Steps to a Cyber-Physical Model of Networked Embodied Anticipatory Behavior

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Abstract. This paper proposes and discusses a modeling framework for embodied anticipatory behavior systems. This conceptual and theoretical framework is quite general and aims to be a, quite preliminary, step towards a general theory of cognitive adaptation to the environment of natural intelligent systems and to provide a possible approach to develop new more autonomous artificial systems. The main purpose of this discussion outline is to identify at least a few of the issues we have to cope with, and some of the possible methods to be used, if we aim to understand from a rigorous standpoint the dynamics of embodied adaptive learning systems both natural and artificial.

Keywords: anticipation, adaptive ,embodiment, intelligent agents, information, entropy, complexity, dynamical systems, network, emergence.

1 Introduction

According to many experimental results, [5,6,7,12,13,15], the human (and mammal) brain might be seen as a complex system which evolved mainly to control movement, in particular walking and what in the robotic domain is known as visual manipulation and grasping. To achieve that it minimizes uncertainty through Bayesian estimation, prediction of actions' consequence, controlling statistics of action effectiveness, comparing with expected outcomes and manage to smooth transition, from energy and information standpoint, from perception to action.

In the natural domain, to our knowledge, at least on our planet, the human brain is the most sophisticated cognitive machine, nevertheless the basic organizational principles are shared with more ancient living beings and are evolved on top of evolutionary earlier solutions.

There are several evidences suggesting that cognition might be an emerging adaptive (meta) process of loosely coupled networks of embodied and situated agents, [24,29]. In the natural domain the most widely used method of 'intelligence', computation and 'cognition' seems to be 'embodied' biological neural networks. Although, see [66], there are good reasons to exclude an 'intelligent design' of natural cognitive systems and although these systems have evolved not only according to 'cheap design', [22], but also 'good enough' principles, it is apparent that not only the more

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evolved human or mammal brains, but even the 'simple' 15-20000 neurons Aplysia nervous system shows much more robust than any current robotic application.

This justifies the search for biomimetic and bioinspired solutions for the co design of cognitive physical agent structure, processes and organizational principles.

Generally biological neural network are modeled by artificial neural networks, a simplified model of their natural counterpart. The original Rosenblatt's 'perceptron' [39], proposed in 1958, represents a neuron as a node of a graph where an output edge signal is triggered when a threshold of a sum of weighted connection values is reached. Although today most current neural network algorithms are more sophisticated as they do not use thresholds, but rather continuous valued squashing functions, they are still an approximation of their natural counterparts not considering plasticity and other characteristics of the biological neurons.

It is interesting to speculate on the system level characteristics which allow autonomous cognitive behavior in natural systems.

In the past years Pfeifer and other researchers, [22,23], have shown the importance of 'embodiment' and 'situatedness' in natural intelligent systems, 'passive walkers' are a clear example of that.

It is possible, anyhow, as it is pointed out by some researchers, that we still miss the quantitative framework to model the interplay between system dynamics and information processing in physical systems. In other terms we have a need to extend the theory of computation to the physical world, [65]. This (new) topic is called Cyber-Physical system theory. A 'cyber-physical' system is a physical system where there is a two ways relationship between its physical behavior and its control system. The study of the so called cyber-physical systems is a priority of US NSF (National Science Foundation).

In this paper we will show and discuss how anticipatory behaviors might emerge from a loosely network of embodied agents and which metrics might be used to develop such systems. The aim is to define a conceptual model capable of emulating the high level behaviors of natural intelligent and simple enough to be described in a quantitative way. We will describe such a conceptual and methodological framework aiming to be a first step towards a general theory on cognition in natural systems. We will derive a few preliminary relations and we will suggest some theoretical tools which in principle might allow to cope with these ambitious objectives.

This is one of the possible approaches to a quantitative representation of an intelligent physical system, equivalent others are possible.

