Theory for Autonomous Functional Learning

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***Abstract*—Multi-scale coherent dynamics of effectuation in a holistic functional structure designed for autonomous pursuit of missions compliant with mainly anticipated functional challenges were described axiomatically, recently. Here, the theory is carried forward to permit functional development in the sense of progressive adjustment of functional capacities in unforeseen scenarios. Potential applications are highly adaptable living systems and those automated engineered system, machinery (robots) or computer code (cyber-systems), that can expand autonomously, on self-registered demand. In a hierarchical structure and multi-scale coherence, even simple generic three-compartment first-order kinetics permit a cellular complexity that admits highest degrees of functional diversity, if needed.**

***Index Terms*—holistic design process, cellular complexity, axiomatic effectuation, production systems, first-order dynamics, intensity function**

I. Introduction

Recent theory of dynamics of effectuation in complex structures was motivated by a purely functional view of whole human-body system [1], [2]; its main features are briefly characterized first, followed by motivation and plain explanation in turn.

A *holistic* approach with simultaneous integration of all functional levels yields substantial added value like well-done architecture of a building, for example, though modular assemblance is widely practiced in engineered systems. The first step in a *holistic design process* is identification of *design motifs*, the second is *functional design* with *separation of material from organization*, and the final third step is a review of applicable *design principles* within *material resource* specifications or limitations.

The merits of an *axiomatic* approach are known from thermodynamics and probability theory, cf. [3] for a recent review and [4], respectively: abstract properties of phenomena, e.g. temperature and probability, can be postulated in mathematical form and implications be obtained for comparison with experimental outcomes, or for prediction, all despite uncertain, incomplete, or inaccessible knowledge about underlying basic mechanisms from which said phenomena emerge.

Multi-scale coherence gives re-assurance that lower-scale properties, e.g. dynamics, translate to upper-scale properties, or *vice versa*, the latter can be interpreted as the former. This is particularly useful in structures that span many scale levels: by ”inductive knitting”, it will suffice to demonstrate this property for a one-step up-scaling.

System Functional Architecture [2] – to be described in the next Section – implies a hierarchical structure of functional scale levels as well as a delegation of all physical properties to a base level, as done in “layer” concepts of computer System Network Architecture and comparable design standards [5]. It is the necessary environment for a holistic and multi-scale coherent axiomatic theory.

Design motifs of living nature and engineered systems can be quite similar, as suggested in the subtitle of Norbert Wiener’s seminal work on cybernetics [6], *control and communication in the animal and the machine*, and already earlier by Fritz Kahn, a German medical doctor, who illustrated human-body physiology as a factory in art-work for lay press, first in Germany in the 1920’s and later in New York [7]: man and machine share in being *made* for purpose – *production* of some kind – but differ in *purpose*. While the animals are made for *reproduction* and must fight through their life to *make their living* by relying only on their own resources to take advantage of opportunities within their habitual environment and their range of operations, the machines more comfortably enjoy a human hand to fill up resources, to guide and maintain them. As for design-phase specification of abilities, closer analogy is then seen between machine and domesticated animals, while design specifications for human-body system are “to be fitted and witted” for wildlife – as any other living creature –, more or less modulated by cultural consensus in prevailing social settings.

Technically, human-body system is an autonomously acting *bio-reactor*, non-autarkic as it is vitally dependent on uninterrupted oxygen-logistics for permanent combustion of ingested nutrients to keep its 10^{14} body cells alive. This *cellular system* is living-nature’s sole *material option* – and in this role comparable to metal, plastics, stone or wood that engineers use in fabrication of their machines and buildings. Accordingly, *design principles* of living nature will be fundamentally different.

