New Trends in Computing Anticipatory Systems : Emergence of Artificial Conscious Intelligence with Machine Learning Natural Language

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Abstract. This paper deals with the challenge to create an Artificial Intelligence System with an Artificial Consciousness. For that, an introduction to computing anticipatory systems is presented, with the definitions of strong and weak anticipation. The quasi-anticipatory systems of Robert Rosen are linked to open-loop controllers. Then, some properties of the natural brain are presented in relation to the triune brain theory of Paul D. MacLean, and the mind time of Benjamin Libet, with his veto of the free will. The theory of the hyperincursive discrete anticipatory systems is recalled in view to introduce the concept of hyperincursive free will, which gives a similar veto mechanism: free will as unpredictable hyperincursive anticipation The concepts of endo-anticipation and exo-anticipation are then defined. Finally, some ideas about artificial conscious intelligence with natural language are presented, in relation to the Turing Machine, Formal Language, Intelligent Agents and Mutli-Agent System.

Keywords: anticipatory systems, computing, artificial intelligence, consciousness, and natural language.
PACS: 07.05.Mh, 05.65.+b

1. INTRODUCTION

The successive CASYS'98, CASYS'99, CASYS 2000, CASYS'01, CASYS'03, and CASYS'05 International Conferences followed the First International Conference, CASYS'97, held at HEC in 1997.

So, this year 2007, with this 8th International Conference, CASYS'07, one celebrates the 10 years of studies and research on Computing Anticipatory Systems.

In looking at the program of this CASYS'07 International Conference, one notices a large number of papers dealing with computational intelligence and intelligent agents related to computing anticipatory systems.

The invited speaker, Professor Igor Aleksander presented his research results in the field of the machine consciousness.

This is a breakthrough, with a shift of paradigm from a living to a non-living origin of conscious intelligence.

A parallel may be made with anticipatory systems that, originally, were thought to be the sole property of living systems. It was demonstrated that anticipation plays a role in many other systems in physics, management and engineering.

It is interesting to notice that the conscious intelligence is entangled to anticipation, and this will open very new applications in the future.

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2. INTRODUCTION TO ANTICIPATORY SYSTEMS

Some definitions about the concept of Anticipatory Systems are presented in the two following sections.

In the first section, I will recall some definitions dealing with Computing Anticipatory Systems. What is important is the fact that Anticipatory Systems can be computed with the tools that I have developed [3, 4, 5, 6, 7].

The second section will recall the definition of Anticipatory Systems by Robert Rosen, with a few comments on his work published in his book [12].

2.1. Computing Anticipatory Systems

My definition of a computing anticipatory system is as follows:

"A computing anticipatory system is a system that computes its current states in taking into account its past and present states but also its potential future states."

I defined two categories of anticipatory systems:

"Strong anticipation refers to an anticipation of events built by or embedded in a system."

"Weak anticipation refers to an anticipation of events predicted or forecasted from a model of a system."

An important class of computing anticipatory systems deal with differential functional differential delayed-advanced difference equations [6, 7].

Let us just gives a simple example of Two Coupled Delayed-Advanced Oscillators [6]:

$$dx(t)/dt = a_1.y(t + \tau) + a_2.x(t) \tag{1a}$$
$$dy(t)/dt = - b_1.x(t - \tau) - b_2.y(t) - \alpha.u(t) \tag{1b}$$
$$du(t)/dt = - c_1.v(t - \tau) - c_2.u(t) \tag{1c}$$
$$dv(t)/dt = d_1.u(t + \tau) + d_2.v(t) + \beta.x(t) \tag{1d}$$

where the first oscillator is characterised by the variables x(t) and y(t), and the second oscillator by the variables u(t) and v(t), and where t is the current time.

These eqs. 1abcd are a system of 4 differential equations with delayed time, $t - \tau$, time and advanced time, $t + \tau$.

