Quantum Cognitive Computation by CICT

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Abstract

We show and discuss how computational information conservation theory (CICT) can help us to develop even competitive advanced quantum cognitive computational systems towards deep computational cognitive intelligence.

*CICT new awareness of a discrete HG (hyperbolic geometry) subspace (reciprocal space, RS) of coded heterogeneous hyperbolic structures, underlying the familiar **Q** Euclidean (direct space, DS) system surface representation can open the way to holographic information geometry (HIG) to recover lost coherence information in system description and to develop advanced quantum cognitive systems.*

This paper is a relevant contribution towards an effective and convenient "Science 2.0" universal computational framework to achieve deeper cognitive intelligence at your fingertips and beyond.

Keywords: *Cognitive intelligence; computational intelligence; CICT; deep learning; deep thinking.*

1. INTRODUCTION

In a different paper published elsewhere we already discussed the major intrinsic limitations of "Science 1.0" brain arbitrary multiscale (AMS) modeling and strategies to get better simulation results by "Science 2.0" approach [1], by using computational information conservation theory (CICT) framework.

Here we like to stress how CICT can help in quantum cognitive computation modeling. In fact, CICT new awareness of the hyperbolic framework of coded heterogeneous hyperbolic structures in reciprocal space (RS), underlying the familiar Euclidean (direct space, DS) surface representation system, emerged from the study of the geometrical structure of the discrete manifold of ordered hyperbolic substructures, coded by formal power series, under the criterion of evolutive structural invariance at arbitrary precision [2].

CICT sees rational geometric series as simple recursion sequences in a wider recursive operative framework where all algebraic recursion sequences of any countable higher order include all the lower order ones and they can be optimally mapped to rational number system ***Q*** operational representations and generating functions exactly. CICT sees natural Integers ***N*** as specific numeric resonances emerging out of the OECS (optimized exponential cyclic sequence) [3] manifold ***Q*** of rational values. In turn, OECS can be thought as emerging out from the peculiar numeric resonances of irrational numeric sequences generated by DS-RS coherent cross-interaction with their duals [4]. DS-RS cross-interaction with their duals is assumed to be our representation fundamental property to model our spacetime quantum field theory (QFT) fluctuations effectively [4].

QFT has emerged from major paradigm shift with respect to Classical Physics which still provides the framework of the vision of nature of most scientists. All the implications of this big change have not been realized hitherto, even less their related, vital applications [5]. The discreteness approach, developed under the Quantum Theory (QT) "discreteness hypothesis" (DH) assumption, has been considered in peculiar application areas only. It has been further slowly developed by a few specialists and less understood by a wider audience to arrive to the fresh QFT approach.

Data, information, knowledge, and intelligence are the four hierarchical layers of cognitive objects in the brain and cognitive systems from the bottom-up (BU). Cognitive Informatics (CI) is a transdisciplinary enquiry of computer science, information sciences, cognitive science, and intelligence science that investigates into the internal information processing mechanisms and processes of the brain and natural intelligence, as well as their engineering applications in cognitive computing.

The LRMB (Layered Reference Model of the Brain) [6], [7] provides an integrated framework for modeling the brain and the mind. LRMB also enables future extension and refinement of the CPs (Cognitive

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Processes) within the same hierarchical framework. LRMB can be applied to explain a wide range of physiological, psychological, and cognitive phenomena in cognitive informatics, particularly the relationships and interactions between the inherited and the acquired life functions, those of the subconscious and conscious CPs, as well as the dichotomy between two modes of thought: "System 1", fast, instinctive and emotional; "System 2", slower, more deliberative, and more logical [8]. CICT can provide LRMB with a natural computational framework to capture even quantum system behavior modeling effectively.

The human brain is at least a factor of 1 billion more efficient than our present digital technology, and a factor of 10 million more efficient than the best digital technology that we can imagine [9]. The unavoidable conclusion is that we have something fundamental to learn from the brain and neurobiology about new ways and much more effective forms of computation representation. Unfortunately, fundamental research, the attitude of embracing the edge of the unknown, the ground training for inspiration and creativity, the engine of transformational progress, is in decline in many current university institutions all over the world and mainly in Italy. Science institutions suffer from the ongoing creation vs. caution conflict. We need revisiting our fundamental research tools and reinventing our scientific ecosystem to enhance solid collaborative, relational competence for real innovation development and beyond, towards a more sustainable economy and wellbeing, in a global competition scenario.

2. BRAIN PERTINENT NUMBERS

The fact that we can build devices that implement the same basic operations as those the nervous system uses leads to the inevitable conclusion that we should be able to build entire systems based on the organizing principles used by the nervous system.

In fact, a major goal of computational neuroscience is to produce predictive mesoscale theories of biological computation that bridge the gap between the cells and behaviors of complex organisms thereby explaining how the former give rise to the latter. Until recently there was little hope of formulating testable theories of this sort. However, with new technologies for recording the activity of thousands, even millions of neurons simultaneously, it is now feasible to observe neural activity at a scale and resolution that opens the possibility of inferring such theories directly from data.

By anatomical and biophysical point of view, estimated adult human total neuron number is 86 ±81 billions and equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain [10]. About 19% of all brain neurons are located in the cerebral cortex (including subcortical white matter) with average cell density (CD) about $10^7/cm^2$ and synapse density (SD) about $10^{11}/cm^2$, while about 80% of all brain neurons are in the cerebellum. The human cerebral cortex is 2 to 4 millimeters (0.079 to 0.157 in) thick. Adult humans have about 100 trillion (10^{14}) synapses.

