Arising information regularities in an observer
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Abstract
Considering a conversion of an observed uncertainty to the observer’s certainty, the paper verifies the
minimax principle of both the optimal extracting and spending of information, which generally refers to
getting a maximum of information from each of its observed minimum and minimize the maximum while
consuming it. This dual complimentary principle functionally unifies observer regularities: integral
measuring each observing process under multiple trial actions; converting the observed uncertainty to
information-certainty by generation of internal information micro and macrodynamics and verification of
trial information; enclosing the internal dynamics in information network (IN), whose logic integrates the
observer’s requested information in the IN code; building concurrently the IN temporary hierarchy, whose
high level enfolds information logic that requests new information for the running observer IN, extending
the logic code; self-forming the observer’s inner dynamical and geometrical structures with a limited
boundary, shaped by the IN information geometry during the time-space cooperative processes.
These regularities establish united information mechanism, whose integral logic self-operates this
mechanism, transforming observed uncertainty to physical reality-matter.
Key words: integral uncertainty-certainty, internal conversion, minimax, information network, logic,
code.

Introduction
Observers are everywhere, from communicating people, animals, different species to any interacting
subjects, accepting, transforming and exchanging information.
Up to now, their common information regularities, emergence, differentiation, and appearance have not
been studied by united information approach.
The paper shows how an information observer gets information from observing random process and how
and why it converts external uncertainty in its certainty-information, creating inner information dynamics
and information network with its logic and code.
Even though multiple physical studies [1-11] reveal information nature of the analyzed physical processes
in an observer, until A. Wheeler’s theory [12-16] of information-theoretic origin of an observer (‘it from
bit’), the observer has studied mostly from physical point of view.
The questions still are: How this bit appears and how does information acquire physical properties?
The information processes of an observer, its information structure and regularities have been not
adequately understood.
A. Weller has included the observer in wave function [16], while according to standard paradigm:
Quantum Mechanics is Natural.
The concept of recent publications [17,18] states that in Quantum Bayesianism, which combines quantum theory with probability theory, ‘the wave function does not exist in the world—rather it merely reflects an individual’s mental state.’

We have shown (in [19-25] and in this paper) that quantum information processes, resulting from Bayesian form of entropy integral measure, arise in observer at conversion of this uncertainty to the equivalent certainty-information path functional measure.

The conversion’s information micro- macro processes finally provide physical information.

This paper extends results [21-25] by analyzing emergence and arises of observer’s regularities.

The paper is organized as following.

Starting with formal introduction of the information observer (Sec.1), it shows that its probability transformations define integral information measure on a random process, expressed by entropy functional on trajectories of controlled Markov diffusion process (Sec.2).

Since information, enfolded in the entropy functional (EF) of a random process, is unknown-uncertain for the observer, it needs to be converted to the observer’s certainty-information.

In Sec.3 we find a conversion process, using the condition of equivalence of the entropy functional with a certain-information functional, defined as information path functional (IPF) on its extremal trajectories, which best approximate the EF. These extremals form the conversion process, satisfying variation equations, determined through dynamic Hamiltonian, which holds both minimal and maximal solutions for the IPF, while the minimal involves imposing a constraint on the Hamiltonian.

Thus, the functionals’ equivalence brings an information maxmin principle for EF-IPF and the information transformation of random uncertain process to a certain process, chosen by this principle.

For the controlled Markov process, this principle entails the impulse controls, extracting the cutoff information from the EF and integrating it through the multi-dimensional process (Sec.4).

It has shown that each cutoff delivers approximately one-bit information, depending on the cutting off correlations of the random process.

The impulse control executes the information transformations, switches the entropy functional from its minimum to maximum and back from maximum to minimum, while absolute maximum of the entropy functional allows the impulse control delivering maximal amount of information from these transformations, which are a source of Feller kernel information. Similarly, the maximin principle, following from the functionals equivalence, is satisfied through the cutoff actions, selecting the suitable EF functional portions and transforming it to the IPF portion of the conversion process.

The cutting impulse control consists of a step-down control function, which cuts the Markov process and transforms it to Brownian process, and a step-up control function, which cuts the Brownian process and starts the conversion process (Sec.5). The step-down function implements transition of the related
process’ probabilities that create the EF, while the Brownian process enfolds the maximal entropy contributions along its multi-dimensional trajectory.

Both controlled functions cut off the process correlations and deliver their hidden maximal information. Each step-up function consists of two almost simultaneous actions (during its switch): the first one intervenes in Brownian process, picking up a pair of simultaneous states (from the cutting off process’ ensemble) with maximal information, while the second one transforms them to starting conversion process, holding the information rate of the killed Brownian movement.

The execution of these actions requires a pair of ‘mirror’ controls, applied to each of the pickup states, which set up a pair of Hamiltonian conjugated trajectories, holding both initial states and information speeds of the ended Brownian process and transferring information from this process.

The delivered maximal information (taken from each cutoff observing minimum) satisfies to the conjugated process’ maximum Hamiltonian, until the dynamic constraint minimizes the Hamiltonian. Each pair of the observer’s conversion process (Sec.6) carries complex conjugated probabilities and components of the entropy’s analogue of function of action, which, interfering near moment \( \tau_{1k} \), entangle on interval \( \Delta_2 \) (Fig.1). By turning on the step-down control nearby moment \( \tau_{1k} \), the observer imposes the constraint, minimizing the current process’ information speed movement on extremals between the moment of turning this control off \( \tau_{1ko} \) and its stopping on \( \tau_{2k} \).

The conjugated dynamics proceed on interval \( \Delta_1 - \delta_0 \), with interval \( \delta_0 \) of switch from \( \tau_{1k} \) to \( \tau_{1ko} \), where unified mirror control \( v_i \) entangles the dynamics up to \( \tau_{2k} \)-locality of turning the constraint off. Overcoming the constraint threshold on a path from the Hamiltonian minimum, with following release of the maximal Hamiltonian, at the \( \tau_{2k} \)-locality, produces impulse \( \delta x_i \); this impulse is consistent with a sharp increase \( \delta x_i \) of killing Brownian motion at the same \( \tau_{2k} \)-locality. The interference and entanglement produce real information \( i_{ap}^a[x_i(\Delta_1)] \) being converted from related entropy \( \tilde{s}_{ap}^a[x_i(\Delta_1)] \).

[A simplified example of these processes analogous to watching a random moving point with both eyes, while a fractional information from the most informative simultaneously appearing points coincides, producing joint information (In Sec.7 we analyze neuronal dynamics of related examples)].

During the dynamic movement, the delivered information is produced via is multiple Yes-No trial actions (from the start-up control through the end of the step-down control, Fig.1).

This information is verified with that required by the observer IN logic. While under the step-down control the delivered information is entangled, its part becomes free information, attracting new information, which drives and finalizes collection of the entropy and information functional in the multi-dimensional process.
Since each cutting fraction of \( n \)-dimensional entropy functional is transferred to Hamiltonian function of actions on interval \( \Delta : \tilde{S}_{ap}[\tilde{x}_t(\Delta)] \), the observer’s actual transforming (control) action allows it not to measure directly the entropy functional, instead dealing with \( \tilde{S}_{ap}[\tilde{x}_t(\Delta)] \), and, therefore, to avoid taking the math expectations for measuring EF.

Moreover, since the observing random process had been killed (cut), the observer operates only with conversion process, currently transforming portion of EF, for each process dimension, while the EF of whole random process disappears with the dissolving last portion of the remaining \( n \)-th dimension.

Explicitly, after ending conversion time interval \( \Delta _2 \), each multiple pair uncertainty-certainty reaches equality
\[
\tilde{S}_{ap}[\tilde{x}_t(\Delta)] = i_{ap}^o[x_t(\Delta)] ,
\]
and the observing process’ \( \tilde{x}_t(\Delta) \) uncertainty \( \tilde{S}_{ap}[\tilde{x}_t(\Delta)] \), transferred to information-certainty:
\[
i_{ap}^o[x_t(\Delta)] = i_{ap}^o[x_t(\Delta)] + i_{ap}^o[x_t(\Delta)] ,
\]
concurrently contributes to both related entropy’s \( \tilde{S}_{ap}^{o} \) and information functionals \( I_p^{o} \):
\[
\sum_{i=1}^{n} \tilde{S}_{ap}^{o}[\tilde{x}_t(\Delta)] = \tilde{S}_{ap}^{o} \text{ and } \sum_{i=1}^{n} i_{ap}^{o}[x_t(\Delta)] = I_p^{o} ,
\]
on interval \( \Delta _n \) for each \( i \)-dimension.

The currently summing integral contributions become automatically equal by the end of each \( k \) trial:
\[
\tilde{S}_{ap}^{ok} = I_p^{ok} ,
\]
satisfying
\[
\tilde{S}_{ap}^{o} = I_p^{o} \quad \text{(0.5)}
\]
at completing the trial for last \( n \)-th dimension. This means, the local controls could act independently and not simultaneously for each independent dimension and the frequencies of considered Brownian diffusion, as soon as their local conditions (0.1) and in (0.3) are reached.

Even though the local equivalence (0.1) is held (at some moments, when the observed information satisfies to maxmin principle), the integration in (0.3) is continued until the equal integral information in (0.1-0.5) approaches to that requested by the observer information network’s (IN) cooperative logic with its code. The observer’s intention to end the conversion process (by applying the step-down control imposing the constraint) coincides with its ability to attract new information via free information for each trial. The free information initiates building a temporary IN with ‘short term memory’, which starts at cooperation of conjugated dynamics and continues until its cooperative force is sufficient for adjoining this local with existing IN. End of these functionals’ collections indicates a temporary IN’s satisfaction with the required information, which symbolizes the observers’ surprise.