The variables with a delayed time, as $x(t - \tau)$ and $v(t - \tau)$, are defined with a temporal retardation, and represents the past value of the variables, known at the current time: these are variables with a memory of the past values. The variables with an advanced time, as $y(t + \tau)$ and $u(t + \tau)$, are defined with a temporal anticipation, and represents the potential future value of the variables, known at the current time: these are variables with the projected future values. The other variables with a current time, as x(t), y(t), u(t) and v(t), are defined at the present time.

Another class of computing anticipatory systems deal with discrete equations. A review of Incursive and Hyperincursive Systems, the Fractal Machine, and Anticipatory Logic, is given in [5].

Let us just recall the definitions of discrete strong and weak incursive systems:

Definition of an incursive discrete strong anticipatory system [6]: an incursive discrete system is a system which computes its current state at time t, as a function of its states at past times, …, t–3, t–2, t–1, present time, t, and even its states at future times t+1, t+2, t+3, ….

$$x(t+1) = A(\ldots, x(t-2), x(t-1), x(t), x(t+1), x(t+2), \ldots;p) \tag{2a}$$

where the variable x at future times t+1, t+2, … is computed in using the equation itself. Such an incursive system is self-referential because it computes its future states from itself and not from a model-based prediction.

Definition of an incursive discrete weak anticipatory system [6]: a weak incursive system is a system which computes its current state at time t, as a function of its states at past times, …, t–3, t–2, t–1, present time, t, and even its predicted states at future times t+1, t+2, t+3, ….

$$x(t+1) = A(\ldots, x(t-2), x(t-1), x(t), x^*(t+1), x^*(t+2), \ldots;p) \tag{2b}$$

where the variable x* at future times t+1, t+2, … are computed in using a predictive model of the system.

Such weak anticipatory systems may be related to the Robert Rosen definition of an anticipatory system, which is given in the following section.

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2.2 The Quasi-Anticipatory Systems of Robert Rosen

Robert Rosen "tentatively defined the concept of an anticipatory system; a system containing a predictive model of itself and/or of its environment, which allows it to state at an instant in accord with the model's predictions pertaining to a later instant" [12, p. 339].

Robert Rosen stated on one hand, that the evolution of an anticipatory system, S, at each time step, is driven by the predictive model, M, at a later time. But, on the other hand, Robert Rosen said that the predictive model, M, is not affected by the system. He also stated explicitly that an anticipatory system works without feedback.

Let us cite Robert Rosen [12, p. 12]:

"We shall now allow M and S to be coupled; i.e. allow them to interact in specific ways. For the present, we shall restrict ourselves to ways in which M may affect S; later we shall introduce another mode of coupling which allow S to affect M (and which will amount to updating or improving the model system M on the basis of the activity of S)."

Let us show that the concept of anticipatory systems by Robert Rosen is similar to an open-loop controller.

In the engineering science, the control systems are classified in two categories. The first category of control system is called "open-loop control" and the second category is called "closed-loop control".

An open-loop-controller, also called a "non-feedback controller", is a type of controller that computes its input into a system using only the current state and its model of the system processes. The main characteristic of the open-loop controller is that it does not use feedback to determine if its input has reached the wanted goal. This means that the controller does not measure the output of the system that it is controlling. Consequently, a true open-loop controller may not engage in machine learning, cannot compensate for disturbances in the system, and cannot correct any errors that it could provoke.

Generally, to obtain a more accurate or more adaptive control, it is necessary to feed the output of the system back to the inputs of the controller. This type of system is called a closed-loop controller.

The open-loop controllers are useful for well-defined systems where the relationship between input and the resultant state can be perfectly modeled by a mathematical formula. This is a very drastic condition.

The fact to make an open-loop control is similar to make a control in blind, without seeing the consequence of what we are doing. This is just accurate for purely fully predictable deterministic systems for which an exact mathematical model can be made and simulated.

So, in the general introduction of his book [12, p. 13], Robert Rosen wrote:

"It would be an anticipatory system in the strict sense if M were a *perfect* model of S (and if the environment were constant or periodic).