A systematic account of exploratory neuroscientific research that would allow researchers to form new concepts and formulate general principles of brain connectivity, and to combine connectivity studies with manipulation methods to identify neural entities in the brain can be found in [11].

The emerging field of connectomics combines such advances with classic methods (e.g., micro-anatomy and electrophysiology) to uncover organizational principles of the human brain. In contrast to hypothesis-driven, task-based research, the discovery science of connectomics often uses data-driven methods and large sample sizes [12],[13]. Human brain is a network of networks [14], but current experimental designs of functional connectivity studies do not provide necessary conditions for identifying large scale networks nor do the different clustering algorithms in such studies equally account for gradually changing connectivity profiles [15]. The validity and integration of system-level results will depend on which organizational units can be experimentally established at the mesoscopic scale.

There is, however, relatively little known about how microscale molecular processes implement the computations that underlie cognition and ultimately cause observable macroscale behavior. New optogenetic devices may supersede current measurement technologies in a few years with more precise tools for intervention and new options for recording [16], but for now we can depend on a relatively mature technology accelerated by Moore's law to sustain us for the next couple of years.

In the meanwhile, we have to refer to reliable past research data sources. It has been noted that different cortical regions display a "vertical" organization of neurons grouped into columnar arrangements that take two forms: macrocolumns, approximately 0.4-0.5 mm in diameter [17], and minicolumns approximately 30 microns in diameter [18]. Macrocolumns were first identified functionally by Mountcastle [19], who described groups of neurons in somatosensory cortex that respond to light touch alternating with laterally adjacent groups that respond to joint and/or muscle stimulation. These groups form a mosaic with a periodicity of about 0.5 mm. Similarly, Hubel and Wiesel [20],[21] using both monkeys and cats discovered alternating macrocolumns of neurons in the visual cortex that respond preferentially to the right or to the left eye. These "ocular dominance columns" have a spacing of about 0.4 mm. In addition, they discovered within the ocular dominance columns smaller micro- or minicolumns of neurons that respond preferentially to lines in a particular orientation. Once these physiological minicolumns were recognized, it was noted that vertically organized columns of this approximate size are visible in many cortical areas under low magnification and are composed of perhaps 100 neurons stretching from layer V through layer II. To prove that the morphologically defined minicolumns are identical to the physiologically defined minicolumn would require directly measuring the response of a majority of the neurons in a single histologically identified microcolumn, but this has yet to be done [22].

Current data on the microcolumn indicate that the neurons within the microcolumn receive common inputs, have common outputs, are interconnected, and may well constitute a fundamental computational unit of the cerebral cortex [22]. The challenge currently debated is how to record from exactly one minicolumn in an awake, behaving model such as a mouse. Most current 2-D microelectrode arrays are on the order 5-10 mm and the latest 3-D optogenetic array from Boyden's lab is on the order of a couple of millimeters with about 150 μm resolution along one of the x or y axis and perhaps a tenth of that along the z axis and the other x or y axis [16]. According to [23], a minicolumn is on the order of 28-40 μm and there are about 2×10^8 minicolumns in human brain. Estimates of number of neurons in a minicolumn range from 80-100 neurons in the average. Computerized image analysis reveals a fairly consistent range for minicolumn size in humans, between 35 and ~60 μm, depending on the area examined [23]. In 2000, a study utilizing a novel approach provided a mean value of 80 μm for "intercolumnar distance" and a 50 μm width for columns [24].

Taking into consideration all previous cerebral cortex data, the minicolumn average size is about 6 x 10^{-12} [m^3]. Assuming the minicolumn as networked computational unit (CU), we can model it as simple harmonic oscillator (SHO) with a resonant frequency of 20 [Hz] and a radius R in Modified Phase Space. In this way, assuming a strength of magnetic field H = ½ picotesla = ½ 10^{-12} Tesla [$kg\cdot s^{-2}\cdot A^{-1}$], we can estimate the SHO equivalent energy of about 10^{-31} joule [J or Kg $(m/s)^2$], corresponding to an associated, hypothetical quantum state. This result effectively indicate that the energy process is at the quantum scale level, and that a small change ΔR in R can give a significant change in the related energy $f(R^2)$.

Therefore, to minimize or overcome major system limitations and to arrive much closer to fourth generation adaptive learning, DL, deep thinking (DT) and real machine intelligence systems, we need to extend our traditional system model representation understanding first, taking into consideration quantum field theory (QFT) main interactions conveniently.

3. QFT MAIN INTERACTIONS

In quantum physics, the space-time distribution of matter and energy has a coarse-grained structure which allows its representation as an ensemble of quanta (particle representation). The local phase invariance is shown to hold if a field exists which is connected to the space-time derivatives of the phase.

In the case of a system made up of electrically charged components (nuclei and electrons of atoms), as, for instance, a biological system, this is just the electromagnetic (e.m.) potential $\mathbf{A}_\mu$, where μ is the index denoting the usual four space-time coordinates $x_0 = ct$, x_1, x_2, x_3 [25],[26]. Let us, first of all, realize that in quantum physics the existence of gauge fields, such as the e.m. potential, dictated by the physical requirement that the quantum fluctuations of atoms should not be observable directly, prevents the possibility of having isolated bodies. For this reason, the description of a physical system is given in terms of a matter field, which is the space-time distribution of atoms/molecules, coupled to the gauge field with the possible supplement of other fields describing the nonelectromagnetic "granularity" interactions, such as the chemical forces. According to the principle of complementarity, there is also another system representation where the phase assumes a precise value; this representation which focuses on the wave-like features of the system cannot be assumed simultaneously with the particle representation. The relation between these two representations is expressed by the uncertainty relation, similar to the Heisenberg relation between position and momentum. This time we have:

$$\Delta N \, \Delta\varphi \geq 1/2 \tag{1}$$

connecting the uncertainty of the number of quanta (particle structure of the system) ΔN and the uncertainty of the system phase (which describes the rhythm of fluctuation of the system) $\Delta\varphi$. Consequently, the two representations we have introduced above correspond to the two following extreme cases.