A recent mathematical theory [1] elaborated on separation of function from material for a holistic view of dynamics by ‘functional drill-down’, layer by layer, from behavior of physical Whole to base functions. In Sect. II, this purely axiomatic approach of successive (upwards) aggregation of smaller functionally cooperating units into larger ensembles and translation of their dynamics from units to ensembles is recapulated from [2], though stripped to the currently most general representation

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by *integrated intensity functions* and expanded for a mechanism of autonomous functional learning, rooted in rhythms that arise from capacity tailored to mainly low-profile demand and is to be seen as a *design principle* of living nature in order to economize on its resources.

Learning is a core requirement to remain "fitted and witted" for self-sustained life, as living nature does not provide the learned competence to meet life's challenges, only a genetic recipe. Learning for wits starts from functional activity and is triggered by *volition to overcome* a met functional deficit, in order to fulfill a task, to pursue in a mission, or to satisfy an ambition: learning just for no purpose is not an option in living nature, and not in engineered systems *made for a purpose*, either. And, learning is tied to a functional option, as horses will never swim like fish, much less fly like bird; it then becomes an issue of expanding an available capacity currently too low for one's intention.

Engineering design that copies living nature seems particularly promising when performance in labor must be adapted to highly variable demand, for example, equally permit very high performance for a short while, as seen in sprinting athletes, as well as lasting elevated performance for a long while, as seen in marathon runners. The living's rhythm of labor and restoration is a distinct *design principle* worth to consider for engineered systems that are designed for a widely unspecified, though not unrestricted, range of operational options in limited resources – similar to human-body system, then.

II. Generic Dynamics

A. System Functional Architecture

Consider a *functional system*(FS) that permits a complete functional description in terms of *functional units*(FU) which combine by joint functional assignment in *functional aggregates*(FA) that are aggregated again, with other FA's to a more comprehensively composed FA, etc. Such *successive aggregation* of functional units generates, step by step of aggregation, distinct *functional levels*(FL) of increasing comprehensiveness and complexity of functionality; it implies an *up-wards embedding* of all FU's into some FA which then emerge as an FU for next-step aggregation thus generating a strict functional hierarchy that stops with the final FA, the anatomical Whole. This kind of built-up is called System Functional Architecture, when material realization can be delegated completely to a base layer of physical interpretation. It applies with living nature's cellular systems to a holistic functional view of human-body system, for example, and shows a close analogy with standard six or seven layers structure of System Network Architecture for distributed computer systems and its base physical layer [5].

B. First-order Kinetics

Consider a logistic supply-chain of some kind of goods from an inexhaustible source (a "factory") via a hub (a "retailer") to an end-consumer. It can be helpful to adopt some terminology of direct-current electric circuits, though no specific real-world physical interpretation is assumed: the setting is strictly axiomatic as in [1].

Have a permanent *driving force* at a ubiquitous *source* and think of a constant potential difference as a voltage, $U_0 > 0$, say. Have the hub's input and output then as a *supply-part condenser* of *capacity* C_s and a *demand-part condenser* of *capacity* C_d, respectively, and assume matching sizes, $C_s = C_d = C$ with $0 < C < \infty$.

Denote total charge transferred from source to supply-part condenser during t time units by $Q_s(t)$; denote total charge *available for discharge* from demand-part condenser at time t by $Q_c(t)$. Note that in the demand-part, different from the supply-part, the *driving force* is the potential difference from t-prevalent charge $Q_c(t)$, in other words: *charge available for transfer* is the acting force for discharge while actual release of charge from hub in the demand-part will depend on end-consumer's demand.

First significant results can now be obtained from intuitive assumptions about *charge transfer dynamics* that are based on *residual charging* and *residual discharging*, i.e. either for completely charging the supply-part condenser or for completely discharging the demand-part condenser. Denote the t-current *residual charge* necessary to reach full charge $Q_{s,\max} = U_0 C$ on the supply-part condenser by

$$Q_{s,\mathrm{res}}(t) = Q_{s,\max} - Q_s(t), t \geq 0, \tag{1}$$

and the t-current *residual charge* on the demand-part condenser by $Q_{d,\mathrm{res}}(t)$ as $Q_{d,\mathrm{res}}(t) = Q_c(t)$.