Since in general M is not a perfect model, for reasons to be discussed in Chapter 5 below, we shall call the behaviour of such systems *quasi-anticipatory*."

Robert Rosen was conscious that the main difficulty in his approach to anticipatory systems is the mathematical modelling of systems. Hence, his book is mainly concerned with seven chapters on modelling and only one chapter on Anticipatory Systems.

3. NATURAL BRAIN AND CONSCIOUS INTELLIGENCE

This section deals with some interesting features about the human brain, the consciousness, and the free will, as an introduction for the next section on artificial conscious intelligence.

The human brain is the source of the conscious and cognitive mind.

The mind is the set of cognitive processes related to perception, interpretation, imagination, memories, and crucially language of which a person may or may not be aware.

Beyond cognitive functions, the brain regulates autonomic processes related to essential body functions such as respiration and heartbeat, and moreover controls all movement.

3.1. MacLean's Evolutionary Triune Brain Theory

It is interesting to know what is the structure of the human brain. This may gives some ideas about the function of the conscious intelligence.

Paul D. MacLean [9] proposed that the human brain was in reality three brains in one: the reptilian complex, the limbic system, and the neocortex. This is called the MacLean's evolutionary triune brain theory.

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This theory seeks to explain brain function through the evolution of existing structures of the human brain.

The reptilian complex controls normal involuntary behavior that the conscious mind does not, such as the cardiac and respiratory functions. The reptilian complex is found in all vertebrates and is the most ancient part of a brain scheme in the evolution.

The Limbic system, which was first introduced by MacLean [10], is similar to the brain of the more primitive mammals and is the source of emotions, behaviour and long term memory.

The neo-cortex, also known as the cerebral cortex, resembles the brain of more recent mammals in that it controls more highly evolved mentation such as reason and speech. It is involved in higher functions such as sensory perception, generation of motor commands, spatial reasoning, and, in humans, language and conscious thought.

3.2. The Four Consciousness Types

In my book, The Labyrinth of Intelligence [2], four types of consciousness are defined.

Firstly, I defined the two states of objective psychological consciousness of the left hemisphere of the brain that are called the "consciousness", that is to say the conscious of our acts, and the "meta-consciousness", that is to say the "consciousness of the consciousness" or the "conscious consciousness".

The "unconsciousness" is the "unconscious consciousness".

NB: The translation of the English words of "consciousness" and "awareness", gives one word in French language: "conscience".

Secondly, I defined the two states of subjective psychological consciousness of the right hemisphere of the brain, that are called "self-consciousness", that is to say the conscious to feel oneself, and the "meta-self-consciousness" that is the "self-consciousness of the self-consciousness" or the "self-conscious self-awareness".

The global conscious is constituted with interaction loops between these four types of consciousness.

Is the consciousness important for the development of intelligence ?

The natural evolution of the life and species was performed in a natural way by a Darwinian mechanism.

No conscious intelligence was at the origin of the creation of intelligent species, as humans, by the natural selection.

Following Jean-Paul Sartre:

"La seule façon d'exister pour la conscience, est d'avoir conscience d'exister".

"The only way to exist for the consciousness, is to have consciousness to exist".

So, the consciousness without a consciousness of itself is a state of "unconsciousness".

3.3. The Mind Time of Benjamin Libet

Benjamin Libet studied, experimentally, how the human conscious awareness emerges in the brain. In his book "MIND TIME – The Temporal factor in Consciousness" [8], Libet describes all his extraordinary discoveries. His experiments reveal a substantial delay, the "mind time", before any awareness affects how we view the human mental activities. If unconscious processes precede any conscious awareness, this means that unconscious processes initiate the conscious experiences. Freely voluntary acts are initiated unconsciously before an awareness of wanting to act.