In the next paragraph we will review the ABC (Anticipatory Behavioral Control) model that we believe captures at least some of the requisites that an intelligent embodied agent should have. In section 3 we will summarize the quantitative aspects of a quite general networked embodied intelligent system, following the discussions in [29,30] based on the findings in [25] and [34]. In section 4 we will highlight the requisites of networked embodied anticipatory systems and a possible system architecture coping with these needs.

Eventually it will be highlighted the work ahead and the open issues involved by such an approach.

2 The ABC Model

The observation of natural intelligent systems and the practice of robotics research and engineering lead us to think that 'intelligence' (and 'meaning' if not 'consciousness') are 'emerging' characteristics springing from the evolution of loosely coupled networks of intelligent 'embodied' and 'situated' agents, [23,24].

In robotics research this has led to develop some systems leveraging on the body dynamics, like in 'passive walker' approach exemplified by MIT biped and others, [35], and 'behavior based' control architecture, starting from the 'subsumption' architecture originally proposed by Brooks, [21].

The behavior based approach, in particular in the context of subsidiary architectures, has also proven capable of obtaining good performances, in tasks like navigation and obstacle avoidance and others, with a limited set of a priori hypotheses and programming effort.

This approach can be seen as a translation to the AI and robotics domain of the Stimulus-Reaction model of animal behavior dating back to Pavlov, [70], and quite popular for some time in behaviorist psychology.

It is also a natural application to robotics of the information processing model of cognition.

This approach shows some limits at least if we consider human psychology and mammals ethology as it does not consider the intentional behavior. It makes more sense to think that the function of cognitive processes is to enable the production of anticipated 'stimuli'.

The ABC theory (Anticipative Behavioral Control), [8,9,10], tries to go beyond those limits on the basis of theoretical considerations and experimental evidence, [8,5] coming from the investigation of animal and human associative learning processes and the impact of behavioral effects on the selection, initiation, and execution of simple voluntary acts.

It is shown that 'intentions', based on the anticipated outcomes of finalized actions, play a key role in the shaping of behaviors of natural cognitive systems and that this approach is different from both the 'behavior based' one and from the top down symbolic processing approach.

It is not surprising that in nature such kind of information structuring have evolved as in an open ended stochastic high dimensional, non linear and even fractional derivatives, environment the capability of generating 'cheap' and 'good enough' finalized actions strongly relies on the capability to generate 'reasonable' predictions at a low computational and energetic cost.

If we assume that the fit behavior generation model for an autonomous cognitive agent is given by something similar to the ABC model, it is interesting to understand how such a model of interaction might emerge from a loosely coupled network of embodied agents without a preset internal explicit representation and exploiting the body dynamics, according to the mentioned 'cheap design' principles. In particular it is interesting to speculate on a model of interaction with (or within?) the environment which makes possible a quantitative or semi quantitative description of the interaction.

Natural neural network themselves could be regarded as 'embodied' and 'situated' computing systems, as they are connected to a body.

So far we miss a quantitative comprehensive theory which allows us to model the interplay between the agents' 'morphology', in other words their mechanical structure, and the emerging of 'intelligence' and 'meaning'. Despite that some preliminary considerations are already possible.

3 Networks of Embodied Agents: Possible Models and Metrics

It is reasonable to think that in nature the biological neural networks are an adaptation of cell based organisms to the intelligent and cognitive tasks. This leaves open the question of which features of these systems are necessary and sufficient in order to achieve a robust cognitive adaptation to the environment (from the unstructured natural outdoor ones to the structured factory floors or human buildings).

If intelligence and cognition are emerging processes springing from loosely coupled networks of embodied physical agents, how can a 'fit' anticipatory behavior emerge from a system of this kind ? And which metrics is it possible to identify?