- **$\Delta N = 0$**

If $\Delta N = 0$, the number of quanta is well defined, so that we obtain an atomistic description of the system, but lose the information on its capability to fluctuate, since $\Delta\varphi$ becomes infinite. This choice corresponds to the usual description of objects in terms of the component atoms/molecules, considered by Classical Physics, where objects interact by exchanging energy. These exchanges are connected with the appearance of forces. Since energy cannot travel faster than light, this interaction obeys the traditional principle of causality.

- **$\Delta\varphi = 0$**

If $\Delta\varphi = 0$, the phase is well defined, so that we obtain a description of the movement of the system, but lose the information on its particle-like features which become undefined since ΔN becomes infinite. Such a system having a well-defined phase is termed coherent in the physical jargon. A common phase arises among different objects because of their coupling to the quantum fluctuations and hence to an e.m. potential. In this case there is no propagation of matter and/or energy taking place, and the components of the system "talk" to each other through the modulations of the phase field travelling at the phase velocity, which has no upper limit and can be larger than c, the speed of light.

The process of the emergence of coherent structures out of a crowd of independent component particles has been investigated in the last decades and is presently quite well understood [27],[28]. The presence of this field has received experimental corroboration [29],[30]. Therefore a weak e.m. field is always present in system about equilibrium, where it often merely produces variation around the mean by performance measurements.

Understanding the human neural coding and brain remains a major challenge of the 21st century [31]. We know that stiff and nonlinear dynamical systems are inefficient on a digital computer. A simple example is the IBM Blue Gene project with 4096 CPUs and 1000 Terabytes RAM, which, to simulate the mouse cortex uses 8×10^6 neurons, 2×10^{10} synapses, 10^9 Hz clock, 40 Kilowatts on digital support. The adult human brain uses about 100 billion (10^{11}) neurons, 10^{14} synapses, 20 Hz clock, and 20 watts [9] on biological support. Biological information processing systems operate on completely different principles from those with which most engineers are familiar [32].

This advantage can be attributed principally to the use of elementary physical phenomena as computational primitives, and to the natural representation of information framework. This kind of adaptation leads naturally to systems that learn about their environment [33],[34]. We need to integrate our current neural coding reductionist interpretation with new neuroscience insights [35],[36]. We will refer to these new systems generically as neuromorphic anticipatory learning system (ALS) [37]. There is nothing that is done in the nervous system that we cannot emulate with electronics if we understand the principles of neural information processing right.

3. NEUROMORPHIC ALS SYSTEM

There is a myth that the nervous system is slow, is built out of slimy stuff, uses ions instead of electrons, and is therefore ineffective. As a matter of fact, there are about 10^{14} synapses in the adult human brain. A nerve pulse arrives at each synapse about ten times/s, on average. So in rough numbers, the brain accomplishes 10^{14} complex operations/s. The power dissipation of the human brain is about 20 watts, so each operation costs only about 2×10^{-15} J of energy. The unavoidable conclusion is that we have something fundamental to learn from the brain about a new and much more effective form of computation.

The disparity between the efficiency of computation in the nervous system and that in a computer is primarily attributable not to the individual device requirements, but rather to the way the devices are used in the system. The fact that we can build devices that implement the same basic operations as those the nervous system uses leads to the inevitable conclusion that we should be able to build entire systems based on the organizing principles used by the nervous system.

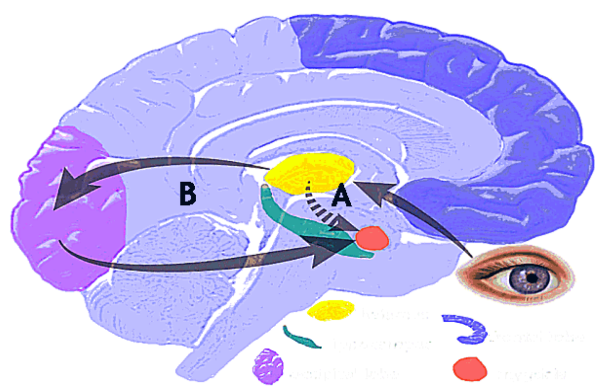

Fig. 1. Information about external stimuli reaches the amygdala by direct pathways from the thalamus (the "low road", A) as well as by pathways from the thalamus to the cortex to the amygdala (the "high road", B) [35],[36],[38].

We will refer to these systems generically as neuromorphic systems. In a different paper, we already discussed the major differences between natural and epistemic uncertainty [1], here we like to underline that at brain level, it is possible to refer to Papez circuit (Fig.1 path B, "high road", Logical Closure) for structured behaviour (i.e. rational thinking, learning, knowledge extraction, etc.…) and to LeDoux circuit (Fig.1 path A, "low road", Logical Aperture) for emotional behaviour (i.e. fear, surviving, emotional intelligence, etc.) as from Fig.1 [35],[36]. Emotional Intelligence (EI) and Emotional Creativity (EC) [38] coexist at the same time with Rational Thinking in human mind, sharing the same input environment information [33],[34] and the same environmental noise, much better, what human beings call noise [39]. Taking into consideration neurophysiological findings, differently from the past, it is much better to consider ontological uncertainty [1] as an emergent phenomenon out of a complex system, arriving to the basic schema for Ontological Uncertainty Management (OUM) System in [1]. Then, our dynamic ontological perspective can be thought as an emergent, natural trans-disciplinary reality level (TRL) [40] out of, at least, a dichotomy of two fundamental coupled irreducible complementary computational subsystems: A) reliable predictability subsystem and B) reliable unpredictability respectively [1]. Therefore, the mathematical method, we are describing, can possess anticipatory computational properties, at design level, needed to the realization of system even capable to interact with its environment in real time (leading property) [41]. We give an operative system example in our second paper presented at this conference [42]. Here, we like to discuss the fundamental anticipation property to develop competitive cognitive computation applications.