Indeed, Benjamin Libet measured the response time between the moment the brain of a patient was stimulated and the time the patient became consciously aware of the stimulus. He found there was a consistent half-second delay between the unconscious reaction of the patient and their conscious awareness of the stimulus.

Moreover, he continued his work with even more experiments to refine his theories of mind, brain and consciousness. Those experiments also involved using electrodes to measure the response times of the brain, and he found, for example, that when a volunteer was instructed to move a finger, the brain unconsciously initiated the movement even before the volunteer was aware that the finger had begun moving.

This seemed to indicate that "free will" might not exist in humans at all. But Benjamin Libet disagreed, because his experiments showed that if his subjects were told not to move a finger, or to stop moving it, their conscious will would maintain complete control. The conscious will could block performance of the act and veto it. These discoveries have profound implications for the nature of free will.

So, after the results of Benjamin Libet, the free will only consists in the possibility to say NO, what is a veto. In consequence, the brain in an unconscious way creates and launches the future event before the knowledge of this event reaches the conscious part of the brain. At that moment, the conscious brain can accept or refuse this event.

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This means that in these experiments, there is no place for the conscious brain to create and launch future event. The unconscious brain anticipates the future decision of the conscious brain, but the conscious brain can block this decision.

In the next section, we will show some properties of Hyperincursive systems related to free will, that I proposed in a preceding paper [4], and which seem in agreement with the Benjamin Libet discoveries on the veto of the free will.

4. THE HYPERINCURSIVE FREE WILL

In view of understanding what is the hyperincursive free will, the next section, reprinted from [6, section 5] deals with the definition and the mathematical relation of an example of Hyperincursive system.

4.1. Hyperincursive Discrete Anticipatory System

Definition of a hyperincursive discrete anticipatory systems: a hyperincursive discrete anticipatory system is an incursive discrete anticipatory system generating multiple iterates at each time step.

4.1.1. Example: Hyperincursive Unpredictable Anticipatory System

The following equation

$$x(t) = a.x(t+1).(1-x(t+1)) \tag{3}$$

defines an hyperincursive anticipatory system. Hyperincursion is an incursion with multiple solutions.
With $a = 4$, mathematically $x(t+1)$ can be defined as a function of $x(t)$

$$x(t+1) = 1/2 \ \pm 1/2 \ \sqrt{(1-x(t))} \tag{4}$$

where each iterate $x(t)$ generates at each time step two different iterates $x(t+1)$ depending of the plus minus sign. The number of future values of $x(t)$ increases as a power of 2. This system is unpredictable in the sense that it is not possible to compute its future states in knowing the initial conditions. It is necessary to define successive final conditions at each time step. As the system can only take one value at each time step, something new must be added for resolving the problem.
Thus, the following decision function $u(t)$ can be added for making a choice at each time step:

$$u(t) = 2.d(t)-1 \tag{5}$$

where $u = +1$ for the decision $d = 1$ (true) and $u = -1$ for the decision $d = 0$ (false).
In introducing eq. 5 to eq. 4, the following equation is obtained:

$$x(t+1) = 1/2 + (d(t)-1/2).\ \sqrt{(1-x(t))} \tag{6}$$

The decision process could be explicitly related to objectives to be reached by the state variable x of this system. This is important to point out that the decisions $d(t)$ do not influence the dynamics of $x(t)$ but only guide the system which creates itself the potential futures. A similar hyperincursive anticipatory system was proposed as a model of a stack memory in neural networks [3].

Some properties of hyperincursive systems related to free will that I proposed in a preceding paper [4], are detailed in the two following sections.

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4.2. Free Will as Unpredictable Hyperincursive Anticipation

This section is reprinted from my paper [4, section 6.1], and is related to the question about the free will. Karl Pribram asked me (by email, after the CASYS'99 conference):

"How can an anticipatory hyperincursive system be modeled without a future defined goal?".

My answer was: an hyperincursive anticipatory system generates multiple potential states at each time step and corresponds to one-to-many relations. A selection parameter must be defined to select a particular state amongst these multiple potential states. These multiple potential states collapse to one state (amongst these states,) which becomes the actual state.