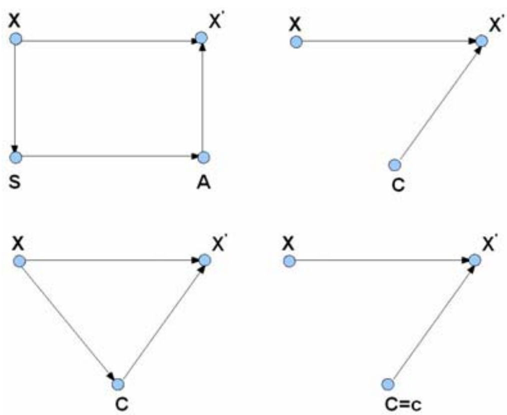

Fig. 1. Directed acyclic graphs representing a control process. (Upper left) Full control system with a sensor and an actuator. (Lower left) Shrinked Closed Loop diagram merging sensor and actuator, (Upper right) Reduced open loop diagram. (Lower right) Single actuation channel enacted by the controller's state C=c. The random variable X represents the initial state, X' the final state. Sensor is represented by state variable S and actuator is represented by state variable A.

After reviewing in this section some metrics of a network embodied system, in the following we will show how the nervous systems of natural intelligent systems might be regarded as huge networks of loosely structured 'resonators' and 'amplificators' of natural coupling processes, which actually, in simpler forms, for example in biped walking down a slope, occur without any specific and dedicated cognitive computing system.

We will first explain how, from a theoretical standpoint, a network of embodied agents can process information in the physical morphology of its agents and the network relations between the agents of the network. This discussion is taken from [25, 29, 30]. If we see, for simplicity, an embodied agent as a controlled dynamical system, as in fig. 1, it is possible to show how the algorithmic complexity of the control program is related to its phase space 'footprint'.

$$\Delta H_{controller} \cong \Delta H_{closed} - \Delta H_{open}^{\max} \leq I(X;C) \tag{1}$$

This is possible starting from [25] where Shannon theory is applied to the modeling of controlled systems and statistical information metrics based definitions of controllability and observability are derived. In equation (1) we recall the most important result in [25] from our perspective. Equation (1) applies to a general control system. The meaning of the variables is given in Fig. 1. It links the variation of Shannon entropy in the controller to the variation of entropy in closed loop (with the controller in the loop) and the maximum variation of entropy in open loop (with feed forward control) to mutual information between the state variable and the controller state. Adding some reasonable hypotheses and exploiting the results described in [34] it is possible to derive:

$$K(X) \overset{+}{\leq} \log \frac{W_{closed}}{W_{open}^{\max}} \tag{2}$$

The equation (2) bounds the algorithmic complexity of the control program (the intelligence of the agent, in a simplified view) to the phase space volume, an estimate of the number of possible system state, of the controlled agent versus the phase space volume of the non controlled system.

From a qualitative standpoint (at least) this relations explains why a simpler walker like the MIT biped or the one described in [35] can be controlled with a 'short' program, while other walkers (like the Honda Asimo, [36], or the Sony Qrio) which don't have a limit cycle and show a larger phase space 'footprint' require more complex control systems.

The Shannon entropy related measures have been shown to be useful to quantitatively characterize sensory motor coordination, the evolution of sensory layouts and the complexity of the agent environment, [26,28,32].

In general the intelligent system is here assumed to be constituted of, and to be part of, a network of weakly coupled agents.

We assume (for simplicity) that the ‘cognitive network ‘ can be accessed by all the agents which are co evolving it and in fact share (constitute) it.

The idea that learning may actually emerge from some kind of evolutionary process was actually already proposed by Turing in a famous 1950’s paper, [57].

It must be noticed that the concept model described here is one in a large class of possible models, in particular one of most convincing is the semiotic dynamics approach, [58,60]. This idea is strongly influenced by Bateson’s concept of an ‘ecology of mind’, [69].

We assume that the model of the environment is distributed among all the agents constituting the network and depends on the (co) evolution of their interactions in time. We will see below how this can be explained and quantified on the basis of relations between some information measures.

In this perspective it is interesting to notice that in [59] the mathematical model of the collective behaviors of systems like that described in [60] are based on the theory of random acyclic graphs which is the basis of most network system physics formalizations.

In [59], the network of agents, where each word is initially represented by a subset of three or more nodes with all (possible) links present, evolves towards an equilibrium state represented by fully connected graph, with only single links.