Supply-part *charge increments* $\mathrm{d}Q_s(t)$ and demand-part *charge decrements* – or synonymously *discharge increments* – $\mathrm{d}Q_c(t)$ are each *proportional* to the pertinent t-current *residual charges "due for transfer"*, $Q_{s,\mathrm{res}}(t)$ and $Q_{d,\mathrm{res}}(t) = Q_c(t)$, respectively. The "proportionality factors" can be taken as quite general constructs such that it will permit the introduction of various influencing factors into the dynamic equation.

Proposition 1: Functions Q_s and Q_c can then be assumed to permit factorizations of their increments on any arbitrarily interval $]t, t + \mathrm{d}t]$ with some non-decreasing positive real-valued differentiable functions, $\Lambda_s = (\Lambda_s(t))_{t>0}$ and $\Lambda_d = (\Lambda_d(t))_{t>0}$, respectively,

$$\mathrm{d}Q_s(t) = \mathrm{d}\Lambda_s(t) Q_{s,\mathrm{res}}(t) \tag{2}$$

and

$$\mathrm{d}Q_c(t) = -\mathrm{d}\Lambda_c(t) Q_c(t) \tag{3}$$

Proof: In fact, let $q_{s,\mathrm{res}}(t)$ and $q_c(t)$ denote the *relative charges* to supply- and from demand-part condensers, respectively, $q_{s,\mathrm{res}}(t) = 1 - Q_s(t)/Q_{s,\max}$ and $q_c(t) = Q_c(t)/Q_{c,\max}$. Then, $0 \leq q_{s,\mathrm{res}}(t) \leq 1$ and $0 \leq q_c(t) \leq 1$ are both monotonically decreasing functions and differentiable in t, with $\dot{q}_{s,\mathrm{res}}(t) = -\dot{Q}_s(t)/Q_{s,\max}$ and $\dot{q}_c(t) = \dot{Q}_c(t)/Q_{c,\max}$. The proposition then follows from choosing

$$\Lambda_s(t) \stackrel{\mathrm{def}}{=} -\log q_{s,\mathrm{res}}(t) \tag{4}$$

$$\Lambda_c(t) \stackrel{\mathrm{def}}{=} -\log q_c(t) \tag{5}$$

□

Note that *cumulative intensity functions* Λ_s and Λ_c are *dimensionless*, irrespective of metric dimensions of charges Q.

These functions permit uniquely defined – up to a constant – representations of their differentials, $\mathrm{d}\Lambda_s(t) = \lambda_s(t)\mathrm{d}t$ and $\mathrm{d}\Lambda_c(t) = \lambda_c(t)\mathrm{d}t$, with λ_s, λ_c positive real functions, called *(charge-transfer) intensities* of charging and discharging condensers, respectively. In reliability analysis, intensities are used to include additional factors that are involved in transfer dynamics. Let $\mathbf{z}$ be a vector of such covariates, then

$$\mathrm{d}\Lambda_s(t;\mathbf{z}) = \lambda_s(t;\mathbf{z})\mathrm{d}t \tag{6}$$

and

$$\mathrm{d}\Lambda_c(t;\mathbf{z}) = \lambda_c(t;\mathbf{z})\mathrm{d}t \tag{7}$$

introduce $\mathbf{z}$ into equations (2) and (3), respectively.

C. Generation of Rhythms

Rhythms arise with faster-than-average release, slower-than-demand refill of reservoirs sized for average consumption-rates – similarly seen with pork-price cycles in economic markets, and measles epidemics in unvaccinated populations. Consider a 24-h power profile as in Fig. 1 with $65 kcal/h$ for a $70 kg$ man in sleep-phase minimum that sustains vital physiological function (low breathing, lying flat with little movement, calm brain activity) while filling up "functional reservoirs", i.e. condensers, within $8h$ as an example of *slow refill* for whole human-body system. For *fast-release* then, consider an athlete who runs $100m$ in $10s$, but at most once a day, and sits with close to minimal wake-phase resting power of $100 kcal/h$ for a while until the energy for moderately normal wake-labor, e.g. $200 kcal/h$ "walking slowly (2.6 miles per hour)", returns from concurrent supply (specific data from a standard physiology textbook [8]).