As it is seen from (0.3), maximum of the observed information is upper bound by its maximal dimension. Since equalities (0.3),(0.5) require theoretically infinite number \( n \), which relates to undefined number of computation, reaching this equality is possible only approximately.
The observer approaches the integral certainty, evaluating its proximity through the growing functional sums of $i_{\text{imp}}[x(\Delta_x)]$, which also evaluates the entropy functional’s math expectations along all random trajectories paths (that actually builds observer’s EF).

The IN logic’s accepted accuracy [23(2)] limits the exactness of equalities (0.3-0.5), which should not exceed the IN’s minimal unavoidable cooperative error in building the code.

Each logic’s triple code consists of digits, whose both highs and time-space intervals depend on incoming information, while the IN triplet’s size discriminates the hierarchical distance between the nearest triplets, which, in turn, depends on the observer’s requested frequency spectrum of information (limited by admissible range of the invariants of information dynamics and the dimension).

Since logic’s code is built by the conversion process, through the equivalence of portions of uncertainty and certainty functionals that is checked concurrently via Yes-No actions, the IN triplet’s logic accumulates a history of verified information, while its each triple digits is selected from retrieved information via minimax (which implies competition to reach it through comparison of the digits history). Saving logic’s history by memorizing it requires energy, but erasing the intermediate computational results of initially irreversible logics will bring a reversible computer, and according to that: ‘The usual general-purpose computing automaton (e.g., a Turing machine) is logically irreversible’ [26].

The observer IN currently builds its logic information code (as a program executing computing with Gödel’s limitations), which operates the observer action that retrieves, processes, collects, and memorizes its information. This coding program logic concurrently structures the information observer, whose microdynamics start with conversion of the observed random information in the conjugated dynamics and end with the entanglement. On the macrolevel, the extremals of information path functional, which averages a manifold of the hidden information, describe the information macrodynamics in terms of information forces acting on the flows, distributed in space-time along the measured process, which are assembling in the IN’s logic. Moment of approaching information $I_\text{op}$ to that, requested by the observer IN cooperative logic, evaluates upper border of time interval, which finally verifies measured integral information of this observation, while the moment of imposing constraint at the entanglement of conjugated dynamics determines its low border. This time border between the observer’s information micro and macrodynamic processes connects information with physics, reversibility and irreversibility.

The paper mathematics identifies all above relations, last part of Sec.6 summarizes the regularities, and shows how the IN bound cooperative dynamics can enclose and generate a Wheeler’s bit.

Sec.7 illustrates the information regularities on examples from neuronal dynamics.

*The paper simple principle of equivalence the observer uncertainty-certainty leads to mathematical and logical self-consistence, which through the minimax law creates observer’s regularity and its reality.*
1. Basic Notions
1.1. Information
On intuitive level, information is associated with diverse forms of changes (transformations) in material and/or non-material observations, expressed universally and unconnectedly to the changes’ cause and origin.

Information is a formal logarithmic comparative measure of the compared states \((\tilde{x}_a, \tilde{x}_p)\) (events):

\[
I_{ap} = -E[\ln(P(\tilde{x}_a)/P(\tilde{x}_p))],
\]

(1.1)

connecting them through diverse forms of transformations, evaluated by mathematical expectation of the logarithm’s ratio of the states’ priory probability \(P(\tilde{x}_a)\) to the posteriori probability \(P(\tilde{x}_p)\).

(Here we conditionally divide an observed process of its posteriori -depended part from a priori part).

Mathematical expectation (1.1), applied to these process’ differential probabilities \(P_{s,s}^a\) and \(P_{s,s}^p\) along process’ trajectories \(\tilde{x}_a(s,t), \tilde{x}_p(s,t)\) (starting at moment \(s\)), acquires form of entropy functional’s measure:

\[
I_{ap} = -E_{s,s} [\ln(P_{s,s}^a / P_{s,s}^p)] = \int_{\tilde{x}} \ln[(P_{s,s}^a(d\omega) / P_{s,s}^p(d\omega))]P_{s,s}^a(d\omega),
\]

(1.2)

which holds the Bayesian probabilities on the trajectories.

This measure integrates the logarithmic relative probability throughout all elementary random outcomes \(d\omega\) of random process \(\tilde{x}_i[\tilde{x}_a(s,t), \tilde{x}_p(s,t)]\) and enables accumulate more process information than the sum of information measures (1.1) counted for the process’ separated states [23(1)].

The probabilistic description generalizes different forms of specific functional transformations, represented through the probabilities ratios (1.1-1.2) for various random events and processes, studied in Kolmogorov’s theory of probability and founded as a logical science [27].

This randomness with their probabilities we consider as a source of information, which implies that some of them, but not all of such randomness produces information.

A logarithmical distance (for each elementary random outcome \(d\omega\) of random process \(\tilde{x}_i\)):

\[
-\ln p(d\omega) = -\ln P_{s,s}^a(d\omega) - (\ln P_{s,s}^p(d\omega)) = \tilde{s}_a - \tilde{s}_p = \tilde{s}_{ap},
\]

(1.3)

represented by a difference of a priory \(\tilde{s}_a > 0\) and a posteriori \(\tilde{s}_p > 0\) entropies, measures uncertainty, resulting from the transformation of probabilities for the source events.

A change brings a certainty or information if its uncertainty \(\tilde{s}_{ap}\) is removed by equivalent elementary information \(\tilde{i}_{ap}: \tilde{s}_{ap} - \tilde{i}_{ap} = 0\). Thus, information is delivered at \(\tilde{s}_{ap} = \tilde{i}_{ap} > 0\), which requires \(s_p < s_a\) with a positive logarithmic density measure at \(0 < p(\omega) < 1\). Condition of zero information: \(i_{ap} = 0\) corresponds to a redundant change, transforming a priory probability to equal posteriori probability, or this
information transformation is an identical—undistinguished, redundant, while information conveys non-redundant changes, decreasing uncertainty.

Whereas the notion of information formally separates the distinguished from undistinguished (or repeating) subsets (events, processes), formulas (1.1-1.3) evaluate numerically this separation. Information generally evaluates various multiple relationships represented via transformations (1.1-1.2) and generalizes them, being independent on the diverse physical entities that carry this information.

Some logical transformations in symbolic dynamic systems theory [28], preserve an entropy as a metric invariant, allowing to classify these transformations.

1.2. Information Observer

Observing a priori and posteriori processes (events), an observer connects them by measuring information (1.1,1.2), and such connection integrates both observations in an information process.

Since word in-for-ma-tion literally means the act or fact of forming-to put a form, measuring information through forming a process (for example, from the observed events) implements that meaning.

In such formal consideration, information builds its observer, which holds these connections as the information. This link implies a dual complementary relation between information and the observer: information means an observer, and observer is a holder of this information.

The observed information creates the observer, and observer builds and holds the observed information through removing uncertainty at its extraction, acquisition, and accumulation.

Information can be produced at the process’ interactions, including their transformation (1.1-1.3) and superposition, but the observer, in addition to that, acquires the produced information and accumulates it.

For each particular observer, an observing process is primarily unknown, and its observed uncertainty should be converted to the observer’s certainty-information through its inner conversion process.

Hence, the above concepts include building the information observer via its self-conversion process.

2. The probability transformation, measured by an entropy functional on trajectories of Markov diffusion process

Let have the n-dimensional controlled stochastic Ito differential equation:
\[
d\tilde{x} = a(t, \tilde{x}, u_t)dt + \sigma(t, \tilde{x})d\xi, \quad \tilde{x}(\eta, t) \in [s, T] = \Delta, s \in [0, T] \subset R^1
\]  
(2.1)

with the standard limitations [29] on drift function \(a(t, \tilde{x}, u_t) = a^u(t, \tilde{x})\), depending on control \(u_t\), diffusion \(\sigma(t, \tilde{x})\), and Wiener process \(\xi = \xi(t, \omega)\), which are defined on a probability space of the elementary random events \(\omega \in \Omega\) with the variables located in \(R^n\); \(\tilde{x} = \tilde{x}(t)\) is a diffusion process, as a solution of (2.1) under control \(u_t\); \(\Psi(s,t)\) is a \(\sigma\)-algebra created by the events \(\{\tilde{x}(\tau) \in B\}\), and \(P(s, \tilde{x}, t, B)\) are transition probabilities on \(s \leq \tau \leq t; P_{s,\tau} = P_{s,\tau}(A)\) are the corresponding conditional probability’s distributions on an extended \(\Psi(s, \infty)\); \(E_{s,t}[\bullet]\) are the related mathematical
expectations. The dimensions holds in dependent Brownian processes with multi-orthogonal eigenvectors of dispersion $2b(t, \tilde{x}) = \sigma(t, \tilde{x})\sigma^T(t, \tilde{x}) > 0$.

Suppose control function $u_t$ provides transformation of an initial process $\tilde{x}_t$, with transition probabilities $P(s, \tilde{x}, t, B)$, to other diffusion process

$$\zeta_t = \int_s^t \sigma(v, \zeta_v)\,d\zeta_v, \quad (2.1b)$$

with transition probabilities

$$\tilde{P}(s, \zeta_t, t, B) = \int_{\tilde{x}(t) \in B} \exp\{-\varphi'_s(\omega)\}P_{s,x}(d\omega), \quad (2.2)$$

where $\varphi'_s = \varphi'_s(\omega)$ is an additive functional of process $\tilde{x}_t = \tilde{x}(t)$ [30], measured regarding $\Psi(s, t)$ at any $s \leq \tau \leq t$ with probability 1, and $\varphi'_s = \varphi'_s + \varphi'_s'$, $\varphi'_s[\exp\{-\varphi'_s(\omega)\}] < \infty$.