4. ANTICIPATION PROPERTY

In intelligent system development, the notion of anticipation is coming to the foreground as an emerging field of study. The future plays an active way in how we think and act in the present. The traditional understanding, that past events are the primary drivers that influence how we understand the present, is undermined.

Both the past and the future are forces that simultaneously and actively influence the present. By interpreting the present as the time where the forces of the past and future meet, our understanding of the present changes from a "thin" (the present as a boundary without any extension between past and future) to a "thick present" (the present as the collection of contemporaneous events) [43]. Moreover, by giving the future scientific legitimacy, a novel vision of science arises where a fully scientific (i.e., not allusive, metaphorical or mystical) treatment of "final" causation (≡ anticipation, intention, purpose) is included and not rejected (Science 2.0 approach) as is the case in the traditional scientific paradigm (Science 1.0 approach).

An in-depth understanding of the work of theoretical biologist, Robert Rosen (1934–1998), holds important insights for how anticipatory systems can be modeled [41] to face uncertainty and ambiguity. Rosen's insight that "science is the art of establishing modeling relations between the natural world and the world of our formalisms" challenges traditional modeling strategies that mainly form simulations of reality, but do not explain causal relations. According to Rosen, the modeling relation (or the main task of "theoretical science") consisted of establishing congruence between "causal relations in the external world, and implicative relations between propositions describing that world." Essentially the mapping relation points to the process we carry out when we "do science" and exposes this process as one in which there can be no biggest model of the world, but only snap-shots thereof. The study of complexity and anticipation can be linked to the modeling relation [41].

The acknowledgement of complexity lays bare the dilemma that there remains a gap between our models and the reality they intend to describe. An irreducible difference exists between the nature of complex reality and our descriptions thereof. By acknowledging that all knowledge of complex, anticipatory systems will always prove to be partial knowledge, one is confronted with the unavoidability of the limitations of human understanding. This recognition opens up a space where the conceptual implications of complexity surpasses epistemological concerns and exposes the normativity that lies in all our modeling strategies. This ethical imperative challenges scholars to engage with the question of re-thinking what it means to be human and calls upon us to proceed differently in this world.

Anticipation can be used to proceed differently in the process of "working" with the future when corporate businesses or governments have to come to terms with complexity, risk and uncertainty [44]. Horizon scanning-like and scenario planning-like tools offer the current best foresight futures studies strategies and tools for making sense of how one could anticipate the future and make better decisions. Because we cannot have the biggest or best model of the future, it means that futurists cannot predict the future. Instead, their task is to rather help find ways to understand the critical driving forces and uncertainties in the (business) environment and to use this almost BU information to make strategic decisions to be less wrong.

By a systemic poet-of-view (POV), the logical answer is to design and to use distributed (self-)control, i.e. BU self-regulating systems. Post-Bertalanffy Cocybernetics (i.e. complex control theory) and Complexity Theory tell us that it is actually feasible to create resilient social and economic order by means of self-organization, self-regulation, and self-governance [45],[46]. Scenario planning-like approaches can be used as tools for exploring system sustainability transition. Through anticipatory scenario planning strategies, a more positive vision of what system interaction evolution could look like, can be developed. Possible change should be scoped out so as to be better prepared to respond to change and surprise and to help influence and drive change along more desirable trajectories, as well as avoid undesirable ones.

There is nothing that is done in the nervous system that we cannot emulate with electronics if we understand the principles of neural information processing right. What kind of computation primitives are implemented by the device physics we have available in nervous tissue or in a silicon integrated circuit? We have to invent or to remember a representation that takes advantage of the inherent capabilities of the medium, such as the abilities to generate exponentials, to do integration with respect to time, and to implement a zero-cost addition using Kirchhoff's law [9],[32].

This kind of adaptation leads naturally to systems that learn about their environment [33],[34]. Shortly, major current deep learning (DL) approaches limitations are:

1-Need for most efficient and effective computational information framework;

2- Need for best architecture selection for a specific task;

3- Computational intensive requirement for best result;

4- Stochastic based clustering only;

5- Time Consuming Training.

To address our first modeling limitation issue, we need to become aware that human beings and most current advanced measurement systems have quite a limited capacity to extract reliable information from complex system analysis [42]. Complex system is characterized by AMS system representation usually. So, we need to extend our traditional system modeling representation understanding to develop more effective applications.

5. EXTENDING OUR UNDERSTANDING

Every approach that uses analytical function applies a top-down (TD) point-of-view (POV) implicitly. These functions belong to the domain of Infinitesimal Calculus (IC) under the "continuum hypothesis" (CH) assumption. From a system computational perspective, all approaches that use a TD scale-free POV allow for starting from an exact global solution panorama of analytic solution families, which offers a shallow local solution computational precision to real specific needs (in other words, from global to local POV overall system information is not conserved, as misplaced precision leads to information dissipation [3],[47]). In fact, usually further analysis and validation (by probabilistic and stochastic methods) is necessary to get localized computational solution of any practical value, in real application. A local discrete solution is worked out and computationally approximated as the last step in their line of reasoning, that started from an overall continuous system approach (from continuum to discrete ≡ TD POV).