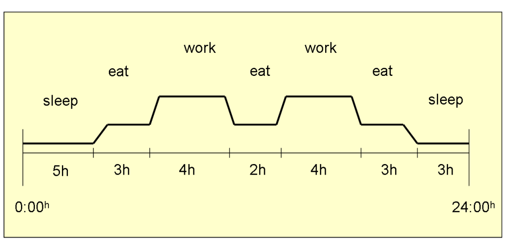

Fig. 1. *A person's schematic 24h energy consumption rate (power) profile (unscaled, vertical axis for $kcal/h$ omitted) around noon time, with "eat" for meals including light activity of daily living, and finite slopes for preparations in transition from one kind of activity to the next (from [2]).*

The reason for rhythms in the living rests in its *design motifs*: for engineered systems, average performance is taken to balance with energy supply from a reservoir for the expected duration of mission, and above-mentioned rhythms are as undesirable as a spluttering engine. Living systems' energy reservoirs will also be sized for average demand, but have an ability for extremely fast release in order to survive in response to sudden vital threats. This will be exploited for functional learning.

III. Generic Functional Learning

Understand *functional learning* as expansion of capacity of a functional unit, specifically the capacity C of the unit's mirrored supply- and demand-part condensers. Learning is then seen as training for higher performance in some functional feature, and shall then emerge from *repeated functional challenging*. This fits into the present mathematical setting, since levels of available charge $Q_c(t)$ on the demand-part condenser generate the driving force for charge transfers to the end-consumer by $U_c(t) = Q_c(t)/C$, and then translate into end-consumer's performance in terms of power; hence, enlarged capacity C in all desirable functionalities is necessary. Note, that larger levels of capacity C imply larger levels of $Q_{s,\max} = U_0 C$ and be reminded that $Q_{c,\max} = Q_{s,\max}$ because of "mirroring".

One first has to digress from the time scale of 24-hours in wake-sleep cycles to the coarser scale of whole days, which may again be taken as practically continuous when observing that one year of life has 365.25 days on average. Denote time in days by τ, then, and consider days at which *exhaustive discharges* from ϵ-almost maximum levels of charge available for transfer occur; assume that permissible discharge would come to a halt before reaching destructive levels of $Q_c(t) < Q_{c,\min}$ on the demand-part condenser. Define size of an ϵ-exhaustive discharge $Q_{c,\max,\epsilon}$ then by

$$Q_{c,\max,\epsilon} + \epsilon = Q_{c,\max} - Q_{c,\min} \ , \tag{8}$$

for some small value of $\epsilon > 0$. Any occurrence of an ϵ-exhaustive discharge is considered as a functional challenge.

Definition 1: [Functional Challenge] A *capacity-enhancing functional challenge (CEFC)* on the demand-part condenser occurs with an ϵ-exhaustive discharge in a very small time interval, in other words, there is some t_c, $0 < t_c < t_{\max}$, such that $Q_{c,\max} - \epsilon \le Q_c(t_c) \le Q_{c,\max}$ and $Q_c(t_c + \mathrm{d}t) = Q_{c,\min}$, equivalently,

$$\mathrm{d}Q_c(t_c) = Q_{c,\max,\epsilon} \ ; \tag{9}$$

note that an ϵ-exhaustive discharge may occur at most once a day, when ϵ is sufficiently small and restoration to full charge levels needs a phase of "restorative sleep".