Then, at this transformation, the transitional probability’s functions $\tilde{P}(s, \zeta_t, t, B)$ (2.2) determine the corresponding extensive distributions $\tilde{P}_{s,x} = \tilde{P}_{s,x}(A)$ on $\Psi(s, \infty)$ with a density measure

$$p(\omega) = \frac{\tilde{P}_{s,x}}{P_{s,x}} = \exp\{-\varphi'_s(\omega)\}. \quad (2.3)$$

Using the definition of a conditional entropy of process $\tilde{x}_t$ regarding process $\zeta_t$, we have

$$S(\tilde{x}_t / \zeta_t) = \varphi'_s - \ln[p(\omega)], \quad (2.4)$$

where $E_{s,x}$ are conditional mathematical expectation, taken along the process trajectories $\tilde{x}_t$ (by analogy with M. Kac [31]). From (2.3) we get

$$S(\tilde{x}_t / \zeta_t) = E_{s,x}[\varphi'_s(\omega)], \quad (2.5)$$

where the additive functional, at its upper limit $T$, has the form [32]:

$$\varphi'_s = 1/2 \int_s^T a''(t, \tilde{x}_t)^T(2b(t, \tilde{x}_t))^{-1}a''(t, \tilde{x}_t)\,dt + \int_s^T (\sigma(t, \tilde{x}_t))^{-1}a''(t, \tilde{x}_t)d\xi(t). \quad (2.6)$$

Since the transformed process $\zeta_t$ (2.1b) has the same diffusion matrix but zero drift, we have

$$E_{s,x}\{\int_s^T (\sigma(t, \tilde{x}_t))^{-1}a''(t, \tilde{x}_t)d\xi(t)\} = 0, \quad (2.6a)$$

and we come to the entropy functional, expressed via parameters of the initial controllable stochastic equation (1.1) in the form:

$$S(\tilde{x}_t / \zeta_t) = 1/2E_{s,x}\{\int_s^T a''(t, \tilde{x}_t)^T(2b(t, \tilde{x}_t))^{-1}a''(t, \tilde{x}_t)\,dt\}. \quad (2.7)$$

The proofs of formulas (2.2), (2.3), (2.6) can be found in [28, 30]. Expression (2.7) and its validation are in [33].

The entropy functional (2.4,2.5) is an information indicator of a distinction between the processes $\tilde{x}_t$ and $\zeta_t$ by these processes’ measures; it measures a quantity of information of process $\tilde{x}_t$ regarding process $\zeta_t$. For the process’ equivalent measures, this quantity is zero, and it is a positive for the process’ nonequivalent measures.
3. Conversion of uncertain entropy functional to certain information functional

Let us have entropy functional (EF) (2.7), defined at transforming process \( \tilde{x}_t \) to \( \zeta_t \) by control \( u_t \): 
\[
(S[\tilde{x}_t] \rightarrow \zeta_t).
\] 
(3.1)

Trajectories of conversion process we find from the condition of equivalence of two functionals at transformation: 
\[
S[\tilde{x}_t] \Rightarrow S[x_t],
\] 
(3.1a)

where \( S[x_t] \) is an equivalent certain-information path functional IPF, defined on the conversion process trajectories \( x_t \).

Holding the equivalence relation (3.1a) requires finding such trajectory \( x_t \) along which the best approximation of the EF by IPF or their least difference is achieved:
\[
S[\tilde{x}_t] - S[x_t] \Rightarrow \min_{x_t} \Rightarrow 0 .
\] 
(3.1b)

Such trajectory should satisfy some variation principle, which implies that \( x_t \) ought to be an extremal of \( S[x_t] \) at the condition of equivalence:
\[
S[\tilde{x}_t] = \extr_{x_t} S[x_t].
\] 
(3.1c)

The solved variation problem [19], determines the extremals via dynamic Hamiltonian \( H \):
\[
-\frac{\partial S}{\partial t} = (a^u)^T X + b \frac{\partial X}{\partial x} + 1/2 a^u(2b)^{-1} a^u = -\frac{\partial S}{\partial t} = H ,
\] 
(3.2)

whose function \( a^u = a^u[u_t(t, x_t)] \) depends on the applied control.

At any fixed initial conditions \( (t_o, x_o) \) and the control functions, satisfying Jacobi –Hamiltonian Eq. for (3.2), its extreme is unique for considered class function: for example, the space piecewise differentiable \( x_t \in KC^l(\Delta, R^n) \) and space piecewise continues at \( t \in \Delta \) functions \( u_t \in KC^l(\Delta, U) \) in \( (R^n, U) \) [20].

The Hamiltonian solutions can potentially bring both minimal and maximal solutions for functional \( S[x_t] \) (at its equivalence with the entropy functional in (2.7)). The minimal solution is reached at
\[
P = (a^u)^T \frac{\partial S}{\partial x} + b^T \frac{\partial^2 S}{\partial x^2} = 0,
\] 
(3.3)

which presents constraint, imposed on the extreme solutions at the equality.

With no constraint, Hamiltonian (3.2) carries the trajectories, bringing maximal solution for IPF, compared to the solution at (3.3).

Since the maximum holds the extreme solutions, as the necessary condition of the functionals’ equivalence, this condition should be reached first (before imposing the constraint), and the minimum, as the sufficient condition, should be reached next.

Thus, the functionals’ equivalence brings an information maxmin principle for EF-IPF with transforming random uncertain process \( \zeta_t \) to a certain process \( x_t \), chosen by this principle. Or the equivalent transformation of uncertainty to certainty originates both this variation principle and the conversion
process carrying this transformation. Finding the certainty process (Sec.5) includes superposition of the extreme conjugated Hamiltonian processes, their entanglement, and movement under the constraint.

The applied control \( u \) implements this principle through a cutting off the Markov process \( \tilde{x}_i \) (Sec.4), optimal extracting of maximum information from each of the cutoff minimum and controlling its consumption, minimizing the maximum (Secs.5, 6).

4. The cutting off entropy functional measure on trajectories of Markov diffusion process by applying the impulse control

Let us define \( u \) on the space \( KC(\Delta, U) \) of a piece-wise continuous as the step functions at \( t \in \Delta \):

\[
\begin{align*}
  u_+ &= \lim_{t \to \tau_{k-o}^-} u(t, \tilde{x}_i), \\
  u_- &= \lim_{t \to \tau_{k-o}^+} u(t, \tilde{x}_i),
\end{align*}
\]

which are differentiable, excluding the set

\[
\Delta^o = \Delta \setminus \{ \tau_k \}_{k=1}^m, k = 1, \ldots, m,
\]

and applied on diffusion process \( \tilde{x}_i \) from moment \( \tau_{k-o} \) to \( \tau_k \), and then from moment \( \tau_k \) to \( \tau_{k+o} \), implementing the process’ transformations \( \tilde{x}_i(\tau_{k-o}) \to \varphi_i(\tau_k) \to \tilde{x}_i(\tau_{k+o}) \).

At a vicinity of moment \( \tau_k \), between the jump of control \( u_- \) and the jump of control \( u_+ \), we consider a control impulse

\[
\delta u_\tau^\pm = u_-(\tau_{k-o}) + u_+(\tau_{k+o}).
\]

The following statement evaluates the EF information contributions at such transformations.

**Proposition.**

Entropy functional (2.7) at the switching moments \( t = \tau_k \) of control (4.2) takes the values

\[
S^\delta_{\tau_k} = 1/2,
\]

and at locality of \( t = \tau_k \): at \( \tau_{k-o} \to \tau_k \) and \( \tau_k \to \tau_{k+o} \), produced by each of the impulse control’s step functions in (4.1), is estimated by

\[
\begin{align*}
  S^u_{\tau_k} &= 1/4, \quad u_- = u_-(\tau_k), \quad \tau_{k-o} \to \tau_k, \\
  S^{u+}_{\tau_k} &= 1/4, \quad u_+ = u_+(\tau_k), \quad \tau_k \to \tau_{k+o}.
\end{align*}
\]

**Proof.** The jump of the control function \( u_- \) in (4.1) from a moment \( \tau_{k-o} \) to \( \tau_k \), acting on the diffusion process, might cut off this process after moment \( \tau_{k-o} \). The cut off diffusion process has the same drift vector and the diffusion matrix as the initial diffusion process.

The additive functional for this cut off has the form [32]:

\[
\varphi_x^{-} = \begin{cases} 
0, t \leq \tau_{k-o}^-; \\
\infty, t > \tau_k.
\end{cases}
\]

The jump of the control function \( u_+ (4.1) \) from \( \tau_k \) to \( \tau_{k+o} \) might cut off the diffusion process after moment \( \tau_k \) with the related additive functional
For the control impulse (4.2), the additive functional at a vicinity of \( t=\tau_k \) acquires the form of an impulse function

\[ \varphi_s^+ = \begin{cases} \infty, t > \tau_k; \\ 0, t \leq \tau_{k-\sigma}. \end{cases} \quad (4.5) \]

which summarizes (4.3) and (4.4).

The entropy functional (2.7), following from (4.4-4.5), takes the values

\[ S_+ = E[\varphi_s^+] = \left\{ \begin{array}{ll} 0, t \leq \tau_{k-\sigma}; \\ \infty, t > \tau_k; \\ 0, t \leq \tau_{k+\sigma}. \end{array} \right. \quad (4.7) \]

changing from 0 to \( \infty \) and back from \( \infty \) to 0 and acquiring an absolute maximum at \( t > \tau_k \), between \( \tau_{k-\sigma} \) and \( \tau_{k+\sigma} \).