The statistical distribution, necessary to determine the information managing capability of the network of physical agents and to link to equation (2) can be obtained from equations derived in the statistical physics of network domain.
From (2) it is possible to derive the relations recalled here below (these relations are demonstrated in the appendix).

$$K(X) \overset{+}{\leq} \log \frac{W_{closed}}{W_{open}^{\max}} \tag{I}$$

As told, relation (I) links the complexity ('the length') of the control program of a physical intelligent agent to the state available in closed loop and the non controlled condition. This shows the benefits of designing system structures whose 'basin of attractions' are close to the desired behaviors in the phase space.

$$\Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I \leq I(X;C) \tag{II}$$

Relations (II) links the mutual information between the controlled variable and the controller to the information stored in the elements, the mutual information between them and the information stored in the network and accounts for the redundancies through the multi information term *ΔI*.

Relations (III) links the program complexity of the controller to the information stored in the elements, the mutual information between them and the information stored in the network.

$$K(X) = \Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I \tag{III}$$

Relations (IV) links the program complexity of the controller to the information stored in the elements the mutual information between them and the information stored in the network.

$$\Delta HN = \log \frac{\Omega_{closed}}{\Omega_{open}^{\max}} + \Delta I \tag{IV}$$

These relations are quite preliminary, and perhaps need a more rigorous demonstration, but give an insight on how information is managed within a network of physical elements or agents interacting with a given environment in a finalized way. They suggest how the cognitive adaptation is at network level: in any environment niche it is possible with small networks of highly sophisticated individual agents, like in human societies, or with many limited autonomy individuals like in ant colonies, with a great variety of possibilities in the middle.

It is worth to observe that the relations reported above are quite general and can also be applied to a continuous intelligent material structure if you consider as physical elements a suitable mesh of material finite elements, see [30]. In this case the information can be stored in the stress-deformation state itself.

On a different respect, these relations can be applied to the whole environment, meaning to the whole network of agents interacting among them over a specified threshold. The 'self' of the single cognitive agent might emerge by means of a process analogue to the mammal and human immune system, [55.56].

3.1 Example

A simple embodied agent is given by the oscillator given in fig. 2.

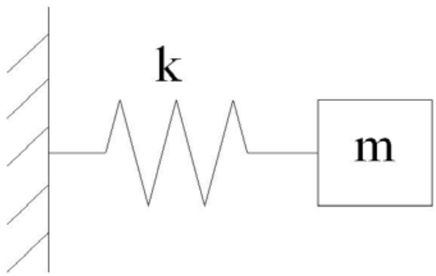

Fig. 2. A simple linear oscillator

If we apply equation (3) representing energy conservation:

$$E_{tot} = \frac{m\dot{x}^2}{2} + \frac{kx^2}{2} \tag{3}$$

We see that in phase space the system follows a closed curve. The shape of the curve depends on m and k and the initial values of x and its first derivative. If we assume an uniform distribution [0,X] for x and [0,XP] for the initial condition the phase space volume of equation (2) is given by the difference of the areas of the ellipses:

$$E_{tot}^{\max} = \frac{mXP^2}{2} + \frac{kX^2}{2} \tag{4}$$

The equation of the ellipses is:

$$\frac{m\dot{x}^2}{2E_{tot}^{\max}} + \frac{kx^2}{2E_{tot}^{\max}} = 1 \tag{5}$$

From which we derive the semi axis, a, b :

$$a = \sqrt{\frac{2E_{tot}^{\max}}{m}} \tag{6}$$

$$b = \sqrt{\frac{2E_{tot}^{\max}}{k}} \tag{7}$$

And we eventually derive the phase space volume:

$$W = \pi ab = \pi \sqrt{\frac{2E_{tot}^{\max}}{m}} \sqrt{\frac{2E_{tot}^{\max}}{k}} = \frac{2\pi}{\sqrt{km}} E_{tot}^{\max} \tag{8}$$

Assuming that the closed loop phase region is inside the open loop region, K becomes, in absolute value, close to 0 when these two area are close, while it tends (in absolute value) to infinite when we want to force the system in an phase space volume (area in this case) going to zero.