Let $D(\tau)$ denote the *indicator* of occurrence of a CEFC event during day τ,

$$D(\tau) = \begin{cases} 1 & : \quad \exists t \in \tau : \mathrm{d}Q_c(t_c) = \mathrm{d}Q_{c,\max} \\ 0 & : \quad \forall t \in \tau : \mathrm{d}Q_c(t_c) \neq \mathrm{d}Q_{c,\max} \end{cases} \tag{10}$$

Denote the *point-function* of occurrences of CEFC events in τ-time by function $D = (D(\tau))_{0<\tau<\tau_{\max}}$: for any $0 < \tau < \tau_{\max}$, τ is an occurrence time of CEFC, if and only if $D(\tau) = 1$. Denote the ordered sequence of occurrence times by

$$0 = \tau_0 < \tau_1 < \tau_2 < \ldots < \tau_k < \tau_{k+1} < \ldots \tag{11}$$

The associated *counting function* of occurrences of CEFC events in τ-time,

$$N_D(\tau) = \sum_{\tau_i \le \tau} D(\tau_i) \ , \tag{12}$$

is a positive and increasing step function with jumps of size 1 at exactly the times in (11), right-continuous with left-hand limits ("cadlag"), and bounded on any finite τ-interval.

Consider the normalized Gamma function $F(\tau;\alpha,\beta)$ in τ, with integer $\alpha > 0$ and real $\beta > 0$ as parameters, $\lim_{\tau\to\infty} F(\tau;\alpha,\beta) = 1$, [9]

$$F(\tau;\alpha,\beta) = \int_0^\tau \frac{1}{\alpha!\beta}\left(\frac{u}{\beta}\right)^\alpha e^{-\frac{u}{\beta}}\mathrm{d}u\,; \tag{13}$$

it approximates integrals of bell-shaped Gaussian densities for integer $\alpha \geq 3$ and real $\beta = 1$, cf. [9].

Definition 2: [Multi-hit Enhancement] A *stress-induced enhancement of functional capacity* from baseline $C(0) = C$ to $C(\tau)$ in τ units of τ-time is then obtained from

$$C(\tau) = C(0)\left[1 + F(\tau;\alpha,\beta)\right]\,, \tag{14}$$

for choices of parameters according to a preferred rate of upgrade. For example, $\alpha = 3$ and $\beta = 1$ will imply largest rates around $\tau = 3$, that can be used to set an adequate training rhythm.

For motivation, function (13) is a multi-hit model

$$F(\tau;\alpha,\beta) = \sum_{l>\alpha}\frac{\left(\frac{\tau}{\beta}\right)^l}{l!}e^{-\frac{\tau}{\beta}} \tag{15}$$

with more than α hits required to generate a response, when expected number of hits in $]0,\tau]$ is τ/β.

IV. Functional Learning in System Functional Architecture

A. Up-scaling First-order Kinetics

Suppose generic functional first-order kinetics as in (2) and (3) for every functional unit FU at every functional level FL; for some fixed level FLk, $k > 1$, say, consider m functional units FU_i, $i = 1,\ldots,m$, to form a functional aggregate FA,

$$\mathrm{FA} = \{\mathrm{FU}_1,\ldots,\mathrm{FU}_m\}\,, \tag{16}$$

then. Counting functional levels from top to bottom, with FL0 for the Whole, FA of FLk emerges as some functional unit FU of FL$(k-1)$, in an intuitive notation,

$$\mathrm{FA}^{\mathrm{FL}k} = \mathrm{FU}^{\mathrm{FL}(k-1)}\,, \tag{17}$$

for all levels $k > 1$. It will then suffice to translate m individual generic first-order kinetics of *elements* of $\mathrm{FA}^{\mathrm{FL}k}$ into *one* for the aggregate. The mechanism – denominated as a *'wirkgefuege'* for short, instead of a clumsier 'structure that generates an effect' or 'structure of effectuation' – by which this can be achieved is a postulate, *axiomatic* then, without realistic physical interpretation as a model, though admittedly inspired by electric direct-current circuits in a parallel connection.