The multiplicative functional, related to (4.4-4.5), are:

\[ p_s^+ = \begin{cases} 0, t \leq \tau_{k-\sigma}; \\ 1, t > \tau_k; \\ 0, t \leq \tau_{k+\sigma}. \end{cases} \quad (4.8) \]

Impulse control (4.2) provides an impulse probability density in the form of multiplicative functional

\[ \delta p_s^+ = p_s^+ p_s^\tau, \quad (4.9) \]

where \( \delta p_s^\tau \) holds \( \delta^i[\tau_i] \)-function, which determines probabilities \( \tilde{P}_{s,x}(d\omega) = 0 \) at \( t \leq \tau_{k-\sigma}, t \leq \tau_{k+\sigma} \) and \( \tilde{P}_{s,x}(d\omega) = P_{s,x}(d\omega) \) at \( t > \tau_k \).

For the cut off diffusion process, the transitional probability (at \( t \leq \tau_{k-\sigma} \) and \( t \leq \tau_{k+\sigma} \)) turns to zero, and the states \( \tilde{x}(\tau_k - \sigma), \tilde{x}(\tau_k + \sigma) \) become independent, while their mutual time correlations are dissolved:

\[ r_{\tilde{x}(\tau_k - \sigma), \tilde{x}(\tau_k + \sigma)} = E[\tilde{x}(\tau_k - \sigma), \tilde{x}(\tau_k + \sigma)] \rightarrow 0. \quad (4.10) \]

Entropy \( \delta S_s^\tau(\tau_i) \) of additive functional \( \delta \varphi_s^\tau(4.5) \), which is produced within, or at a border of the control impulse (4.2), is define by the equality

\[ E[\varphi_s^+ + \varphi_s^-] = E[\delta \varphi_s^\tau] = \int_{\tau_{k-\sigma}}^{\tau_{k+\sigma}} \delta \varphi_s^\tau(\omega) P_\delta(d\omega), \quad (4.11) \]

where \( P_\delta(d\omega) \) is a probability evaluation of the impulse \( \delta \varphi_s^\tau \).

Taking integral of the symmetric \( \delta \)-function \( \delta \varphi_s^\tau \) between the above time intervals, we get on the border

\[ E[\delta \varphi_s^\tau] = 1/2 P_\delta(\tau_k) \text{ at } \tau_k = \tau_{k-\sigma}, \text{ or } \tau_k = \tau_{k+\sigma}. \quad (4.12) \]

The impulse, produced by deterministic controls (4.2) for each process dimension \( i = 1, ..., n \), is a non random with

\[ P_{s,x}(\tau_k) = 1, k = 1, ..., m. \quad (4.13) \]

This probability holds a jump-diffusion transition probability in (4.12) (according to [34]), which is conserved during the jump.
From (4.11)-(4.13) we get estimation of the entropy functional’s information increment when the impulse control (4.2) is applied (at \( t = \tau_k \) for each \( i, k \)) in the form
\[
S_{t_k}^{\delta u} = E[\delta \varphi_{t_k}^{i+}] = 1/2 ,
\]
which proves (2.3).

Since that, each of the symmetrical information contributions (4.6) at a vicinity of \( t = \tau_k \):
\[
E[\varphi_{t_k}^{i-}] = S_{t_k}^{u_{-}} \quad \text{and} \quad E[\varphi_{t_k}^{i+}] = S_{t_k}^{u_{+}}
\]
is estimated by
\[
S_{t_k}^{u_{-}} = 1/4 , \quad u_{-} = u_{-} (\tau_k) , \quad \tau_{k-o} \rightarrow \tau_k ; \quad \text{and} \quad S_{t_k}^{u_{+}} = 1/4 , \quad u_{+} = u_{+} (\tau_k) , \quad \tau_k \rightarrow \tau_{k+o} ,
\]
which proves (4.3a,b).

The entropy functional (2.7), defined through Radon-Nikodym’s probability density measure (1.3), holds all properties of the considered cut off controllable process, where both \( P_{s,t} \) and \( \tilde{P}_{s,t} \) are defined.

**Corollaries**

From (2.7) and (4.4, 4.3) it follows that:

(a)- The stepwise control function \( u_{-} = u_{-} (\tau_k) \), implementing transformation \( \tilde{x}_{i}(\tau_{k-o}) \rightarrow \zeta_{i}(\tau_k) \), converts the entropy functional from its minimum at \( t \leq \tau_{k-o} \) to the maximum at \( \tau_{k-o} \rightarrow \tau_k \);

(b)- The stepwise control function \( u_{+} = u_{+} (\tau_k) \), implementing transformation \( \zeta_{i}(\tau_k) \rightarrow \tilde{x}_{i}(\tau_{k+o}) \), converts the entropy functional from its maximum at \( t > \tau_k \) to the minimum at \( \tau_k \rightarrow \tau_{k+o} \);

(c)- The impulse control function \( \delta u_{t_k}^{i} \) implementing transformations \( \tilde{x}_{i}(\tau_{k-o}) \rightarrow \zeta_{i}(\tau_k) \rightarrow \tilde{x}_{i}(\tau_{k+o}) \), switches the entropy functional from its minimum to maximum and back from maximum to minimum, while the absolute maximum of the entropy functional at a vicinity of \( t = \tau_k \) allows the impulse control to deliver the maximal amount of information (4.14) from these transformations;

(d)- Dissolving the correlation between the process’ cut off points (2.10) leads to losing the functional connections at these discrete points, which evaluate the Feller’s kernel measure [35].

(e)- The relation of that measure to additive functional [36] in form (4.6) allows evaluating the kernel’s information by the entropy functional (4.5).

(f)- The jump action (4.2) on Markov process, associated with “killing its drift”, selects the Feller’s measure of the kernel [37, 38, other], while the cutoff” information functional provides information measure of the Feller kernel, and is a source of a kernel information, estimated by (4.14).

In a multi-dimensional diffusion process, the stepwise controls, acting on the process’ all dimensions, sequentially stops and starts the process, evaluating the multiple functional information.

The dissolved element of correlation matrix at these moments provides independence of the cutting off Markov process’ fractions, leading to orthogonality of their correlation matrix.

**5. The specific of the transformed processes**

**5.1. The cutoff process**
First, it is a random, following from Eq.(2.1) under applying the cutoff control to the drift function in (1.1). Secondly, it should integrate non-random information contributions \( \delta S_k^{\text{nu}}(\tau) \) along its \( n \)-dimensional trajectory, formed during the transformation of probability \( p_s^- \) to \( p_s^+ \) in (4.8).

The first control \( u_- = u_-(\tau_k) \) transfers Markov process \( \tilde{x}_i(\tau_k) \) to Brownian process \( \zeta_i(\tau_k) \), which holds probability \( \tilde{P}_{s_i}(d\omega) \to 1 \), carries maximal \( \delta S_k^{\text{nu}}(\tau) \), delivered at this transformation, and can be measured via the killed correlation of process \( \tilde{x}_i(\tau_k) \).

Such transformation is associated with killing the Brownian process at the rate of increment of related additive functional \( d\varphi^i(\tau_k)/\varphi^i(\tau_k) \) for each single dimension \( i \) [38].

The killing Brownian motion can take a sharp increase at locality of hitting a time varying barrier [39].

The second control \( u_+ = u_+(\tau_k) \), cutting the Brownian process, might transfers the rate of killed Brownian process \( \zeta_i(\tau_k) \) to a Markovian process \( \tilde{x}_i(\tau_k) \) at

\[
p_s^+ = \tilde{P}_{s_i+x} / P_{s_i+x} \to 0, \quad P_{s_i+x}(d\omega) \to 1.
\] (5.1)

And control \( u_+ = u_+(\tau_k) \) starts a certain (non-random) process \( x_i(\tau_{k+0}) \), satisfying the variation conditions (Sec 3), with the eigenvalue of diffusion operator [39,40] for the process \( \zeta_i(\tau_k) \), determined by that rate.

The transferred eigenvalue \( \alpha_{i2r} \) holds information frequency and speed, driven by the generated maximal entropy contribution

\[
\delta S_k^{\text{nu}}(\tau) = \delta_\nu \alpha_{i2r}
\] (5.2)

during interval of observation \( \delta_{li} = \tau_k - \tau_{k-o} \), where \( \tau_{k-o} \) here is the moment preceding moment \( \tau_k \) of applying control \( u_+ = u_+(\tau_k) \).

The initial conditions of the starting dynamic process are determined by a boundary, defined through the step-up control function \( u_+ = u_+(\tau_k) \), which absorbs the terminated (killed) process and transfers \( \alpha_{i2r} \) to the conversion process at the moment \( \tau_{k+0} \) [24]. Elementary information contribution (5.2) of \( S(\tilde{x}_i / \zeta_i) \) should coincide with that required by conversion process’ variation principle(Sec.3), which is determined by the VP maximal information invariant \( a_i(\gamma_{io}) \) of starting dynamic process [23(2)]. We get equality

\[
\delta_\nu \alpha_{i2r} = a_i(\gamma_{io}) \quad (5.2a)
\]

which, at the known rate of diffusion operator (or additive functional), identifies \( \delta_{li} \) and, hence, the locality of boundary moment \( \tau_k \) (at a fixed moment of opening observation \( \tau_{k-o} \)) of cutting off the Brownian process.

The minimax principle, applied to an ensemble of the boundary-absorbed process, chooses a pair of the ensemble mirror states, possessing maximal information of their information distinction simultaneously with probability (5.1) for such minimal chosen number of the process’ states at the cutting moment.
The control \( u_+ \) transfers these captured boundary pair-mirror states and the eigenvalue of the killed Brownian movement to the complex conjugated dynamics.

