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Interdisciplinary Engineering of Intelligent Systems. Some Methodological Issues

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Abstract. For the engineering of systems it is necessary to test systems during validation with regard to the given requirements specifications. This paper argues for an interdisciplinary standard which should allow the qualification of the behavior of a system to be 'intelligent' or not. The proposed standard is characterized as an open process allowing different kinds of 'intelligence profiles'. An intelligence profile is a collection of basic intelligence units of which each unit represents an operational test case with a given task and an expected outcome (final goal state.)

Key words: interdisciplinary standard for intelligent behavior, intelligence, intelligence profile, basic intelligence unit, systems engineering, software engineering, behavior model

1 Intelligence as a Fuzzy Term

As can be easily verified the terms 'intelligent' and 'intelligence' within the field of *computer science* as well as in the thematically more focused field of *computational intelligence* are not sharply defined.

A positive message which can be drawn from these varying usages of the term 'intelligence' can be that the 'intended meaning' of the various expressions are manifesting a subject matter *intelligence*, which can not be grasped completely and sufficiently from a single point of view. Such a situation is within the empirical sciences the 'usual case': exploring the target object 'nature' by different viewpoints like physics, chemistry, biology, geography etc. has some tradition and everybody accepts that the models describing nature are constantly evolving and not yet really unified.

2 The Engineering Viewpoint

In software engineering and also the more general disciplin of systems engineering the use of fuzzy terms poses a real challenge. It is necessary in an engineering

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process to *validate* the engineered system against the requirements. The requirements are established and agreed at the beginning of the engineering process. Strictly speaking in this context, validation is a *measurement process* [7]: one compares a target object –the engineered system– with a reference object that is described by the requirements [14]. Today as the engineered systems become larger and larger and if they are real-time or safety critical systems, e.g. airplanes or nuclear power plants, these systems' "requirements for the requirements" are described in large and complex documents following international standards. For the discussion in this paper, a small subset of one of these standards is selected, namely ISO/IEC 15288:2002(E) (cf. figure 1).

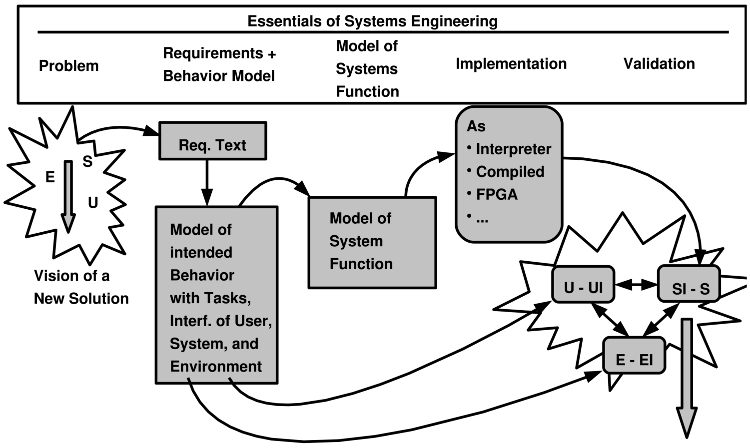

Fig. 1. Minimal Elements of the Engineering Process of ISO/IEC 15288

The elements in figure 1 are characterized as follows: The process starts with a *problem* $\mathcal{P}$ of a stakeholder. Through a communication process, the systems engineer translates P into a *behavior model* $\mathcal{M}_{\mathcal{S}-\mathcal{R}}$[1] that represents the complete expected behavior of the system to be designed:

$$requirementsAnalysis : \mathcal{P} \longrightarrow \mathcal{M}_{\mathcal{S}-\mathcal{R}}$$

Based on $\mathcal{M}_{\mathcal{S}-\mathcal{R}}$, the systems engineer develops a *system model* $\mathcal{M}_{\mathcal{SyS}}$ that fullfills the condition $\mathcal{M}_{\mathcal{S}-\mathcal{R}} \Longleftrightarrow \mathcal{M}_{\mathcal{SyS}}$:

$$synthesis : \mathcal{M}_{\mathcal{S}-\mathcal{R}} \longrightarrow \mathcal{M}_{\mathcal{SyS}}$$

The $\mathcal{M}_{\mathcal{SyS}}$ is converted into a *real system* $\mathcal{M}_{\mathcal{SyS}*}$:

$$implementation : \mathcal{M}_{\mathcal{SyS}} \longrightarrow \mathcal{M}_{\mathcal{SyS}*}$$

[1] The $S - R$ index reminds one of the stimulus-response paradigm from the experimental behavior sciences.