4 A possible Networked Embodied Cognitive System Model

In the previous section we have reviewed some of the metrics that a multi agent embodied intelligent system will comply to. Here we describe a conceptual model which on one side exhibit the capabilities that we think characterize the behavior of natural cognitive agents and on the other side allows the development of a a quantitative model. This quantitative model may eventually be compared to the reality and experimentally tested.

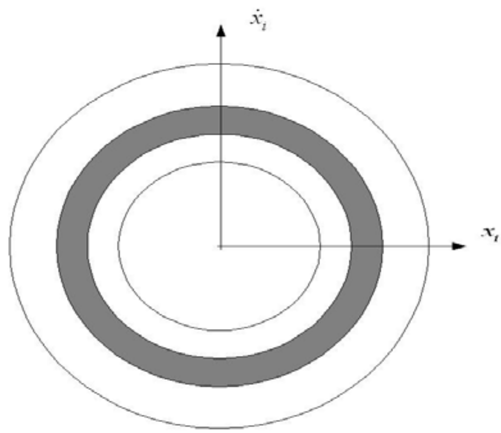

Fig. 3. Phase space portrait of the elementary oscillator

We define here a 'minimal set' networked embodied anticipatory behavior system architecture for an intelligent agent. We summarized above the requisites that an anticipatory networked embodied system should have, here we describe at functional level a possible system architecture believed to be capable of generating through self organization the required behaviors.

It seems reasonable to think that what we need is the capability to generate a wide set of coupled dynamical behaviors. Even in simpler and older cases like a moving target tracking by a rotating automated missile launch platform part of the anticipation is done by means of the inertial rotation of the platform.

A method to provide to a system a 'rich' internal dynamics is to model it as an n-dimensional set of oscillators, randomly oscillating, (modeled like in figure 3), which for simplicity can be represented as in the figure below. This set evolves into a directed acyclic graph where the links between the oscillators evolve dynamically according to homokinetics and others criteria, see [45,46,47,48]. The dynamical couplings of a chain of oscillators are described in [64].In this context 'modules' , whose 'economical' usefulness is discussed in [67], must be seen as hierarchies of basins of attraction (see genome activation schemes). Each oscillator is governed by its equations, simpler as in our example above, or more sophisticated like in [43]. The 'modules' are embodied into fractional distributed form and spring from a self organizing co evolution process extended to the environment network of relations. This constitutes an high dimensional system. Hierarchical modules are an useful way to structure data analysis as they allow to reduce uncertainty through iterated processing, [11,14,16].

In summary we connect a hierarchical modular system in the sense specified above from the sensors to a similar hierarchical modular system managing the actuators through a rich homokinetic massive loosely coupled network of chaotic self organizing oscillators. In principle a simplified version of the mathematics of Schwinger fields might be of some help here, although this has to be investigated.

As shown above in paragraph 3 the length of a control program is linked to the difference between the reachable phase space volume in open loop and the desired closed loop behaviors.

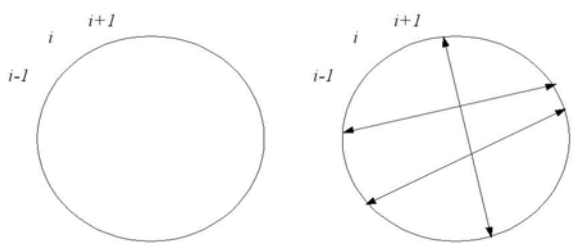

Fig. 4. Schematic representation of a network where coupling is only with the adjacent nodes, (Left). Schematic representation of a network with (weak) coupling with adjacent nodes, (Right).