On the spot of switching this control, there are two simultaneous events (pair-mirror states), each of which can be controlled separately by observer inner controls \( v_+ = v_+^{12}(v_1^+, v_2^+) \), being a pair of mirror reflection of \( u_+ \). Such controls, applying within time intervals \( \delta_0 < t \leq \Delta_2, \delta_\alpha = \tau_{20k} - \tau_{2k} \) (Fig.1):

\[
\mathbf{u} = u_+(t) = \begin{cases} 
\alpha_+ v_+, & \delta_\alpha < t \leq \Delta_2 \\
0, & t > \Delta_2
\end{cases}
\]  

(5.3)

where \( v_+ \) is a component of \( u_+ \), act directly on the process’ pair-mirror states. The transformed \( \alpha_+ \) provides frequency function \( f_{\alpha} \sim \alpha_+ \) to a new (conversion) process through spectral representation of related Furies transformations, which is connected with parameter \( \gamma_{\alpha_0} \) of the VP invariant (5.2a).

5.2. Conversion process

Since the conversion process, is a solution of Hamiltonian Equations (with conjugated Hamiltonians \( H(H^1, H^2) = H^{12} \), Sec.3), it is described by complex conjugated trajectories \( x^{12}_+(x_+, x_-) \) with their functions of action \( S^{12} = -\int H^{12} dt \), having complex conjugated components \( S_+(x_-), S_+(x_+) \) and their probabilities, determined on these processes accordingly.

Control functions \( v^{12}_+ = f(x^{12}_+) \), at \( u_+ = \alpha_+ v_+ \) in (5.3), convey the transition from the captured boundary states \( \bar{x}_+^{12}(\bar{x}_+, \bar{x}_-) \) and eigenvalues \( \alpha_+ \) (of the killed Brownian movement) to the starting complex conjugated dynamics. Multi-dimensional process holds many extremals with different information speeds. The minimax criterion selects both sequences of the criterion’s ranged eigenvalues and related pair states for all dimensions. The generated multi-dimensional information dynamics evolve in information form of Schrödinger’s process with its bridge and entanglement [22], which cooperates in information hierarchical network of the conversion process [23,24].

Chapters 1-5 have explained the formal EF-IPF connections and their associated processes; more details bellow brings inside of observer’s specifics.

6. The observer’s proceeding of the conversion process and holding its information

Suppose, the EF uncertainty affects an observer at some random interval \( \Delta \) of the process’ \( \bar{x}_r \) potential observation \( \bar{x}_r(\Delta) \), which randomly divides \( \bar{x}_r \) on a priory \( \bar{x}_a(t) \) and a posteriori \( \bar{x}_p(t) \) processes.

Using maxmin prediction, the observer virtually (imaginably) trials \( \bar{x}_a(t) \) and \( \bar{x}_p(t) \) by a set of impulses \( u_\Delta = \Delta_\alpha[u^a, u^p] \), which control the related random parts \( \bar{x}_a(t), \bar{x}_p(t) \) of process \( \bar{x}_r \).
Each observer testing actions $u^a$ and $u^p$ produce transformation of the probabilities, generating the observer’s portions of the entropy functional $\tilde{s}_{ap}[\tilde{x}_i(\Delta)]$ for process $\tilde{x}_i(\Delta)$.

By observing uncertainty $\tilde{s}_{ap}[\tilde{x}_i(\Delta)]$ of the process $\tilde{x}_i(\Delta)$, each observer intervenes in random process, changing the process’ initial probabilities ($P_a$, $P_p$) and entropy measure of this observation.

Observing multi-dimensional process involves numerous such interventions, generating the process’ functional uncertainty measure of an observer.

Observer’s EF also comprises external collective (cooperative) information affecting observation [41]. We assume that the uncertainty measure is defined before the probing changes, and it can be considered as an objective measure of some random process.

If each cutting actions $u^a(\tau_i)$ and $\tilde{u}^p(\tau^*)$ potentially curtail the random process’ parts $\tilde{x}_i(\tau_i)$ and $\tilde{x}_i(\tau^*)$ on interval $\Delta$, killing the cutoff by moment $\tau_{2k}$ (Fig.1), then the problem consists of converting entropy portion $\tilde{s}_{ap}[\tilde{x}_i(\Delta)] \to \tilde{s}_{ap}[\tilde{x}_i(\Delta)]$ to related information functional portion $i_{ap}^o[x_i(\Delta_o)]$ using the step-up control’s $u^p(\tau_i)$ during the conversion process $x_i(\Delta_o), \Delta_o = \Delta_1 + \Delta_2$, where the related symbols indicate random $\Delta$ and non-random $\Delta_o$ intervals. The conjugated dynamics proceed on interval $\Delta_1 - \delta_o$, with interval $\delta_o$ of control $\tilde{u}^p(\tau^*)$ switch from $\tau_{ik}$ to $\tau_{iko}$, where unified mirror control $\nu_i$ entangles the dynamics on interval $\Delta_2$ up to $\tau_{2k}$-locality of turning the constraint off.

Both observers’ external and internal processes on Fig.1, which the observer proceeds simultaneously, are combined in a common time, as a difference from Fig.2, where these processes are shown sequentially in time for comparison. The observer’s time course might differ in the time scale from external process.

Control $u^a(\tau_i)$ transforms the process’ probabilities $p_i^o = P_{t,x} / P_{t,s}$ (in (4.8)) from Markovian $P_{t,x}$ to Brownian $P_{t,s}$ process, cutting entropy $\tilde{s}_{ap}[\tilde{x}_i(\Delta)]$ jointly with control $\tilde{u}^p(\tau^*)$. This control transforms probabilities $p_i^e = P_{t,s} / P_{t,s}$+ , converting portion $\tilde{s}_{ap}[\tilde{x}_i(\Delta)]$ to $i_{ap}^o[x_i(\Delta_i)]$, and concurrently starts the process with probability $P_{t,s}+$ on interval $\Delta_2$, finishing it by the moment of killing $\tau^* + \Delta_2 \to \tau_{2k}$, where $\Delta_i \equiv \tau_{iko} - \tau_{1o}, \Delta_1 = \tau_{ik} - \tau_{1o} + \delta_o, \delta_o \equiv \tau_{iko} - \tau_{ik}, \Delta = \Delta_o$ (Fig.1).

By ending moment $\tau_{2k}$ of this transformation (Sec.4), both the cutoff random process $\tilde{x}_i(\Delta)$ and its entropy portion $\tilde{s}_{ap}[\tilde{x}_i(\Delta)]$ disappear, transforming it to information functional portion $i_{ap}^o[x_i(\Delta_o)]$.

Other dimensions with the cutoff controls supply the related contributions, which are integrated by the EF-IPF using the minimax criterion for all dimensions.
The required minimax means stepwise jump probabilities, changing each maximum entropy $\tilde{s}_{ap}[\tilde{x}_i(\Delta_\ast)]$ to minimum (at cutting moment $\tau_\ast$) and to related information $i_{ap}^o[x_i(\Delta_2)]$ on interval $\Delta_2$ of its accumulation. Among multiple random copies of such jumps, the observer’s maxmin satisfies the most probable opposite jumps, that could be produced by some the opposite controls $u_+^{1\ast}(\tau_\ast) \to v_{o1}, u_+^{2\ast}(\tau_\ast) \to v_{o2}$, which, we assume, are reflections of control $u^a = u_+^{1\ast}, u_+^{2\ast}$, extending its action internally. These observer’s opposite inner controls $v_o(v_{1o},v_{2o})$ are functions $v_{1o} = f_{1o}(\tilde{x}_+), v_{2o} = f_{2o}(\tilde{x}_-)$ of the cutting maximum information states $\tilde{x}_+, \tilde{x}_-$, holding the maximal information distinction simultaneously in the selected random ensemble, while the step-up control $u^a$ starts complex conjugated dynamics (Secs.3,5) with initial states $x_-, x_+$. The inner controls functions $v_{\ast\xi} = f(x_+,x_-), v_{\ast\xi} = f(x_-,x_-)$ initiate opposite directional-conversion process, which, being the solution of Hamiltonian Eqs, is described by complex conjugated trajectories $x_-, x_\ast\xi$. These processes carry their complex conjugated probabilities and components of the entropy’s analogue function of action, interfering nearby moment $\tau_{ik}$ (Fig.1).

Moment of their joining $\tau_{iko}$ indicates disappearance of the entropy imaginary components of Hamiltonian dynamics:

$$\tilde{s}_{ap}^o[\tilde{x}_i(\Delta_\ast)] + \tilde{s}_{ap}^o[\tilde{x}_i(\Delta_\ast)] = 2\tilde{s}_{ap}^o[\tilde{x}_i(\Delta_\ast)] = i_{ap}^o[x_i(\Delta)]$$

(6.1)

producing real information $i_{ap}^o[x_i(\Delta)]$ converted from entropy $\tilde{s}_{ap}^o[\tilde{x}_i(\Delta_\ast)]$, where interval $\delta_o$ is defined by the control function (5.3). The complex conjugated dynamics entangle on interval $\Delta_2$ holding information $i_{ap}^o[x_i(\Delta_2)]$. Hence, initial observer uncertainty $\tilde{s}_{ap}^o[\tilde{x}_i(\Delta)]$ is transferring to its information-certainty

$$i_{ap}^o[x_i(\Delta_o)] = i_{ap}^o[x_i(\Delta_2)] + i_{ap}^o[x_i(\Delta_2)]$$

(6.2)

By turning on the step-down control at moment $\tau_{ik}$, the observer imposes the constraint, minimizing the process information speed movement on extremals, which determines the moment of turning this control off $\tau_{iko}$ and its stopping $\tau_{2k}$, Fig.1. Whereas step-up control $\tilde{u}^o[v_o]$ launches complex dynamics at moment $\tau_{io}$, its step-down action, as $\tilde{u}^o[v_i]$, starting at moments $\tau_{ik}$, allocates its interval of control switch $\delta_o$ to interfering processes $x_i(x_+,x_-)$, and ends the control action during a finite time interval $\Delta_2 = \tau_{2k} - \tau_{iko}$ until it stops at moment $\tau_{2k}$, finishing $\Delta_o$.