Unfortunately, the IC methods are NOT applicable to discrete variable. To deal with discrete variables, we need Finite Difference Calculus (FDC) under the "discreteness hypothesis" (DH) assumption. FDC deals especially with discrete functions, but it may be applied to continuous function too. As a matter of fact, it can deal with both discrete and continuous categories conveniently. In other words, if we want to achieve an overall system information conservation approach, we have to look for a convenient BU scale-relative POV (from discrete to continuum view ≡ BU POV) to start from first, and NOT the other way around! Then, a TD POV can be applied, if needed.

Current human made application and system can be quite fragile to unexpected perturbation because Statistics can fool you, unfortunately. Deep epistemic limitations reside in some parts of the areas covered in risk analysis and decision making applied to real problems [44].

To grasp a more reliable representation of reality and to get stronger biological and physical system correlates, researchers and scientists need two intelligently articulated hands: both stochastic and combinatorial approaches synergistically articulated by natural coupling [1]. The former, applied to all branches of human knowledge under the CH assumption, has reached highly sophistication level, and a worldwide audience. Many "Science 1.0" researchers and scientists up to scientific journals assume it is the ultimate language of science. The latter, less developed under the DH assumption in specific scientific disciplines, has been considered in peculiar application areas only. It has been further slowly developed by a few specialists and less understood by a wider audience. Unfortunately, over the years, the above two mathematical research areas (CH and DH) have followed separate development paths with no articulated synergic coupling. In the past, many attempts to arrive to a continuum-discrete unified mathematical approach have been proposed, all of them with big operational compromises, and we can go back at least to the introduction of the Riemann–Stieltjes integral, published in 1894 by Dutch mathematician Thomas Joannes Stieltjes (1856–1894) [48], which unifies sums and integrals. Let's say we need a fresh "Science 2.0" approach.

We need tools able to manage ontological uncertainty more effectively [49],[50]. To achieve reliable system intelligence outstanding results, current computational system modelling and simulation has to face and to overcome two orders of issues at least, immediately:

1- To minimize the traditional limitation of current digital computational resources that are unable to capture and to manage even the full information content of a single Rational Number $\boldsymbol{Q}$ leading to information dissipation and opacity [3],[47].

2- To develop stronger, more effective and reliable correlates by correct arbitrary multi-scale (AMS) modelling approach to complex system [2],[9],[32].

Both issues are addressed and solutions proposed to, in our second paper presented at this conference [42]. In fact, even the most sophisticated, advanced research laboratory or instrumentation system is completely unable to reliably discriminate so called "random noise" (RN) from any combinatorically optimized encoded message, called deterministic noise" (DN) in [39], by statistical signal processing tools only.

This ambiguity emphasises the major "information double-bind" (IDB) problem in current most advanced research laboratory and instrumentation system, just at the inner core of human knowledge extraction by experimentation in current science [51]. Therefore there is a strong need to develop more effective and reliable experimental observation correlates by the correct AMS modelling approach for complex system understanding, like CICT. The reader interested in deeper computational details is referred to [3].

6. CICT

CICT defines an arbitrary-scaling discrete Riemannian manifold uniquely, under hyperbolic geometry (HG) metric, that, for arbitrary finite point accuracy level L going to infinity, under scale relativity invariance, is isomorphic (even better, homeomorphic) to classic information geometry (IG) Riemannian manifold (exact solution theoretically). In other words, HG can describe a projective relativistic geometry [52] directly hardwired into elementary arithmetic long division remainder sequences, offering many competitive computational advantages over traditional Euclidean approach. It turns out that, while free generator exponentially growing sequences can be divergent or convergent, their closures can be defined in terms of polynomials. Furthermore, combinatorically OECS have strong connection even to classic DFT algorithmic structure for discrete data, Number-Theoretic Transform (NTT), Laplace and Mellin Transforms [39]. In this way, even simple scalar moduli can emerge out from sequences of phased generators.

CICT can help to reach a unified vision to many current physics and cognitive informatics problems and to find their optimized solutions quite easily. Expected impacts are multifarious and quite articulated at different system scale level. One of the first practical result was that usual elementary arithmetic long division remainder sequences can be even interpreted as combinatorically optimized coding sequences for hyperbolic geometric structures, as point on a discrete Riemannian manifold, under HG metric, indistinguishable from traditional random noise sources by classical Shannon entropy, and contemporary most advanced instrumentation systems [3]. Specifically, CICT showed that classical Shannon entropy computation is completely unable to reliably discriminate so called computational "random noise" from any combinatorically optimized encoded message by OECS, called "deterministic noise" (DN) in [3]. As a matter of fact, for any free generator, CICT can provide us with an "ecoco-domain" multiscale evolutive structured family of sequences that can be used for checking for the presence of the specific generator in laboratory or system "background noise" [3].

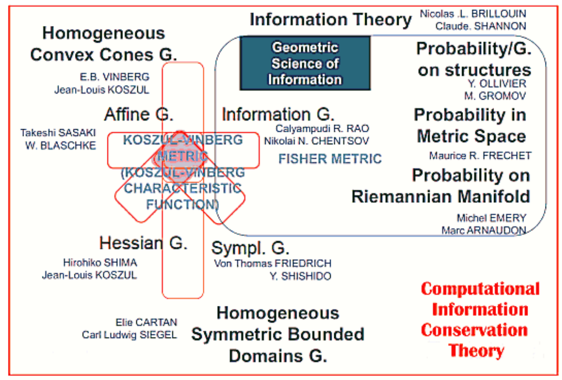

Fig. 2. Computational Information Conservation Theory (CICT) is a Natural Framework for Arbitrary Scale Computer Science and Systems Biology Modeling in the current landscape of modern Geometric Science of Information (GSI), Geometric Algebra (GA) and Geometric Calculus (GC). (Here, to avoid display cluttering, the word “Geometry” is shortened to “G.”).

