2}$$

stating that the infinitesimal arc $d\mathbf{r} =< dx, dy >$ traced by the vehicle during the time interval *dt* is parallel to the *vector field* $< u, v >$.

Generally, (2) is not an exact differential form even if it always exists an integrating factor by which it becomes exact. If we search such a factor with the form $\frac{1}{E}$, equation (2) yields

$$\frac{v}{E}dx - \frac{u}{E}dy = dS \tag{3}$$

where *S(x,y)* denotes a scalar function which implicitally defines a trajectory family, one of which is actually covered by the vehicle in according to the initial conditions.

Now, it can be easily shown that (3) holds if and only if the following differential equation holds

$$u\frac{\partial E}{\partial x} + v\frac{\partial E}{\partial y} = 2\sigma E \tag{4}$$

where $\sigma$ represents the *dissipative factor*, defined as an half of the divergence of the vector field. Equation (4) suggests us to interpret *E(x,y)* as the **energy** a vehicle is sharing with its environment while it is moving along the trajectory. This interpretation stems from making explicit the contribution of the vector field in (4), so that we can write

$$\frac{dE}{dt} = 2\sigma E \tag{5}$$

expressing the *decay law* of *E* referred to the dissipative factor. On the other hand, equation (3) provides a general way to build the dynamical law of a vehicle

$$\dot{x} = -E\frac{\partial S}{\partial y} \qquad \dot{y} = E\frac{\partial S}{\partial x} \tag{6}$$

as soon as both a trajectory family *S(x,y)* and an energy function *E(x,y)* have been given. In the case that *E(x,y)* takes a constant value, so that (2) becomes an exact differential form, we say the system to be *hamiltonian* or *conservative*.

## 3 ROBOTICLES

Complex dynamical system theory provides a general framework to deal with entities, built on several component parts and specified by one or more quantities changing over time. No mention is done about the choice of state variables, dynamical law, and so on because it strongly depends on the specific problem at the hand.

Thus, the dynamical law (1) which solve the navigation problem for an autonomous vehicle, make no assumption on the specific control mechanism, actually implemented to govern its trajectory. In any case, the cartesian coordinates are not the best choice as state variables because their values must be acquired from the environment.

On the contrary, a real mobile robot is equipped with proximity sensors and range finders, and it is driven by two motor wheels which are supplied with two independent pulse voltage regulators. Within this robot structure the most appropriate state variables we can choose are the speed $V_R$ and $V_L$, which drive the right and the left wheel, respectively.

However, if we introduce the distance *2a* between the wheels along the motor axis, the speed *V* of its middle point (*vehicle moving center*) and the steering angle $\theta$ are completely adequate to the aim. The choice is a consequence of the following relations

$$V_R = V + a\dot{\theta} \qquad V_L = V - a\dot{\theta} \tag{7}$$

whose validity stems from the definition of the *bending radius* $R = \frac{V\,dt}{d\theta}$ of the moving center, on which the two motor wheels are symmetrically placed.

The corresponding dynamical law can be immediately obtained from (1) as time derivatives. Since both *V* and $\theta$ define a vector tangent to the vehicle trajectory, the cartesian component *u* and *v* appearing in (1) are easily expressible by

$$u = V\cos\theta \qquad v = V\sin\theta \tag{8}$$

which allow us to rewrite the original dynamical law (1) in terms of the new state variables *V* and $\theta$

$$\begin{aligned} \dot{V} &= (\sigma + \gamma_1 \cos 2\theta + \gamma_2 \sin 2\theta)V \\ \dot{\theta} &= \omega + \gamma_2 \cos 2\theta - \gamma_1 \sin 2\theta \end{aligned} \tag{9}$$

By so doing we have split the contribution of the environment dynamics from which explicitally caused by the vehicle, in according to the figure 1. It should be noticed that the coefficients appearing in