At moment $\tau_{iko} \to \tau_\ast$, control $\tilde{u}^o[v_i]$ cuts off posteriori process $\tilde{x}_p(\tau_\ast)$, while starting entanglement of processes $x_-, x_\ast\xi$ and continues it until moment $\tau_{2k}$ of killing both Brownian process and this.
entanglement. A sudden rise $\delta x_i$, at $\tau_{2k}$-locality, corresponds turning off the constraint by the control end, while slight growth $x_i(\tau_2-o)$ in this locality is limited by the Hamiltonian maximum. At imposing the constraint, potential function (Sec.3) approaches zero: $P(t,x) = (a^u)^T x + b^T \frac{\partial X}{\partial x} \rightarrow 0$, which is possible when its controllable left part reaches a threshold, restricted by its diffusion right part, at $-(a^u)^T X = b^T \frac{\partial X}{\partial x}$. Overcoming this threshold on a path from the Hamiltonian minimum, with following release of the maximal Hamiltonian at the $\tau_{2k}$-locality, produces impulse $\delta x_i$. This impulse is consistent with a sharp increase $\delta x_i$ of the killing Brownian motion (Sec.5) at the same $\tau_{2k}$-locality, while the killing proceeds between the boundary moments $\tau_{1k} \rightarrow \tau^*$ and $\tau_{2k}$ of the process' cutoff and stopping.

According to [39] and [22], a sudden death of entanglement, associated with its killing in finite time [42], is estimated by information $\sim 1/8 \text{Nat}$ of total $\sim \ln 2 \text{Nat}$, accumulated by entanglement, which could deliver Brownian process $\delta x_i$ that implies observer’s $\delta x_i$ at $\tau_{2k}$-locality of ending the inner control $\nu_i$.

Imposing the constraint requires the same information, which the observer spends on this control [24]. Both starting-up and starting-down observer’s controls require approximately $2/3$ of total information, delivered by observation. The step-up control information and $1/3$ of delivered information are spend on the conjugated information dynamics, while under the step-down control this dynamic information is entangled in the adjoint conjugated processes on $\tau_{1k} = \tau_{ik} + \delta_o$ up to $\tau_{2k}$.

This means, $1/3$ of total information becomes free information (that is covering $\delta x_i$), needed for turning on a next step-up control, being a self-driven by observer.

The conversion process' time interval $\Delta_1 = \Delta_*$ is determined by both carried $\tilde{s}_{ap}[\tilde{x}_i(\Delta_*)]$ and the transformed eigenvalues $\alpha^+ = \alpha^+(\tau_{1o})$ for each trial, which hold different process’ dimensions frequencies:

$$\Delta_1 = \tilde{s}_{ap}[\tilde{x}_i(\Delta_*)] / \alpha^+.$$  \hspace{1cm} (6.3)

Time interval $\Delta_2$ is determined by both known $i_{ap}^o[x_i(\Delta_o)]$ and the eigenvalues $\alpha_o^+ = \alpha_o^+(\tau_{ik})$ defined via the minimal Hamiltonian:

$$\Delta_2 = i_{ap}^o[\tilde{x}_i(\Delta_2)] / \alpha_o^+.$$  \hspace{1cm} (6.4)

Thus, after ending the conversion time interval, each multiple pair reaches equality

$$\tilde{s}_{ap}[\tilde{x}_i(\Delta_o)] = i_{ap}^o[x_i(\Delta_o)].$$  \hspace{1cm} (6.5)

At fulfillment (6.5), the ending (killed) conversion process holds its information by producing the information code [20,21].
Hence, the observer’s multiple trial starts with random \( u^a \) cutting, reflected by pair \( u^a = u^{a1}_o, u^{a2}_o \) and inner control \( v_o(v_{i_o}, v_{2_o}) \), which minimizes \( u^a \) actions by Yes-No probes in the conjugating process and ends with joint control \( v_i = (v_{1_i}, v_{-1_i}) \rightarrow \tilde{u}^p[v_i] \) that finally cuts the chosen observed part.

Theoretically, if whole cutoff external impulse infinitively small (Sec. 2), then both \( \tilde{u}^o(\tau^*) \) and \( \tilde{u}^p(\tau_c) \) cut process at the same moment \( \tau^* = \tau_c = \tau_1 \), providing information \( \tilde{i}^a_{op}[x_i(\Delta_o)] \) at internal \( \Delta_o \rightarrow \tau_1 \).

Each equal multiple pair (6.5) concurrently contributes to the related entropy and information functionals on their time intervals \( \Delta_i, \Delta_{oi} \) respectively:

\[
\sum_{i=1}^{n \rightarrow \infty} \tilde{s}_{ap}^{oi}[\tilde{x}_i(\Delta_{oi})] = \tilde{S}_o^a \quad \text{and} \quad \sum_{i=1}^{n \rightarrow \infty} \tilde{i}_{ap}^{oi}[x_i(\Delta_{oi})] = I_p^o, \quad (6.6)
\]

which become equal automatically on the end of each multiple probing trial:

\[
\tilde{S}_o^a = I_p^o. \quad (6.7)
\]

The disappearing multiple trial process retains the trial integral information, encoding it in a local information network as the IN logic [24].

Because each equality in (6.6) requires theoretically infinite number \( n \), which relates to undefined number of computation, reaching these equality and (6.7) are possible only approximately. The equality’s proximity increases with growing functional sums of \( i_{ap}^o[x_i(\Delta_{oi})] \), which evaluate the entropy functional’s math expectations along all random trajectories paths (that actually builds observer’s EF).

Since each \( n \)-dimensional portion of entropy functional EF (2.7) is transferred to related Hamiltonian function of action \( \tilde{s}_{ap}^{oi}[\tilde{x}_i(\Delta_s)] \) on a fixed interval \( \Delta_s \), the observer actual transforming action allows not to measure directly the entropy functional, instead dealing with dynamic \( \tilde{s}_{ap}^{oi}[\tilde{x}_i(\Delta_s)] \), and therefore to avoid taking the math expectations for measuring EF. Moreover, once an externally observing random process had been killed, the observer deals with reflected inner conversion process on its extremal segments.

Since under the step-down control the delivered information is entangled, its part becomes a free information, attracting new information, which allows collect the entropy and information functional in the multi-dimensional process. Indeed, the observer conjugated dynamics produce \( \tilde{i}_{ap}^{oi}[x_i(\Delta_{oi})] \), whose free information allows the automatic continuation of retrieval each secondary \( \tilde{i}_{ap}^{oi+1}[x_i(\Delta_{oi+1})] \) from the EF until their summary satisfies (6.6). As the observer progressively summarizes \( \tilde{s}_{ap}^{oi}[\tilde{x}_i(\Delta_s)] \), each following sum of these extremes determines its next conversion process with its minimax for each observer’s inner information dynamics.
Hence, the observer’s intention to end the conversion process (by applying the step-down control satisfying the process minimax) coincides with its ability to attract new information via free information for each trial.

The controls could act independently and not simultaneously for each dimension, as soon as conditions (6.4), (6.7) are reached at some moments, determined by the maxmin principle of observed information.

Getting the observer EF deterministic value brings actual the IPF value, i.e. it holds the quantity of equivalent information automatically. Each observer evaluates its expectations along the trajectories path by integrating sequentially the EF contributions along the path.

Mathematically it corresponds to EF integral (2.7) with not fixed upper limit $T$, while the end of this evaluation process is a priori unknown. This means, the local contributions could reach the extreme and maxmin values sequentially in time (for different dimensions), while their consecutive adding determines the current, deterministic EF values over each random path, as the current IPF. Moreover, both the current functionals’ equal values (6.5), completing the sum (in (6.6)), and their single upper limit (6.7) will determine the last contribution at its final moment $t_n \rightarrow T$.

Each local EF transformation $p_i^{-}$, to $p_i^{+}$ will be converted to a non-random conversion process, until trials end, terminating this EF. Observer yields the integral Bayesian information, collected during the trials, whereas its uncertainty portion are converted in the related certainty portion until all portions of the EF will be converted in the total IPF. The consecutive EF and IPF contributions are built by cutting each local correlation of random process $\tilde{x}_i$ (between its parts $\tilde{x}_a(t), \tilde{x}_p(t)$) and integrating all of them along trajectories of the multi-dimensional process.

Even though the local equivalence (6.5) is satisfied, the integration (summing) in (6.6) continues until the integral information from the observation $I_p$ approaches to that requested by the observer information network’s (IN) cooperative logic $I_{m+1}$, satisfying equality [24]:

$$I_p^o = I_{m+1}(a(\gamma_{12}^o), a_s(\gamma_{12}^s)).$$

This currently requested information in the form of a quality messenger (qmess) [24], being sent by observer, is measured by the VP information invariants $a(\gamma_{12}^o), a_s(\gamma_{12}^s)$ (Sec.3), which depends on the cooperative logic of the IN existing $m$-th upper level, generating the qmess. The invariants are functions of density of collected information $\gamma_{12}^o = \gamma_{12}^o[f_{\omega}(\gamma_{12}^s)]$, where frequency $f_{\omega}$ of delivered information is determined via the observer’s parameter of uncertainty $\gamma_{12}^s$.

The observer selects the requested information depending on the frequency of information spectrum, while the information invariants, restricted by VP, limit $\gamma_{12}^s$ and therefore restraints each density. Since information density determines the IN attracting information cooperative force:

$$X_{12}^o = [\gamma_{12}^o - 1],$$

(6.9)
which evaluates observer’s intentional effort, it limits both the obtainable frequency and the observer’s intention to get this information spectrum, holding the observer attention during each observation process [24]. These relations implicates building temporary (for each qmess) a local IN for each IPF collection, which should support the observer’s existing IN and its logic.

The local IN starts building, verifies and binds its triplet’s nodes with “short term memory”, and continues building until its final density will match that by (6.8).