Following CICT approach, it is possible even to extend the classic Shannon entropy concept to arrive to a stronger and specific "Coherent Shannon entropy" (CSE) approach [3]. Second result was to realize that classical experimental observation process, even in highly ideal operative controlled condition can capture just a small fraction only, with misplaced precision, of overall ideally available information from unique experiment. The remaining part is lost and inevitably added to something we call "background noise" or "random noise" usually, in every scientific experimental endeavor [39].

CICT can help us to develop strategies to gather much more reliable experimental information from single experiment and to conserve overall system information. In this way, coherent representation precision leads to information conservation and clarity. The latest CICT claim has been that the "external" world real system physical manifestation properties and related human perception are HG scale related representation based, while Euclidean approximated locally.

Furthermore, the fundamental play of human information observation interaction with an external world representation is related by the different manifestation and representation properties of a unique fundamental computational information structuring principle: the Kelvin Transform (KT) [53]. KT is key to efficient scale related information representation, structuring "external space" information to an "internal representation" and vice-versa by projective-inversive geometry.

More generally, CICT is a natural framework for computer intelligence and systems biology AMS modeling in the current landscape of modern GSI, GA and GC as depicted in Fig. 2. Next section will show two computational examples from our CICT approach.

7. TURNING THEORY INTO PRACTICE

According to CICT [54], the full information content of any symbolic representation emerges out of the capturing of two fundamental coupled components: the linear one (unfolded) and the nonlinear one (folded). If we like to refer to the transdisciplinary concept presented in [55], we see that for full information conservation any transdisciplinary concept emerges out of two pair of fundamental coupled parts. As an example, for the Space-Time Split (STS) [55], we can arrive to better operative understanding of usual terms, with added possibility of information conservation, as shown by "The Four Quadrants of The Space-Time Split" [55].

In other words by CICT, if we want to capture the full information content of any linear elementary symbolic representation, we need a quadratic support space at least. Of course, we can apply our dichotomizing process in a recursive way to achieve any precision we like. The CICT fundamental relationship that ties together numeric body information of divergent and convergent monotonic power series in any base (in this case decimal, with no loss of generality), with D ending by digit 9, is given by the following CICT fundamental (Left-To-Right) LTR-RTL (Right-To-Left) correspondence equation [47]:

$$\frac{1}{D} = \sum_{k=0}^{\infty} \frac{1}{10^W}\left(\frac{\overline{D}}{10^W}\right)^k \Rightarrow \cdots \Leftarrow \; Div\left(\frac{1}{D}\right) = \sum_{k=0}^{\infty}(D+1)^k \qquad (2)$$

where $\overline{D}$ is the additive 10^W complement of D, i.e. $\overline{D}$ = (10^W - D), W is the word representation precision length of the denominator D and "*Div*" means "Divergence of". Further generalizations related to D ending by digit 1 or 3 or 7 are straightforward [39]. Furthermore, When $\overline{D}$ > D the formal power series on the left of (2) can be rescaled mod$D$, to give multiple convergence paths to 1/D, but with different "convergence speeds." The total number of allowed convergent paths, as monotonic power series, is given by the corresponding Q_L value, at the considered accuracy level L [47]. So, increasing the level of representation accuracy, the total number of allowed convergent paths to 1/D, as monotonic power series (as allowed conservative paths), increases accordingly and can be counted exactly, and so on, till maximum machine word length and beyond: like discrete quantum paths denser and denser to one another, towards a never ending "blending quantum continuum," by a TD perspective. In this way, rational representations are able to capture two different type of information at the same time, modulus (usual quotient information) and associated exterior or extrinsic period information which an inner or intrinsic phase for each combined phased generator can be computed from. So, rational information can be better thought to be isomorphic to vector information rather than to usual scalar one, at least. Furthermore, our knowledge of RFD Q_L and corresponding RFD R_L can allow reversing numeric power convergent sequence to its corresponding numeric power divergent sequence uniquely. Reversing a convergence to a divergence and vice-versa is the basic property to reach information conservation, i.e. information reversibility, as from (2). CICT results have been presented in term of classical power series to show the close relationships to classical and modern control theory approaches for causal continuous-time and discrete-time linear systems [47].

As a further specific example, for solid number SN = 7.0 = D [47], to conserve the full information content of rational correspondence at higher level, we realize that we have to take into account not only the usual modulus information, but even the related external or extrinsic *RFD* periodic precision length information W = 6 (numeric period or external phase representation) in this case (i.e. D ≡ "000007" as base *RFD*, and yes for CICT leading zeros do count [56]!). For system external or exterior phase computation, we can use Euler's formula to establish the usual fundamental relationship between trigonometric functions and the complex exponential function:

$$e^{ix} = \cos x + i \sin x \;, \qquad (3)$$

where e is the base of the natural logarithm and $i = \sqrt{-1}$. It establishes the fundamental relationship between the trigonometric functions and the complex exponential function. We obtain:

$$CQ1 = \frac{1}{7} e^{i\frac{\pi(2n+1)}{3}} = \frac{1}{7}\left(\cos\left(\frac{2\pi(n+1)}{6}\right) + i\sin\left(\frac{2\pi(n+1)}{6}\right)\right) \qquad (4)$$

and

$$CD1 = \frac{1}{CQ1} = 7e^{-i\frac{\pi(2n+1)}{3}} = 7\left(\cos\left(-\frac{\pi(2n-1)}{3}\right) + i\sin\left(-\frac{\pi(2n-1)}{3}\right)\right) = 7\left(\frac{1}{2} - i\frac{\sqrt{3}}{2}\right) \;\text{p.v} \qquad (5)$$