Definition 3: [Axiomatic Wirkgefuege [1]] If generic first-order kinetics of $\mathrm{FA} = \{\mathrm{FU}_1,\ldots,\mathrm{FU}_m\}$ arise from those of individual FU_i, $i = 1,\ldots,m$, by summing respective capacities and charges in supply-parts and demand-parts,

$$C_s^{\mathrm{FA}} = \sum_{\mathrm{FU}\in\mathrm{FA}} C_s^{\mathrm{FU}}\,, \tag{18}$$

$$C_d^{\mathrm{FA}} = \sum_{\mathrm{FU}\in\mathrm{FA}} C_d^{\mathrm{FU}}\,, \tag{19}$$

$$Q_s^{\mathrm{FA}}(t) = \sum_{\mathrm{FU}\in\mathrm{FA}} Q_s^{\mathrm{FU}}(t)\,, \tag{20}$$

$$Q_d^{\mathrm{FA}}(t) = \sum_{\mathrm{FU}\in\mathrm{FA}} Q_d^{\mathrm{FU}}(t)\,, \tag{21}$$

for all functional levels FLk, $k > 1$, in a given *System Functional Architecture*, then this set of equations constitutes an *axiomatic wirkgefuege*.

One next has to show that *generic dynamics* of Eqs. (2) and (3) in Section II, active within each element of a FLk functional aggregate, actually translate to those of a functional unit at FL$(k-1)$, in the sense of (17).

Lemma 1: [Supply-part Intensities] Consider $\Lambda_s(t)$ as in Proposition 1 for FA as in (16), then

$$\mathrm{d}\Lambda_s^{\mathrm{FA}}(t) = \sum_{\mathrm{FU}\in\mathrm{FA}} \mathrm{d}\Lambda_s^{\mathrm{FU}}(t)\frac{C^{\mathrm{FU}}}{C_s^{\mathrm{FA}}} \tag{22}$$

Proof:

$$\sum_{\mathrm{FU}\in\mathrm{FA}}\left[U_0 C_s^{\mathrm{FU}} - Q_s^{\mathrm{FU}}(t)\right]\mathrm{d}\Lambda_s^{\mathrm{FU}}(t) = \sum_{\mathrm{FU}\in\mathrm{FA}} \mathrm{d}Q_s^{\mathrm{FU}}(t) \tag{23}$$

and by (20), the right-hand side equals $\mathrm{d}Q_s^{\mathrm{FA}}(t)$ with its analogous representation

$$\mathrm{d}Q_s^{\mathrm{FA}}(t) = \left[U_0 C_s^{\mathrm{FA}} - Q_s^{\mathrm{FA}}(t)\right]\mathrm{d}\Lambda_s^{\mathrm{FA}}(t)\,; \tag{24}$$

the terms in square brackets represent the *residual charges* for transfer to respective supply-part condensers. As all supply-part condensers are assumed to be in a parallel connection, equal potential differences cancel out,

$$\frac{Q_{s,\mathrm{res}}^{\mathrm{FU}}(t)}{Q_{s,\mathrm{res}}^{\mathrm{FA}}(t)} = \frac{C_s^{\mathrm{FU}}}{C_s^{\mathrm{FA}}} \tag{25}$$

□

Lemma 2: [Demand-part Intensities] Consider $\Lambda_c(t)$ as in Proposition 1 for FA as in (16), then

$$\mathrm{d}\Lambda_c^{\mathrm{FA}}(t) = \sum_{\mathrm{FU}\in\mathrm{FA}} \mathrm{d}\Lambda_c^{\mathrm{FU}}(t)\frac{C_d^{\mathrm{FU}}}{C_d^{\mathrm{FA}}} \tag{26}$$

Proof: Replace C_s with C_d; assume that all demand-part condensers are in a parallel connection and then use

$$\frac{Q_c^{\mathrm{FU}}(t)}{Q_c^{\mathrm{FA}}(t)} = \frac{C_d^{\mathrm{FU}}}{C_d^{\mathrm{FA}}}\,, \tag{27}$$

the proof is along the same lines as for Lemma 1. □

Up-scaled intensities of charge transfers at functional level FL$(k-1)$ are then *capacity-weighted sums of intensities* of next-lower functional level FLk, which reflects the "knitting".