The free information initiates this IN building, which provides its following triple cooperation enables attracting the IN subsequently build node. The temporary IN builds until concentration of maximums of information, enclosed in its final nodes, reaches the density, predicted by (6.9), whose cooperative force is sufficient for adjoining the local with existing IN. Moment of approaching information \( I_p \) to that, requested by the observer IN cooperative logic, evaluates an upper border of this time interval, while the moment of imposing constraint at the entanglement of conjugated dynamics determines its low border.

The ending functionals’ collections coincides with the IN’s satisfaction with the needed information (evaluated by (6.8),(6.9)), which symbolizes the observer expression of a surprise, when the integrated information, being temporary memorized in the local IN, starts memorizing in the observer IN.

After memorizing, the IN absorbs the local IN, being compressed in the observer IN upper level (with information density \( \gamma^a_{m+1} \)), which generates information invariant \( a(\gamma^a_{m+2}) \) with an elevated information density that requests the related frequency of new information.

(Before such memorized attachment, the observer could not be surprised, even though its existing IN might predict this invariant for a future request of new validating information).

Each such invariant evaluates a quality of observer’s information enclosed in this IN level [20].

The observer starting-up control’s information \( a \), through interaction with incoming information \( a \), produces sufficient information [21], capable the sequential and consecutive increase of the observer triplet’s quality of the IN information, which is required for both forming next triplet and adjoining it subsequently to the observer IN’s node. The observer’s self-imposing dynamics guarantee persistence of the entire observer’s operations and the continued extension of its information as needed.

Therefore, the observer initiates observation by its free information (from previous actions) that starts build temporary IN (with its STM) until its enlarging density approach to that requested by existing observer’s IN and its main logic. With the satisfaction, observer uncertainty disappears, evaluating his expectations from the entropy functional via math expectations along all random trajectories paths, which actually builds its EF, IPF and finally the IN logic.

The conversion process’ time interval finalizes dynamic measuring of initial hidden information, concentrated in the external cutoff correlations, which is correlated with the observer process during the control’s intervention in this process. Such destruction of initial correlations and then formation of correlations during the measurement potentially erases the primary hidden information, leading to
decoherence [43]. At these moments, the observer acquires each portion of the requested information (carrying invariant \( a(\gamma^\alpha_{m+2}) \)), while the IN bound, cooperative information dynamics self-memorize it. Remembering information indicates the process irreversibility and physical activity [44]. Since memorizing spends an energy, which equals to that spent on the memory erasure, the IN memorized information has physical properties [45,46,47].

The observer’s microdynamics start with conversion of the observed random information in the conjugated dynamics and end with the entanglement. On the macrolevel, the VP extremals of information path functional (which averages via the EF a manifold of the hidden information), describe the information macrodynamics in terms of the information forces acting on the flows [20,21], distributed in space-time along the measured process; the macrodynamics are assembled in the INs’ logics.

Moment of acquiring the requested information finally verifies the measured information of observations, providing the time interval as the border’s macro parameter between the observer’s information micro- and macrodynamic processes, which connects information with physics, reversibility and irreversibility.

Each logic’s triple code consists of digits, whose both the highs and time-space intervals depend on incoming information, whereas the triplet’s size discriminates the IN hierarchical distance between the nearest triplets, which, in turn, depends on the observer’s requested frequency spectrum of information (limited by admissible range of the invariants of information dynamics). Since logic’s code is built by the conversion process through the equivalence of portions of uncertainty and certainty functionals (that is checked concurrently via Yes-No actions), the IN triplet’s logic accumulates a history of verified information, while its each triple digits is selected from retrieved information via minimax (which implies a competition to reach it through comparison of the digits history).

Saving logic’s history by memorizing it requires energy, but erasing the intermediate computational results of initially irreversible logics will bring a reversible computer [26], and according to that: ‘The usual general-purpose computing automaton (e.g., a Turing machine) is logically irreversible’.

The observer’s IN currently built its logic information code (as a program executing computing with Gödel’s limitations), which operates the observer action that retrieves, processes, collects, and memorizes its information. This coding program logic concurrently structures the information observer.

**The regularity summary**

*General principle: Get maximum information from each of its observed minimum and minimize the maximum at transformation of observed uncertainty to equal observer’s certainty-information.*

This dual complementary principle functionally unifies the observer *main* regularities:

1. Integral measuring each observing process under multiple trial actions;
2. Converting the observed uncertainty to information-certainty by generation internal information micro- and macrodynamics and verification of trial information;
3. Enclosing the internal dynamics in information network (IN), whose logic integrates the observer’s requested information in the IN code;

4. Building concurrently the IN temporal hierarchy, whose high level enfolds information logic that requests new information, while the enclosed logic is attached to observer’s running IN, extending the logic code;

5. Self-forming the observer’s inner dynamical and geometrical structures with a limited boundary, shaped by the IN information geometry during the time-space cooperative processes;

*And their specifics:*

1. Extracting max min information under observer’s impulse actions, which convert the observed process by generating internal pair-wise conjugated cooperative dynamics at each trial;

2. Producing entangled information-certainty through the dynamic cooperation, which generates free information, requesting information for each next trial, until the total integrating information satisfies the needs of the observer information network’s (IN) according to its logic; this includes building a temporary IN with ‘short term memory’, initiated by free information, until its cooperative force is sufficient for adjoining this local with observer existing IN;

3. Self-cooperating the entangled information in the IN triple nodes, which are sequentially and hierarchically enclosed by applying the minimax;

4. Creating the IN nodes’ triplet code, whose double spiral information geometry follows from the conjugated space-time cooperative dynamics;

5. Providing the observer’s integral logic via the triple code’s hierarchy.

These regularities establish a united information mechanism, whose integral logic self-operates this mechanism, transforming observed uncertainty to physical reality-matter. The formally described information regularities are specified on particular information and physical processes via their identification, control and implementation [19-20], serving for prediction of new detail discoveries.

The regularities of inner dynamics allow us discussing the appearances of a bit, which could potentially enclose high-level intelligent information. Let’s have two examples.

Human genome code contains approximately (by different estimations) between $6 \times 10^9$ and $6.5 \times 10^9$ bits excluding redundant information.

This code information logic can be enclosed in the IN’ $m$ -level triplet structure, whose final information compresses $N = 3^n \text{bits} (70)$ [23], with number of conversion process $n = 2m$. It gives $n = 22 - 23$ for human code, whose IN’s final bit compresses all its (715-778) non-redundant MB.

The Universe light horizon is evaluated by $10^{122} \text{bits}$[48], which could be enfolded and compressed in the IN integral information code with final ~1 bit that, according to above estimation, potentially encloses $n = 512$ conversion processes within its ending $m = 250$-th triplets’ hierarchical level, absorbed by the IN border [20].(The computable $n \rightarrow \infty$ -from (6.6)). A bit, through the observer cooperative dynamics, being memorized in its IN, holds physical properties within the observer created inner code logic.
7. Illustration of the information regularities on examples from neuronal dynamics.

Discussion

Analyzing these examples, presented in reviews and studies [49-59] (which include extensive References), we explain and comment some of their information functions using formal results [20-25] and this paper. Here, we relate observer’s external processes to sensory information, while its internal processes uphold reflected information through the internal dynamics (IMD) synchronized proceedings. According to review [49], a single spike represents an elementary quantum information, composed from the interfering wave neuronal membrane potentials, which is transferred to post-synaptic potential. While the synaptic transmission is a mechanism of conversion of the spike, or a sequence of spikes, into ‘a graded variation of the postsynaptic membrane potential’ that encodes this information... The pre-synaptic impulse triggers connection with the synaptic space, which starts the Brownian diffusion of the neuro-transmitter, opening the passage of information between the pre- and the postsynaptic neuron. The transferring 'quantum' packet determines the amplitude and rate of the post-synaptic response and the type and quality of the conveyed information.

Instead of the authors term ‘quantum’, we use information conjugated dynamics that convey this information.

‘Although there are several possibilities to start releasing the states on the border the post synaptic transmission, usually only a single one close to the centre of the Post Synaptic Density have a higher probability to starts the opening formation of binding the receptors’. This ‘eccentricity’ influences the rate of neuro-transmitters that bind the postsynaptic receptors [49].

It illustrates selectiveness of the specific minimax states of the Brownian ensemble (located on a border the Brownian diffusion, Sec.5), allowing to chose the maximum probable states of the ensemble, having the rate, amplitude, and the time course of the post-synaptic potential, which is triggered by the impulse (Sec.4,6, Fig.1), related to the spike.

Each Post Synaptic Density is composed of four chains arranged by any combination of four subunits, which have two types of binding receptors [49].

It is a straight analogue of our four units in each elementary information level of information network(IN) with two biding actions of the controls (Fig.3), composing the triplet’s node.

The starting composition of the receptors subunits depends on the level of 'maturation' of the synapse, which is changed during the development and as a function of the synaptic activity.

‘The real interaction between excitatory and inhibitory synapses is based on delicate equilibriums and precise mechanisms that regulate the information flow in the dendrite tree. There is a sort of equilibrium between the cooperative effect due to the summation of the synaptic activities of excitatory
neurons and the inhibitory effect due to the reduction of the driving force that produces the information transmission’. The minimax mechanism includes regulation, equilibrium and cooperation [21], whose joint proceeding limits both internal and external information processing, Sec.6.