.

for n = 1, 2, 3, …in $\boldsymbol{N}$, where p.v. means principal value. CICT shows that any natural number D in $\boldsymbol{N}$ has associated a specific, non-arbitrary external or exterior phase relationship [39] that we must take into account to full conserve its information content by computation in Euclidean DS. The interested reader will have already guessed the relationship of our result to de Moivre number or root of unity (i.e. any complex number that gives 1.0 when raised to some integer power of n. In this way, we can exploit Rational numbers $\boldsymbol{Q}$ full information content to get effective and stronger solutions to current system modelling problems. We have shown how to unfold the full information content hardwired into Rational OR representation [47] (nano-microscale discrete representation) and to relate it to an assumed continuum framework (meso-macroscale) with no information dissipation. CICT natural mathematical language can offer an effective and convenient "Science 2.0" universal framework [54], by considering information not only on the statistical manifold of model states but also on the combinatorical manifold of low-level discrete, phased generators and empirical measures of noise sources, related to experimental high-level overall perturbation [3]. A synergic coupling between geometric algebra (GA) and CICT [54],[57] can offer stronger arbitrary-scale computational solutions which unify, simplify, and generalize many areas of mathematics that involve geometric information ideas. Furthermore, CICT phased generator (PG) approach can allow multiarticulated dynamic reframing of *RFD* [47] internal or interior phased generators to system external or exterior phase, for multi-harmonics resonant system behavior modeling [3].

Scale related, coherent precision correspondence leads to transparency, ordering, reversibility, cosmos, simplicity, clarity, and, as you saw from previous discussion, to algorithmic quantum asymptotic incomputability on real macroscopic machines [56]. CICT fundamental relation (see (2)) allows to focus our attention on combinatorically optimized number pattern generated by LTR or RTL phased generators and by convergent or divergent power series with no further arbitrary constraints on elementary generator and relation. Thanks to subgroup interplay and intrinsic phase specification through polycyclic relations in each SN remainder sequence, word inner generator combinatorical structure can be arranged for "pairing" and "fixed point" properties for digit group with the same word length [47]. As a matter of fact, those properties ("pairing" and "fixed point") are just the operational manifestation of universal categorical irreducible dichotomy hard-wired into integer digit and digit group themselves (i.e. "evenness" and "oddness") and to higher level structures (i.e. "correspondence" and "incidence"). Actually, since space is limited, the discussion here will not be extended further to the subgroup interplay of the family group and polycyclic groups. We refer the interested reader to good general references on polycyclic groups [58],[59].

8. OPERATIVE CONSIDERATIONS

In current application, the classical experimental noise discrimination problem is still faced by the single domain channel passive transfer function concept (Shannon's noisy channel, Fig.3 top diagram), starting from classic Shannon's information theory concept [60], and then applying traditional perturbative computational model under either additive or multiplicative perturbation hypothesis [61]. Agreeing with Taleb [44], our main idea is that an assessment of system fragility (and control of such fragility) is more useful, and more reliable, than probability risk management and data-based methods of risk detection [44]. Main attention focus should not be to attempt to predict black swan events, but to build system robustness against negative ones that occur and be able to exploit positive ones [44]. In the past five decades, trend in Systems Theory, in specialized research area, has slowly shifted from classic single domain information channel passive transfer function approach (Fig.3 top diagram) to the more structured ODR Functional Sub-domain Active Transfer Function approach (by Observation, Description and Representation Functional Blocks, Fig.3 middle diagram) [62]. Shortly, the ODR approach allows fitting theoretical system design consideration to practical implementation needs much better (according to information "Input, Processing, Output" paradigm, respectively), than classic single domain channel approach, as shown by Fig.3 middle diagram.

As a matter of fact, by iterating full process over repeated scale-related controlled "Observations", it is possible to improve the accuracy level of any associated "Description", validated by a related and endorsed scale related "Representation", and therefore to better the overall system knowledge extraction process under test: human beings call this process "learning by experience." Thanks to the ODR approach, a deeper awareness about information acquisition and generation limitations by classical experimental observation process has been grown. In fact, usual elementary arithmetic long division remainder sequences can be even interpreted as combinatorically optimized coding sequences for hyperbolic geometric structures, as points on a discrete Riemannian manifold, under HG metric, indistinguishable from traditional random noise sources by classical Shannon entropy computation, and current, most advanced instrumentation system [39]. Specifically, CICT showed that classic Shannon entropy is completely unable to reliably discriminate so called computational "random noise" (RN) from any combinatorically optimized encoded message by OECS, called "deterministic noise" (DN) in [39]. Paradoxically if you don't know the generating process for the folded information, you can't tell the difference between an information-rich message and a random jumble of letters. This is "the information double-bind" (IDB) problem in contemporary classic information and algorithmic theory [39]. Therefore, one of the first practical result has been to realize that classical experimental observation process, even in highly ideal operative controlled condition, like the one achieved in current, most sophisticated and advanced experimental laboratories like CERN [63], can capture just a small fraction only of overall ideally available information from unique experiment. The remaining part is lost and inevitably dispersed through environment into something we call "background noise" or "random noise" usually, in every scientific experimental endeavor.