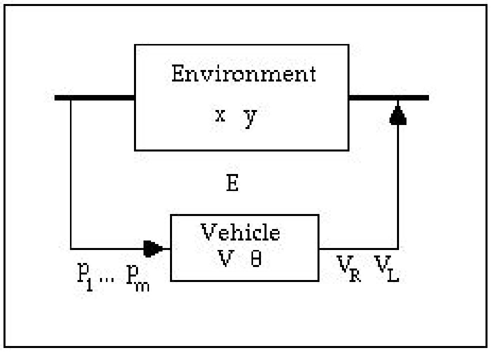


**Figure 1.** Roboticle: a wheel driven vehicle

(9) are possibly functions of the vehicle position and they take the values

$$\begin{array}{rclrcl} \sigma & = & \frac{1}{2}(\frac{\partial u}{\partial x}+\frac{\partial v}{\partial y}) & \omega & = & \frac{1}{2}(\frac{\partial v}{\partial x}-\frac{\partial u}{\partial y}) \\ \gamma_1 & = & \frac{1}{2}(\frac{\partial u}{\partial x}-\frac{\partial v}{\partial y}) & \gamma_2 & = & \frac{1}{2}(\frac{\partial v}{\partial x}+\frac{\partial u}{\partial y}) \end{array} \tag{10}$$

showing how the vector field components are monitored by the governor unit which drives vehicle motor wheels. We have termed **roboticles** such kind of vehicles.

A similar approach has been used by Schöner [17], who considers vehicles moving with a fixed speed V, where the single state variable $\theta$ represents the amount of steering referred to a given pose. This variable can be interpreted as a mark of the vehicle apparent horizon where obstacles and the target are reflected as fixed stars.

The dynamical law (9), however, is a particular case of the most general one, appearing below

$$\begin{array}{rcl} \dot{V} & = & \alpha(V,\theta,p_1,\ldots,p_m,\lambda) \\ \dot{\theta} & = & \zeta(V,\theta,p_1,\ldots,p_m,\lambda) \\ \dot{x} & = & V\cos\theta-\frac{\partial G}{\partial x} \\ \dot{y} & = & V\sin\theta-\frac{\partial G}{\partial y} \end{array} \tag{11}$$

which makes explicit how the state variables *V* and $\theta$, ascribed to the vehicle, affect the position variables *x* and *y*, representing the environment. The last two equations express the necessary coupling of the vehicle with its environment, caused by the vehicle embodiment. In this case the vehicle is assumed to move on a generic surface, whose features are defined by the function *G*, which becomes a perfectly rigid plane when G is taken as a constant.

It should also be noticed in (11) the presence of the parameters $p_1,\ldots,p_m$ which usually depend on the vehicle position, with the same rôle played by $\sigma,\omega,\gamma_1$ and $\gamma_2$ in (9). We have called them **virtual sensors** and the functions $p_1(x,y),\ldots,p_m(x,y)$ can be interpreted as their models.

## 4 NON-SYMBOLIC REPRESENTATION

From equations (6) it follows immediately that a point $<x_e,y_e>$ is an equilibrium point if the vehicle energy becomes null. This means that a negative dissipative factor forces a vehicle to move along its trajectory with a positive amount of energy when it's traveling towards an attractor. So, the initial positive amount of energy will be eventually dissipated by vehicle wheel controller.

### 4.1 Effort

Let us now define the product *Vds* as the **effort** delivered by the vehicle effectors to support its movement, along a trajectory arc *ds* with speed *V*. Using the components *u* and *v* of the vector field the preceding definition yields

$$Vds = udx + vdy \tag{12}$$

whose value along a finite trajectory arc depends on initial and final positions only if the following condition holds

$$\frac{\partial u}{\partial y}=\frac{\partial v}{\partial x} \tag{13}$$

In such a case there exists a scalar function *F(x, y)* which generates the vector field components as partial derivatives

$$\dot{x}=-\frac{\partial F}{\partial x} \qquad \dot{y}=-\frac{\partial F}{\partial y} \tag{14}$$

Attractors and repellors are easily identified by simply looking at the distribution of minima and maxima of the scalar function *F* which defines the landscape for system basins of attraction. Because its value can be used to estimate how much residual *energy* must be dissipated before reaching an attractor, it motivates the term *dissipative* for the function *F*.