B. Up-scaling Functional Learning

Generic functional learning was based on repeated occurences of demand-part condenser's rapid discharge down to critical levels, called *functional challenges*. In a System Functional Architecture with its sequence of functional levels, FLk, $k = 0, 1, \ldots$, expanded capacities of lower-level functional units can only affect capacities of upper-level functional units when embedded via functional aggregation, as seen by Eqs. (18) and (19).

Then, expanded functional capacities from lower functional levels translate into functional capacities at upper functional levels, but effects get 'diluted' from other functional units' unchanged capacities, the higher one follows the expanded capacity up:

$$\frac{C_s^{\rm FU}(\tau)}{C_s^{\rm FA}(\tau)} = \frac{C_s^{{\rm FU}_i}(\tau)}{C_s^{{\rm FU}_1}(0)+\cdots+C_s^{{\rm FU}_{i-1}}(0)+C_s^{{\rm FU}_i}(\tau)+C_s^{{\rm FU}_{i+1}}(0)+\cdots+C_s^{{\rm FU}_m}(0)} \tag{28}$$

For illustration, training of a single muscle will not make a champion. This inconspicuous remark points top-down: define the capacity goal – as well as limits – of functional Whole, the single FU at FL0, understand it as a functional aggregate in the sense of (17) with $k = 1$, and find its level FL1 functional units as in (16); for example, an athlete will focus on physical functions, a chess-champion on cognitive functions.

In further drill-down, FL1 components in human-body system are interpreted as aggregates and decomposed into their respective functional units of FL2, as suggested for *vital functions* in [10], [11] – leading to a preliminarily suggested "factory model" in the spirit of [7]. Similar decompositions of two further FL1 components, *productivity functions* and *operational functions*, into their respective FL2 functional units have to be found, still.

V. Discussion

The present approach is a mathematically phrased abstract theory of learning based upon and designed for functional dynamics within hierachical structures of effectuation; though inspired by observation of biology of human body system, it is not modeling the neurobiology of human learning, as other nominally related *dynamic systems approaches* successfully do [12], and it may have wider applications. It is then axiomatic by intent.

Functional learning in the present theoretical set-up is about functional task-solving capacity-enhancement. For example, a town map will be very useful to prepare a trip, while functional learning is about finding one's way in city streets - even without a street map. Functional learning is not watching how to do things, nor is it taking up abstract knowledge, or theory in education, as this can provide only concepts that have to be translated for implementation into an intended action. It is then kind of "learning by doing".

Learning because of "met functional deficit" needs an operational understanding of "functional deficit" as a hindrance in pursuit of a path of action; when hindered by a wall, one solution may be to climb the wall and to upgrade one's physical abilities first, another option may be to find a way around the wall by reconnoitering, upgrading one's cognitive ability. However, the present approach can not provide solutions as how to climb the wall, or how to find one's way in city streets, as said dynamic systems approaches to development of cognition and action [12] do.

Dropping the qualification as "functional", "met deficits" have a wider interpretation as a discrepancy between observation and expectation, known as *innovation* in communication theory and Kalman filtering [13], or as – what I call a *paradigm of empirical research* – the comparison of observed (sample mean) and (probabilistic) expected values (under a hypothesis) for design of statistical testing methods (then often divided by the sample standard deviation, of course, to invoke a central limit theorem in probability theory).