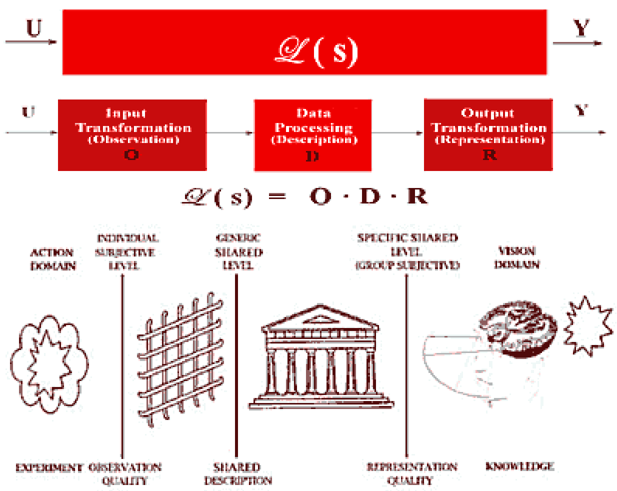

Fig. 3. Top diagram: Traditional Single Domain Channel (SDC) Passive Transfer Function. Middle diagram: Decomposition of SDC Transfer Function into more structured ODR Functional Sub-domain Active Transfer Function (Observation, Description and Representation Functional Blocks). Bottom diagram: ODR Information Channel Co-domain Diagram for System Information Conservation.

The amount of information an individual can acquire in an instant or in a lifetime is finite, and minuscule compared with what the milieu presents; many questions are too complex to describe, let alone solve, in a practicable length of time [64]. The same is true for all other cascading functional blocks in the ODR transmission channel from source to destination, if careful information conservation countermeasure is not provided at each step. Traditionally, the horizons of accumulating ignorance are expanding faster than any person can keep up with. The proliferation of new sciences extends our powers of sense and thought, but their rigorous techniques and technical language hamper communication; the common field of knowledge becomes a diminishing fraction of the total store. By biomedical Cocybernetics point of view, to get closer to real computational information conservation, ODR Functional Sub-domain Transfer Function block diagram (Fig.3 middle diagram) must be completed by a corresponding irreducible complementary "ODR Information Channel Co-domain Diagram" to get reliable strategic overall information functional closure (Fig.3 bottom diagram) [62].

Starting at the Observation step, interaction between an Experimental Field with a scale related Action Domain is established and discrete data are captured. Observation is properly described as a fact-finding rather than a fact-collecting procedure, because the idea of finding includes both selection by controlled perturbation and efficient structured collection. The quality of Observation does then depend on the degree of completeness by which experimental folded information is allowed to be efficiently captured from our experimental field into our subjective structured Action Domain and properly formatted, according to observation experience and shared rules (System Input Transformation), to be passed to next processing block. Then the second step, Description, can format and formalize folded subjective observation into an unfolded systemic minimal insured scale precision and/or accuracy Representation Domain, to be shared by the majority of interacting entities which use the same formal language to communicate (Overall System State), to be passed to the last step. Finally, the quality of the Representation stage does depend on the degree of scale related completeness by which unfolded information is allowed to be focused and re-folded to be efficiently presented to specific shared, human knowledge (System Output Transformation). Then a validation process can start and an endorsement can be assigned eventually, according to convenient Representation support quality level for scientific knowledge synthesis, cultural analytics, information/perceptual aesthetics, etc.

The ODR approach has contributed to create deeper awareness about traditional information acquisition, formalization and reproduction process limitations, constrained by classical experimental observation scale finiteness and new multimedia data acquisition and reproduction implementation. As a matter of fact, traditional rational number system $\boldsymbol{Q}$ properties allow to generate an irreducible co-domain for every computational operative domain used. Then, all computational information usually lost by using the classic information approach, based on the traditional noise-affected data model stochastic representation, can be captured and fully recovered to arbitrary precision by a corresponding evolutive irreducible complementary co-domain, step-by-step [3]. Co-domain information can be used to correct any computed result, achieving computational information conservation (theoretically, virtually noise-free data), according to CICT Infocentric

Worldview [39]. A further detailed description of the diagrams of Fig.3 far exceeds the scope of present discussion and the interested reader is referred to [62].

9. CONCLUSION

The current living generation is experiencing a transition from history to hyperhistory. Advanced information societies are more and more heavily dependent on ICTs (Information and Communication Technologies) for their normal functioning and growth. Processing power will increase, while becoming cheaper and cheaper. The amount of data will reach unthinkable quantities. And the value of our networked resources will grow almost vertically. However, our current storage capacity (space), speed of communications (time) and abstract intelligence (αI) are lagging behind. Hyperhistory is a new era in human development, but it does not transcend the spatio-temporal constraints that have always regulated our life on this planet. The question to be addressed next is: "given all the variables we know, what sort of hyperhistorical environment do we like to build for ourselves and for future generations?" The short answer is the "Intelligent Infosphere" (II).

Our humble contribution is CICT new awareness of a discrete HG (hyperbolic geometry) subspace (reciprocal space) of coded heterogeneous hyperbolic structures, underlying the familiar $\boldsymbol{Q}$ Euclidean (direct space) surface representation. It can open the way to powerful holographic information geometry (HIG) computational POV. CICT can help us to develop strategies to gather much more reliable experimental information from single experimentation and to conserve overall system information. In this way, coherent representation precision leads to information conservation and clarity. Specifically, advanced mathematical modeling, advanced wellbeing applications (AWA), high reliability organization (HRO), mission critical project (MCP) system, very low technological risk (VLTR) and crisis management (CM) system will be highly benefitted mostly by these new techniques.

This paper is a relevant contribution towards an effective and convenient "Science 2.0" universal computational framework to achieve deeper cognitive intelligence your fingertips and beyond, towards a more sustainable economy and wellbeing [65], in a global competition scenario.

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