This reminds me the following comment an auditor made after a conference on anticipatory hyperincursion I made: "You have found the basic theory of free will".

Indeed, the brain may be considered as an anticipatory hyperincursive neural net which generates multiple potential future states which collapse to actual states by learning: the selection process of states to be actualized amongst the multiple potential states is independent of the fundamental dynamics of the brain, independent of initial conditions and so completely unpredictable (and computable). The selection by learning deals with inputs from the brain itself (via the genetic code and self-reflection) and from environment. These inputs are final causes at each time step. This creates a memory and at the same time a program, which give rise to the mind, what I called a computing memory. Each mind is unique in the sense that this is the subjective experience of each brain that actualized potential states. The free will means that we can choose a state amongst the multiple potential states emerging from the preceding already actualized states. The free will depends strongly on the history of all the past memorized events and is not identical for each mind. The free will does not means that the mind can make what he wants but that he can choose amongst multiple possible choices. For a human being, this is not possible to fly by itself, like a bird, but man invented airplanes to actualize that.

4.3. Endo-Anticipation and Exo-Anticipation

This section, reprinted partially from Dubois [4, section 6.3], deals with exo-anticipation and endo-anticipation, in relation with the free will.

4.3.1.Definition of Exo-Anticipation

An exo-anticipation is anticipation made by a system about external systems.

The anticipation can be based on a model of the environment, for the prediction of the weather, for example.

We can define three classes of prediction for general system models.

1. Totally predictable systems: Laws of mechanics and physics. The space flight is an excellent example.

2. Partially predictable systems. A chaotic system is partially predictable for a short period of time, like the prediction of the weather. Stochastic systems are statistically predictable. Statistical trends (used from experimental values) are also partial predictable systems.

3. Totally unpredictable systems: The non-decidable problems are unpredictable as formalized by Gödel. Example: the halting problem for a Turing Machine is unpredictable. A Turing Machine cannot predict if an other Turing Machine will halt or not: the Turing Machine will halt if it doesn't halt and halt if it doesn't halt: $H = 1 - H$. After the "cat in the box" problem of Schrödinger, in quantum mechanics, before opening the box, we do not know if the cat is dead or alive. When you throw a dice, or a coin, you cannot predict the issue: the dice and the coin have no memory.

4.3.2. Definition of Endo-Anticipation

An endo-anticipation is anticipation built by a system or embedded in a system about its own behavior.

The free will is an endo-anticipation: human being builds its behavior by anticipation (he can write her/his anticipatory behaviors in her/his agenda: this is not predictive anticipation but built anticipation).

It is also important to not confound the anticipation with a final goal as defined in cybernetics and system science.

Let us give an example of endo-anticipation with the theorems building. In mathematics, all the theorems are written following the sequence Hypothesis, Thesis, Demonstration. The goal of this mathematical game is to find the

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connection (the demonstration) between the hypothesis and the thesis. For creating a new theorem, two strategies exist. At one hand, the mathematician starts with a hypothesis without any idea about the thesis; so he builds several (potential) mathematical developments from the hypothesis and looks at the different thesis he obtains and then he selects (actualizes) one thesis which will give rise to a new theorem. At the other hands, the mathematician tries to find the hypothesis from a thesis he has created and for which he would like a confirmation. The demonstration process is then reversed: starting from a potential thesis, he builds mathematical developments until he obtains results in agreement with the previous theorems. The potential thesis will be actualized when the hypothesis will be found, and a new theorem is then created. Moreover, the mathematician will nevertheless present his theorem as Hypothesis, Thesis, Demonstration, even if this does not correspond to the time sequence of steps for the construction of the theorem. The final goal of the mathematician is to build a theorem and for making this, the mathematician anticipates all the steps of construction of the theorem, but all the multiple potential anticipations are not actualized.