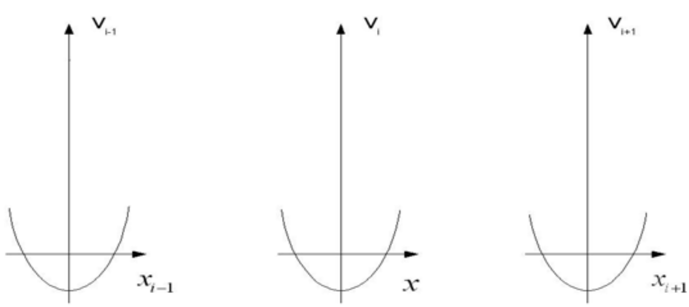

Fig. 5. Potential functions for three adjacent not coupled nodes

The Lie symmetry of the physical world, [27], as it is experienced by a mechanically extended body strongly reduces the reachable portion of the configuration and phase spaces making easier the control. The anticipation is based on the fixed point, limit cycles, attractors of the internal dynamics coupled to the 'external' environment. Consistency is guaranteed by homokinesys, energy minimization, complexity minimization criteria.

CPG will emerge naturally from a system like that described here, see [63].

A schematic representation is given in fig. 4 the links of the network allow to shape the information managed. Chaotic behaviors are induced from the outside environment noise.

There are chances that such a system might exhibit sensory substitution behaviors like those observed in the mammal and human brains and sensory motor systems, see [41,42], this has to be thoroughly investigated.

The most suitable tool to study such a system seems to be simulation as deducing closed form equations is challenging.

5 Discussion

Behavior based approaches in Robotics and AI have proven quite successful and might be considered a 'mapping ' of the S-R approach in psychology to the artificial domain. On the other end, as shown in section 2 there are hints that this might not be the best approach for the 'fit' interaction of an artificial or natural cognitive system with its environment. If we agree on that we must define an architectural framework capable to manage different anticipatory behavioral schemes.

Traditionally in GOFAI (Good Old Fashioned Artificial Intelligence), the model of the environment is explicitly mapped into the artificial system with a specifically designed symbolic structure superimposed and preimposed from the outside, by a supposedly 'omniscient' agent, the designer of the system. (and here we may observe that the knowledge of the environment of the designer is still incomplete and with an inherent probabilistic nature not necessarily capable of anticipating the real conditions with which the agent will have to cope). In control theory model based adaptive controls methods share the same inherent limitations. Predictive schemes based on stochastic identification methods like various kind of Kalman filters or less constraining polynomial observers have the advantage of doing very limited assumptions on the controlled system equations (linearity for Kalman), but lack of flexibility as the objective of the control actions must be defined in advance.

Under a certain respect, for a given physical system, the physical morphology and the natural dynamics force the possible combinations of sensor and actuator variables to a subset of all the values that in theory the system variables may assume while performing a specific task, leading to 'morphological computation', [22,23].

We need a complex adaptive system which, exploiting his embodiment and situatedness and its network relations within its environment, it is capable of interacting within its environment in a proactive and purposive way anticipating 'desired' sensor input.

A model of a typical environment should be a non linear (fractional derivatives?) stochastic many variable system exhibiting quite often itinerant chaos behavior with a constant creation and disruption of new symmetries in a fractional (in the fractal sense) context.

Actually we should not 'carve' in advance into the agent or network of agents such model as this will in any case restrict the autonomy and behavioral flexibility of the agent and limit them to the advance knowledge of the designer, but, instead we should conceive a framework which allows the 'spontaneous' emerging of the embodied model into the agent itself.

We need a general behavioral structure generator exploiting its body dynamics and environment interaction patterns. The physics of the environment allows to limit the generality of the 'abstraction' that the system must be capable to generate.
The prediction machine will be in general given by a wide set of interleaved fractional dimension – due to the attractors' fractional dimension in the phase space - internal processes continuously evolving multiply coupled with the 'external' processes originating by the active interactions (patterns) of the agent.

There is a need to explain statistical learning as an emerging process from a network of embodied agents with their own natural dynamics, [31].

As simple as it is, the model described above in the example given in paragraph 3.1 allows to represent two essential aspects of our world: inertia (through the position second derivative and mass, and a basic (linear) force, or potential field (through the linear term in x), and energy conservation. The importance of 'time delay',i.e. phase relations, have proven to be important in the human and animal brains, [40]: they are a natural outcome of a physical oscillating system.