In general, however, condition (13) doesn't hold so that the vector field components must be generated using the auxiliary scalar function *U(x,y)*. It provides the conservative part of the vector field appearing in (14) as an additive term in according with the schema (6). Hence, the most general dynamics of a continuous-time system is given by

$$\dot{x}=-\frac{\partial F}{\partial x}-\frac{\partial U}{\partial y} \qquad \dot{y}=-\frac{\partial F}{\partial y}+\frac{\partial U}{\partial x} \tag{15}$$

where the interaction between the dissipative function and the internal energy makes emerging the observed trajectory.

Starting from the definition (12) of effort, we can multiply equations (15) for the cartesian components of the infinitesimal trajectory arc *ds* and, then, sum the corresponding members. The new differential form, so obtained,

$$Vds=-dF+\left(\frac{\partial U}{\partial x}dy-\frac{\partial U}{\partial y}dx\right) \tag{16}$$

provides an attractive interpretation. In fact, if you suppose that the effort *Vds* spent by the vehicle motor wheels must be compensated by the same amount *-Vds*, with opposite sign, delivered by the vehicle governor unit, the preceding equation (16) becomes

$$dF-(-Vds)=d\mathcal{M} \tag{17}$$

where dM is defined by the follow relation

$$dM=\frac{\partial U}{\partial x}dy-\frac{\partial U}{\partial y}dx \tag{18}$$

It should be noticed that the scalar quantity M is not properly a function because its integral evaluation depends on the integrating path, so it plays the rôle of a vehicle memory. Since the value of M also depends on the so called *internal energy* U(x,y) of the vehicle, there is a close relation with the flow of sensor data, as it will be discussed in the next subsection.

### 4.2 Far from Equilibrium

Because the vehicle is requested to adapt continuously to a rapidly changing environment, it needs to be provided with a reactive mechanism which tries to get the most useful benefit from the interaction with the environment. In this sense, the governor unit for autonomous vehicles must be reactive and deliberative at the same time and this means that information acquired from the environment should affect, with some respect, the internal model of the world the vehicle is dealing with.

A possible implementation of this model is provided by the interpretation of incoming sensor data as a flow of energy whose effect is that of increasing the current amount of energy the vehicle holds. Environment changing, detected as sensor signals, results in moving the representation point of the system on the energy surface.

The starting point is considering that equation (2) is identically satisfied only in the ideal case where the environment is perfectly compliant with the vehicle. In any real situation, however, the trajectory covered by the vehicle cannot satisfy (2).

To the aim of the follow discussion we can assume (2) which allow us to equate (6) with (15). By so doing we can multiply these two new equations for the cartesian components of the infinitesimal trajectory arc *ds* and, then, sum the corresponding members. The differential form, so obtained,

$$EdS = dU + \left( \frac{\partial F}{\partial x} dy - \frac{\partial F}{\partial y} dx \right) \tag{19}$$

can be used to estimate the variation of value of *S(x,y)* that in an ideal case should remain unchanged.

If we introduce the following definitions

$$\begin{aligned} dP &= E(x,y)dS \\ dQ &= \tfrac{\partial F}{\partial x} dy - \tfrac{\partial F}{\partial y} dx \end{aligned} \tag{20}$$

where *dP* is the increment of sensor flow, due to a positive fluctuation of *S*, while *dQ* is the corresponding increment on the activity of vehicle effectors, we can rewrite (19) as a couple of relations

$$dU = dP - dQ \qquad dS = \frac{dP}{E} \tag{21}$$

which admit the following interpretation. The former states that the increment of vehicle internal energy results from an overbalancing between the variation of sensor data flow and its corresponding dissipation on its effectors. The latter simply establishes how the variation of sensor data, acquired by the environment, affects the nominal trajectory S(x,y) = K with the respect of a given energy.