5. ARTIFICIAL CONSCIOUS INTELLIGENCE WITH NATURAL LANGUAGE

The most important challenge in the Artificial Intelligence Technology deals with the possibility to create an Artificial Consciousness in a computing machine.

5.1. Artificial Consciousness

Igor Aleksander [1] gives the following definition of Artificial Consciousness:

"Artificial consciousness (AC), also known as machine consciousness (MC) or synthetic consciousness, is a field related to artificial intelligence and cognitive robotics whose aim is to define that which would have to be synthesized were consciousness to be found in an engineered artifact".

The ability to predict or anticipate foreseeable events is considered important for AC by Igor Aleksander. Anticipation could be used to make a machine appear conscious. An artificially conscious machine should be able to anticipate events in order to respond to them when they occur. Learning is also considered necessary for AC.

There are fundamental questions on the relation between Brain and Turing Machine, and between Natural Language and Formal Language.

Any real computer is based on the model of the Turing Machine.

A Turing machine, described by Alan Turing in 1936, is a basic abstract symbol-manipulating device that, despite its simplicity, can be adapted to simulate the logic of any computer algorithm. The Turing machine mathematically models a machine that mechanically operates on a tape on which symbols are written, which it can read and write one at a time using a tape head; operation is fully determined by a finite set of elementary instructions.

Any computing machine use artificial languages, based on Formal Language.

A formal language is a set of words, given by finite strings of letters, or symbols. The inventory from which these letters are taken is called the alphabet over which the language is defined. A formal language is defined by means of a formal grammar, and based on purely syntactical rules, so there is not necessarily any meaning associated with it. Formal languages are studied in the fields of logic, computer science and linguistics. Their practical application is for the precise definition of syntactically correct programs for a programming language.

The Formal Language theory is the field of mathematics and computer science that is concerned only with the purely syntactical aspects of such languages, given by their internal structural patterns. Although it is not part of the language, the words of a formal language have a semantic dimension, which is always tied very closely to the structure of the language, and a formal grammar can help to deal with the meaning of (well-formed) words.

5.2. Toward an Artificial Conscious Intelligence with Natural Language

The concept of Artificial Intelligence was created in the years 1940's, with the fundamental paper of W. S. McCulloch and W. Pitts [11] on the formal neuron. This opened a new area of research in the domain of Neural Networks. This was also at this period that the first computers appeared. With the evolution of the technology, the computing power of the computers evolves continually.

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Since the years 1990’s, the development of neural networks began to be important, because computers became sufficiently powerful to simulate them.

Another field dealing with distributed artificial intelligence appeared with the development of Intelligent Agents and Multi-Agent Systems. An Intelligent Agent is an entity that can observe and act upon an environment and directs its activity towards achieving goals. Intelligent Agents may also use learning and knowledge to help them achieve their goals. A Multi-Agent System (MAS) is a system composed of multiple interacting intelligent agents. Multi-agent systems can be used to solve problems that are difficult or impossible for an individual agent. Typically Multi-Agent Systems refer to software agents. However, the agents in a multi-agent system can be robots, or contain combined human-agent teams. Multi-Agent Systems can manifest self-organization and complex behaviours even when the individual strategies of all their agents are simple. Agents can share knowledge using any agreed language, within the constraints of the communication protocol.

Since its origin 50 years ago, Artificial Intelligence has not resolved the fundamental property of Natural Intelligence: our computers understand nothing and are not able to comprehend the meaning of our language.

At my personal view, I believe that the logical framework of the description of intelligence and consciousness is too restrictive to be able to efficiently work, and I propose the following conjecture:

“When a machine will be able to comprehend our language and to dialogue with us, thus an artificial conscious intelligence will naturally emerge in the machine”.

6. CONCLUSION

This paper deals with the challenge to create a computing system, which will show the emergence of an Artificial Conscious Intelligence with machine learning the Natural Language.

This will be a new trend for the field of computing anticipatory systems.

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