Thanks to equation (2) we have a substantial equivalence between the computing made by the controller and that 'embodied' into the system. While the relations recalled above, in section 3, show how the tasks can be split between the different agents. A system however implemented capable of representing these basic aspects is capable to have coupled oscillations with the external environment. Biological neurons themselves can be modeled as non linear oscillators, [23,24]. On an different respect, also groups, subnetworks and networks of artificial neurons can show oscillatory behaviors. We will see below some of the consequences we can (may) draw on the basis of these facts.

In the classical target tracking example quoted above the PID controller together with 'body morphology' and the sensors allow this coupling. In this case the coupling is possible thanks to the external off line 'design' of an intelligent cognitive embodied agent: the system engineer who designed the 'intelligent' weapon.

If dynamical coupling with 'external processes' is the basis of 'fit' interaction with the external environment, what we need is a system with a rich high dimensional dynamics, capable of establishing a wide set of multi scale recursive coupled oscillations with the environment. From what we have seen above in section 3 there is a substantial equivalence between the 'extensive' information managed by the body morphology and the 'intensive' information managed by a computer or by a biological neural network.

The nervous system function in natural intelligent system might be that of massively increasing the number of dimensions of the system phase space allowing richer internal trajectories and making possible a wider number of dynamical couplings with the exterior processes. The sensors and actuators translate from the 'extensive' dynamics of the external world.

The modeling framework discussed in this paper is not the only possible one.

For example, it has been shown that artificial neural networks may show attractors and limit cycles, so a possible alternative implementation can be by means of (a special class) neural networks. It makes sense to think that the economy of program length and power absorption are more likely in nature in emerging structures coming from the evolution optimization process.

Artificial autonomous systems have the same needs. We may think anyhow that any fit quantitative model of cognition should try to unify at deep level, information, control and non linear dynamics theory and general AI to be able to account for the behavioral complexities of what we observe in nature.

We hypothesize here that hierarchical Bayesian systems observed in natural systems might be implemented as small-world networks of non linear oscillators. A single neuron might be modeled as a chaotic non linear oscillator. From this perspective there is a continuous path from the the 'cognitive' processes in metabolic networks to the higher level behaviors in animals and humans.

The basys of information processing is seen in system dynamics: like in a dance the coupled synchronized movements of the dancers deeply rely on their body inertial dynamics and the sympathetic knowledge of the other dancer inertial dynamics and 'intentions'.

It is thought that the symmetries of the physical world must be represented and mimicked inside a cognitive system. The biological neuron networks do that in a compressed volume, with limited program complexity and reduced power consumption. This is possible thanks to the signal transduction operated by the sensor actuation systems: from and to mechanical/electromagnetic (distributed) measures to chemical electrical gradients. This gives a specific meaning to the interpretation of biological neural networks as embodied massive parallel cognitive systems.

6 Conclusions

Although the theoretical framework discussed above may show serious mathematical challenges it is thought that it exemplifies some of the features that a working quantitative general models of system of the kind we investigate and we aim to reproduce technically should have. An important characteristics of this conceptual model is the attempt to ground coordination of physical intelligent agents between them and with the environment on system dynamics and related information metrics, through the relations typical of stochastic control.

In general what we need is a high dimensional system model with a rich internal dynamics capable of evolving over time many complex adaptive internal sub dinamycs coupled with the 'external' environment dynamics.

This paper aims to suggest a methodology and to highlight a few of the challenges that the development of a working example of an embodied anticipatory cognitive system still presents.

Perhaps what we need is an integrated approach putting together concepts and methods from fields so far considered separated like non linear dynamics, information, computation and control theory as well as general AI and psychology.

A lot of work has still to be done.