‘The post-synaptic regulation of the information, passing by synaptic transmission, is governed by several different mechanisms involving: the diffusion of the neuro-transmitter in the synaptic space, the absolute and relative number of receptors’ Post Synaptic Density, their dynamics and/or composition. These functions’ depend on geometry of dendric tree, which has hierarchical structure’ analogous to the IN, (Fig.3). ‘Distinctive levels of potentials between different dendrite tree branches produce information flows between the grafting (joint) points of the dendrite tree’s branches. Dendrites of the level $A_n$ are embedded onto ‘mother branches’ that are at the level $A_{n-1}$ that, in turn, are grafted to their mother branches at the level $A_{n-2}$ and so on up to the main dendrite ($A_0$) emerging directly from the starting information. As the synapses are the points of passage of the information among the neurons, the grafting points can be considered the points of passage of information among the dendrite branches. A good approximation to this situation could be a model where each daughter branch is considered a sort of a bidirectional “electrical synapse” of the mother branch: ‘the activity of each branch of the level $A_n$ can influence the activity of the branch of the level $A_{n-1}$ and vice versa... The direction of the current depends on the values of the potential level of two sides of grafting point $VA_n$ and $VA_{n-1}$, being in the direction of the mother for $VA_n > VA_{n-1}$, and in the direction of the daughter in the opposite case’. ‘The grafting points represent “nodes” for information flowing in the dendrite tree’ [49]. This network holds the structural functions of dendrite tree, its hierarchically dependent nodes, bidirectional flows of information, concurrent formation of all structure with starting flow of information, selective maxmin influence of nearest nodes and their decrease with the distance from the node. The described structure has a direct analogy of the IN nested structure, holding two opposite directional information flows, which models not only observer’s logical structure, but rather real dendrite bran structure during each of its formation.

‘Although it is generally accepted that the spike sequence is the way the information is coded by, we admit that neuron does not use a single neural code but at least two’ [49]. Hence, the authors suppose that there is a spike code (that might hold the IMD controls with actual impulse’s high and length), another is the triplet’s code, composed of four subunits, which is transferred between IN nodes [21].
Formally dealing with an impulse (Sec.4) and considering its simultaneous actions, we actually apply it in IMD with the impulse’ amplitude distributed on a distance (time), which can be implemented only for real distance impulse-spike potential (involving our simplification of the control impulse). The control impulse rises at the end of the extremal segment (Fig.1), after information, carried up by the propagating dynamics, compensates the segment’s inner information (determined by the segment macroequations, dynamic constraint and invariants, Secs. 3,5). First, this establishes the direct connection between the information analogies of both the spike and the threshold. Second, it brings the spike information measure for each its generation, evaluated in bits (Sec.6). The interspike intervals carry the encoded information, the same way that the discreet intervals between the applied impulse controls do it. Conductivity of an axon depends mainly on inter-neuronal electrical conductance, which, in IMD model, is determined by the diffusion conductivity of the cooperative connections, computed via a derivation of the correlation functions. A signal, passing through this conductivity, might modify a topology of a single, as well as a multiple connection, changing its macrodynamic functions (and a possibly leading to distinct networks) under different inputs.

Neural oscillatory networks, measured by the brain oscillation’s frequency, power and phase, dynamically reduce the high-dimensional information into a low-dimensional code, which encodes the cognitive processes and dynamic routing of information [50].

The IMD model is characterized by the sequential growth of the information effectiveness of the impulse and step controls along the IN spatial-temporal hierarchy. This is connected with changing the quality of the IN node’s information depending on the node’s location within the IN geometry. These changes increase the intensity of the cooperative coupling and its competitive abilities, which make the segment’s synchronization more stable and robust against noise, adding an error correction capability for decoding [21].

Even though these results were published [19, others], the reviewers [49] conclude; ‘None of the approaches furnishes a precise indication of the meaning of the single spike or of the spike sequences or of the spike occurrence, in terms of “information” in the symbolic language of the neurons’.

Now is widely accepted [50,51] that brain system should integrate the observed information, using ‘working memory’- long-term potentiating (LTD) for a predictive learning. ..

There are different LTD experimental and simulation studies [51-56] for integration of observation and verification of dendrite collected information. It’s specifically shown [51,52] that a single neuron could be decomposed into a multi-layer neural network, which is able to perform all sorts of nonlinear
computations. The bimodal dendritic integration code [54] allows a single cell to perform two different state-dependent computations: strength encoding and detection of sharp waves.

Key components of integral information processing are the neuron's synaptic connections, which involve the LTD slow-motion information frequency.

The information observer concurrently verifies the entropy integral's Bayesian information, whereas its parts are converted in the certainty parts until all portions of the EF will be converted in the total IPF (Sec.2). Information, memorized in observer's existing IN level, has less information frequency, compared to the current collection of the requested "qmess" high-level information (Sec.6). When information is temporary assembled in the local IN (with STM), its reverse action works as an information feedback from the existing to a running level of the IN. If the memory retrieval coincides with requested information, such IN reactive action could enforce extraction of information and its synchronization (working as a modulation in the LTD) with that needed by the observer's IN. That helps integration of both EF and IPF by binding their portions according to the time course, which operates as a LTD.

The experiments and simulation [56] show that maximizing minimum of the EF integral Bayesian probability information measure (corresponding the authors' multiple probabilities) allows to reach the effective LTD learning [55].

The review results [51,53] confirm that the dendrite branches pyramidal neurons function, working as single integrative compartments, are able to combine and multiplicate incoming signals according to a threshold nonlinearity, in a similar way to a typical point neuron with modulation of neuronal output. According to studies [57,58], an observer automatically implements logarithmic relationship between stimulus and perceptions, which Weber's law establishes. Additionally, Fechner's law states that subjective sensation is proportional to the logarithm of the stimulus intensity.

Both results imply that observer's neuronal dynamics provide perceptibly of both entropy measure and acceptance of information (as a subjective sensation).

Review [59] provides the evidence of converging the motivational effect on cognitive and sensory processes, connecting attention and motivation.

The IMD related sensory-cognition processes build and manage a temporal-space pathway to information stored in the IN [19,20].

The cited and many other neurodynamics studies (including cited in [19]) support and confirm the paper formal results.
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\[ u^\alpha = \Delta_u [u^a, u^p] \]

\[ \tilde{\mathcal{S}}_{ap} [x_t(\Delta)] \]

\[ v_{+t} \]

\[ \tau_{1o} \]

\[ \Delta_1 \]

\[ i^{\circ}_{ap} [x_t(\Delta_1)] \]

\[ \delta_{\o} \]

\[ i^{\circ}_{ap} [x_t(\Delta_2)] \]

\[ \delta x_t \]

\[ i^{\circ}_{ap} [x_t(\Delta_o)] \]
Fig. 1. Illustration of the observer's simultaneous proceeding of its external and internal processes and holding information.

In this Figure: \( \tilde{x}_i \) is external multiple random process, \( \tilde{x}_i(\Delta) \) is potential observation on interval \( \Delta \), which randomly divides \( \tilde{x}_i \) on a priory \( \tilde{x}_a(t) \) and a posteriori \( \tilde{x}_p(t) \) parts; \( u_x = \Delta_x[u^x,u^{x'}] \) are impulse control of parts \( \tilde{x}_a(t), \tilde{x}_p(t) \); \( \tilde{s}_{ap}[\tilde{x}_i(\Delta)] \) is observer's portions of the entropy functional; \( \tilde{x}_i(\Delta_x), \Delta_x, u^x(\tau^x), \tilde{u}^{x'}(\tau^*) \) and \( \tilde{s}_{ap}[\tilde{x}_i(\Delta_x)] \) are related indications for each cutting process; \( x_i(\Delta_o) \) is observer's internal (conversion) process with its portion of information functional \( \tilde{h}_{ap}[x_i(\Delta_o)] \); \( \tau_{2k} \) is ending locality of \( \tilde{x}_i \) with its sharp increase \( \delta \tilde{x}_i \); \( \tilde{x}_-, \tilde{x}_+ \) are the cutting maximum information states; \( v_o(\nu_{1o}, \nu_{2o}) \) are observer's opposite inner controls starting with \( x_-(\tau_{1o}), x_+(\tau_{1o}) \) complex conjugated trajectories \( x_-, x_+ \) interfering nearby moment \( \tau_{1k} \); \( v_{+t} = f(x_+, x_{+t}), v_{-t} = f(x_-, x_{-t}) \) are inner control functions; interfering nearby moment \( \tau_{1k} \); \( \delta_o \) is interval of the control switch from \( \tau_{1k} \) to \( \tau_{k+1} \), where unified mirror control \( v_i \) entangles the dynamics on interval \( \Delta_2 \) up to \( \tau_{2k} \)-locality of turning the constraint off with sudden rise \( \delta \tilde{x}_i \).

The shown external and internal intervals could have different time scale.
Fig. 2. Illustration of the observer’s sequential proceeding of its external and internal processes.

In this Figure: \( \tilde{x}_i \) is external multiple random process; \( \tilde{x}^+_{i}, \tilde{x}^-_{i} \) are copies of random process’ components, selected via intervention of the double controls \( u_+, u_- \) at the moment \( \tau_2 \); \( \tilde{x}^+_{i}, \tilde{x}^-_{i} \) are conjugated dynamic processes, starting at the moment \( \tau_{20} \) and adjoining at the moment \( \tau_{2k} \); \( \tau_{20k} \) is a moment of turning controls off; \( \tilde{x}^+_{i} \) is adjoint process, entangled during interval \( \Delta_2 \) up to a moment \( \tau^1_{10} \) of breaking off the entanglement; \( \tau_{1k}, \tau_{10k}, \Delta_1, \tau_{10} \) are the related moments of adjoining the conjugated dynamics, turning off the controls, duration of entanglement, and breaking its off accordingly, in the preceding internal dynamics; \( \delta_1 \) is interval of observation between these processes. Below are the illustrations of both double controls’ intervals, and their impulse \( u_{\pm} \) actions.

All illustrating intervals on the figure are expanded without their proper scaling.
Fig. 3. The information structure of cooperating triplets' segments with applying impulse controls.