This model defines a typical dynamical system opened with respect to energy where actions issued by vehicle effectors dissipate energy in a way to maintain the working point of the system in a *stationary state* where the energy supplied by sensor signals is balanced by the effort delivered to the effectors.

## 5 BREITENBERG'S VEHICLES

Several properties can be obtained from the definition of roboticles and which can be used to simulate many situations arising with both single and multi-robot framework. The simplest situation is that described by Breitenberg [4] within his vehicle *I*.

In this case, the scenario is easily depicted. There is a fixed light source and a vehicle, moving along a straight line. It is equipped with a sensor which triggers the vehicle speed by increasing its value while the source is decreasing its intensity. Using the results presented in the preceding sections it can be easily shown that, for any given energy function *E*, equations (1) take the form

$$\dot{r} = -\frac{E(r)}{r} \qquad \dot{\varphi} = -\frac{a}{\sqrt{r^2 + a^2}} \frac{E(r)}{r} \tag{22}$$

using a polar frame of reference, centered on the light source, and having made the assumption that the vehicle is moving along a straight line passing nearby the light source with a minimal distance *a*.

The dynamical law of the corresponding roboticle is immediately obtained as a time derivative on $\dot{r}$, which represents the speed *V* of the vehicle,

$$\dot{V} = -p(r)V \tag{23}$$

$$\dot{\theta} = 0 \tag{24}$$

where *p(r)* is the vehicle virtual sensor. It is defined by the differential relation

$$p(r) = \frac{1}{r}\frac{dE}{dr} - \frac{E}{r^2 - a^2} \tag{25}$$

involving the total *energy* of the vehicle. Of course, the actual vehicle behaviour depends on the specific choice of the sensor. For example, you can suppose to equip the vehicle with an infrared sensor detecting the intensity of the light in according to an inverse quadratic law

$$p(r) = \frac{ca}{r^2} \tag{26}$$

which gives rise to the energy function appearing below

$$E(r) = (V_a + c \arccos \frac{a}{r})\sqrt{r^2 - a^2} \tag{27}$$

The figure 2 illustrates the relation between the curve depicting the *sensor response* p(r) and the approximate straight line which represents the *vehicle energy* E(r). The light perturbation enters the vehicle control and it is stored as an increment *dU* of the current value of the internal energy. At the same time, a decrement *dF* of the amount of dissipative function triggers the increment dM which causes the actual transferring of energy towards the vehicle effectors.

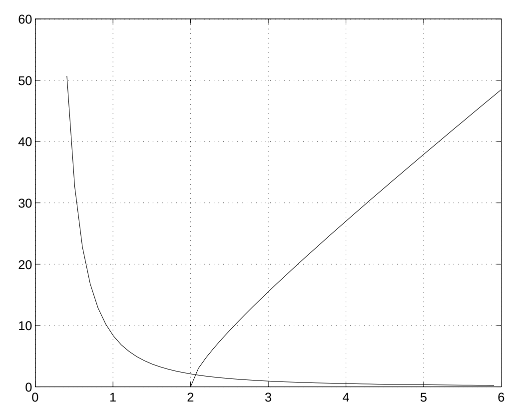


**Figure 2.** Sensor Response and Energy of Breitenberg's vehicle I

## 6 CONCLUSION

At the present the proposed *roboticle paradigm* appears to be the most promising framework where to cast autonomous agent results and perspective. As well as concepts like *non-linearity* or *far from equilibrium*, we have found that a more general definition of *energy* can play a fundamental rôle, especially as a tool to interpret and use sensor information.

This paradigm provides autonomous agents with a simple but powerful mechanism to build and maintain a world model by moving the current state of the system on the energy surface which also works as interpretation mask for sensor data. Moreover, the definition of roboticles seems very attractive for both the explanation and the design of autonomous agent control.

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