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Appendix: Information Metrics Relation Proofs

We will derive in the following the relations given in section 3.
In a network model like those adopted in this discussion, [53,54], the probability βi that a new node will connect to a node i already present in the network is a function of the connectivity k_i and on the fitness ηi of that node, such that

$$\prod_i = \frac{\eta_j k_i}{\sum_j \eta_j k_j} \tag{A.1}$$

A node *i* will increase its connectivity *ki* at a rate that is proportional to the probability that a new node will attach to it, giving

$$\frac{\partial k_i}{\partial t} = m \frac{\eta_i k_i}{\sum_j k_j \eta_j} \tag{A.2}$$

The factor m accounts for the fact that each new node adds m links to the system.
In [26] it is shown that the connectivity distribution, i.e. the probability that a node has k links, is given by the integral

$$P(k) = \int_0^{\eta_{\max}} d\eta \frac{\partial P\left(k_\eta(t) > k\right)}{\partial t} \propto \int d\eta \rho(\eta) \left(\frac{m}{k}\right)^{\frac{C}{\eta}+1} \tag{A.3}$$

where $\rho(\eta)$ is the fitness distribution and C is given by:

$$C = d\eta \rho(\eta) \frac{\eta}{1-\beta(\eta)} \tag{A.4}$$

We define a proper ηi function which may basically be a performance index of the effectiveness of sensory motor coordination and which control the growth of the network.

The physical agents constituting the system are connected physically, but also from an information standpoint.

Equation (A.5) gives the expression for the Shannon entropy of the network of elements:

$$HN = -\sum_{k=1}^{\infty} P(k) \log P(k) \tag{A.5}$$

where *P(k)* represents the distribution of node connections and the 'infinite' in the summation is actually the big finite number of physical elements, considered, as a simplification, coinciding with the finite elements.

It is important to notice that this is only a part of the information 'stored' into the system: the information in a single neuron or body element is given by equation (2).

The aim of this short discussion is to show that a network of physical elements can actually manage information into the structure of its internal relations, as it can be shown starting from equation (A.5). The concept model described here actually represent a large class of similar models.

In this section the discussion is related to the one in section 3, as the networks of agents we are considering here are actually embodied and situated dynamical systems, which do have a phase space representation. This allows to derive a few further relations.

We can state, for a network of n physical elements, that:

$$\Delta H_{controller} = \Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I \tag{A.6}$$

where $\Delta H_{controller}$ represents the information variation due to the controller, ΔHN is the information variation in the network itself, ΔH_i is the information variation for a single embodied agent, ΔI the multi information between the n agents of the network and the network itself, this last term account for redundancies in information measures between the individual 'intelligent elements' of the structure and the structure itself.
From equation (1), we have:

$$\Delta H_{closed} - \Delta H_{open}^{\max} = \Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I \tag{A.7}$$

And:

$$\Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I \le I(X;C) \tag{A.8}$$

This is relation (II)
Furthermore:

$$K(X) = \Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I \tag{A.9}$$

This is relation (III)
And from (2) and (A.6):

$$\Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I = \log \frac{W_{closed}}{W_{open}^{\max}} \tag{A.10}$$

Applying again equation (2):

$$\Delta HN + \sum_{i}^{n} \log \frac{W_{closed(i)}}{W_{open(i)}^{\max}} - \Delta I = \log \frac{W_{closed}}{W_{open}^{\max}} \tag{A.11}$$

We derive:

$$\Delta HN - \Delta I = \log \frac{W_{closed}}{W_{open}^{\max}} - \log \prod_{i}^{n} \frac{W_{closed(i)}}{W_{open(i)}^{\max}} \tag{A.12}$$

If we define the quantities in (A.13), (A.14):

$$\Omega_{closed} = \frac{W_{closed}}{\prod_{i}^{n} W_{closed(i)}} \tag{A.13}$$

$$\Omega_{open}^{\max} = \frac{W_{open}^{\max}}{\prod_{i}^{n} W_{open}^{\max}} \tag{A.14}$$

We obtain equation (A.15):

$$\Delta HN = \log \frac{\Omega_{closed}}{\Omega_{open}^{\max}} + \Delta I \tag{A.15}$$

This is relation (IV)