Further, "met deficits" have two commonly experienced interpretations in social life, one as a "surprise", with discrepancies understood as a nice gesture, for example an unexpected hand waiving in good-bye, and another as a "disappointment" in unfriendly actions, unpleasant verbal comments, or failed dating appointments. Such *social learning* will then need more than to understand that a physical wall is too high to jump over, and autonomously learning machines will have to collect *real-life experience* for improved social aptitude and performance as any human and animal in respective social context. But as soon as *functional units* and *functional aggregates* for *operational activity* in social interaction are identified, the same "mechanics" of functional learning become applicable, again. (Note that "real-life experience" may not match "digital-life experience", implying that feeding a thesaurus of social scenarios into computer memory may not yield desirable levels of social competence.)

This understanding of social learning does not involve *coping* with "disappointment", or any physico-chemical processes in human-body system's psychophysical response to impact from physical body's outside world. The functional viewpoint takes social learning as a process of receiving signals, interpreting the information, deciding on how to re-act, enacting the decision, observing the outcome and then comparing observed outcome to the one expected in order to obtain the 'innovation' necessary for further improvement. It is then amenable to the present theory as soon as respective functional units and aggregates have been defined.

Similarly designed for purposeful action are a wide range of *tactical units* of engineered machinery with human operators, e.g. an excavator at work, a cruising ship with captain, or an aircraft with pilot in flight. *Productive systems* by design, engineered or by evolution, share a *canonical functional decomposition* of their anatomical Whole into the three *"wirk-components"* of *vital functions*, *productivity functions*, and *operational functions* that interactively cooperate [1],[14]. At any moment, interaction between these three high-end wirk-components emerges as Whole's currently visible *behavioral activity* – modulated according to functional limitations or enhancements, if any, that might have occurred within each of the high-end components at much lower functional levels and that could still make their way up, diluted or strengthened when not neutralized in translation of functional dynamics by successive aggregation through all up-wards levels, as it is visible in (28).

Though systems differ substantially in mission, design, and material realization for a designated environment, effectuation dynamics characterized by intensity functions with their translations apply throughout and across all levels in functional up-scaling or down-scaling within a system. However, effects of an expanded – or a shrinking, for that purpose – capacity can be followed only upwards from the functional level at which they occur, notwithstandingly.

As three technical points to make,

- the immediate release (9) adopted for "upgrading mechanics" can be spread out to a short interval during the day; it was chosen for convenience in the present setting of infinitesimal time steps which permits formulation of growing, or shrinking, without interference from control regimens, because *coordination* is considered to be independent of size of capacity in infinitesimally small time steps, and
- in human-body system during child development to adulthood, also capacities of vital functions (lung, cardio-vascular logistics, digestive systems, nervous system) are expanded, parallel to growth of osseous structures, by genetic programs though possibly also by an implied demand for matching the sizes in making the Whole.
- By the generality of "charges", a remark on identification and estimation of charge-transfer dynamics is mandated: suggestion is to consider implied charge-transfer *work* [2] as this was seen not to change the intensity functions that characterize dynamics. For application, ability to measure energy consumption will be the main issue, then.

An additional remark, requested by a reviewer, shall explain the setting of System Functional Architecture in slightly different words: Starting from top, "whole" is a logical cell, and also a functional aggregate – logical tissue, then – of logical cells, and interaction of the latter generates dynamics of "whole". With increasing granularity, this is repeated in successive decomposition: each logical cell is next-level's logical tissue composed of that level's functional units as applicable, and again, logical tissue's dynamics arise with interaction of its logical cells' dynamics. Respective cell dynamics translate to tissue dynamics in simple direct ways as stated in the Lemmata 1 and 2, though such simplicity may be deceptive as it will only apply within any infinitesimally short time interval of length $\mathrm{d}t$, and the contributions of each functional unit within its functional aggregate during any larger time interval may vary considerable in order to produce a specific pattern of activity of the aggregate. Embedding simple cellular dynamics in such hierarchical complexity was chosen to avoid what may otherwise grow into a nightmare of higher order kinetics across several scale levels. When to be used as a model for even the simplest kind of realistic behavior, an appropriate management and control regimen must be added, first.

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