Validation is realized as a measurement process:

$$validation : \mathcal{M}_{\mathcal{S}-\mathcal{R}} \times \mathcal{M}_{\mathcal{SYS}*} \longmapsto \mathcal{V}$$

where $\mathcal{V}$ is a set of validation values indicating the correlation between the behavior model $\mathcal{M}_{\mathcal{S}-\mathcal{R}}$ and the system model $\mathcal{M}_{\mathcal{SYS}}$.

The process to convert $\mathcal{P}$ (in the *non-symbolic* space) into formalized requirements $\mathcal{M}_{\mathcal{S}-\mathcal{R}}$ (in the *symbolic* space) and the *symbolic* system model $\mathcal{M}_{\mathcal{SYS}}$ into the *real* system $\mathcal{M}_{\mathcal{SYS}*}$ cannot be fully automated, because full automation is restricted to the symbolic space. The challenge of relating symbolic and non-symbolic spaces with each other also occurs during validation, when non-symbolic objects are compared with a symbolic description [14].

The general structure of the behavior model $\mathcal{M}_{\mathcal{S}-\mathcal{R}}$[2] can be described as a sequence of combined states $\langle z_0, ..., z_f \rangle$. A combined state z is defined by the participating surfaces of the user $SURF_U$, the intended system $SURF_{SYS}$, and the assumed environment $SURF_E$, thus, $z_i \in Z \subseteq SURF_U \times SURF_{SYS} \times SURF_E$. A state change from a state z_i to a state z_{i+1} is caused by an action $\alpha_i \in ACT \subseteq Z \times Z$. Every sequence p of states for which it holds that $(z_i, z_{i+1}) \in \alpha_i$ is called a *usage process* or short *behavior* of the behavior model. The complete set of all possible behaviors of $\mathcal{M}_{\mathcal{S}-\mathcal{R}}$ is described by the generating function δ that maps a start state z_0 into the possible usage processes ending in the *final states* or *goal states*. A complete *behavior model* $\mathcal{M}_{\mathcal{S}-\mathcal{R}}$ can then be defined as

$$\mathcal{M}_{\mathcal{S}-\mathcal{R}} = \langle \mathcal{SURF}_{\mathcal{E}/\mathcal{U}/\mathcal{SYS}}, \mathcal{Z}, \mathcal{ACT}, \delta, \mathcal{S}, \mathcal{G}_{\mathcal{F}} \rangle$$

where $G_F \subseteq Z$ is a set of goal states which shall be reached starting with the beginning state S.

The constraints induced by the systems engineering process challenge the systems engineer to specify the required properties of a system in terms of its observable behavior, including the interactions with the users and the environment. Thus, in the case of *intelligent systems* one has to assume that the behavior labeled "intelligent" $\mathcal{M}_{\mathcal{I}}$ is a subset of the general behavior, thus $\mathcal{M}_{\mathcal{I}} \subseteq \mathcal{M}_{\mathcal{S}-\mathcal{R}}$

3 Can Structure Replace Behavior?

The behavior oriented approach in systems engineering – which has some resemblance to psychology during the end of the 19th and the beginning of the 20th century (see below) – is not very common in artificial intelligence (AI). In AI, *structure* often dominates *behavior*. An example for this conflict can be found in the PERMIS workshops running annually since 2000 [31]. Although it is the main goal of PERMIS to measure *intelligent* systems, the leading concept is not "intelligence" but "performance". The meaning of intelligence is generally presupposed and only occasionally papers deal with intelligence as the main topic.

[2] This topic belongs to the field of Human Machine Interaction (see e.g. [26], [13], [23]).

In the seminal paper [1] Albus locates intelligent systems in the context of biological systems which have developed in an evolutionary manner. But when it comes to definitions he shifts from *observable* intelligent *behavior* to *systems*, which *have the ability* to act appropriately. He assumes as 'systems of intelligence' modular systems like 'sensory processing', 'world modeling', 'behavior generation', and 'value judgement' configured into a possible architecture (cf. Albus [1], pp.477ff). With this 'behavior' is replaced by some 'structure' and thereby 'intelligence' as a property of behavior is turned into the property of a structure by speaking of 'capabilities' or 'abilities' as the subject matter of 'intelligence'.

The systems engineering process emphasizes that more than one functional and physical architecture (structure) is possible to implement a required set of behaviors. Therefor, it is highly questionable to bound the term "intelligence" to one single structure. It is Berg-Cross who thematizes these limits inherent in the architecture of Albus (cf. [6],p.1). He returns to the *adaptive* view of human intelligence and the resulting human behavior by explicitly including the views of evolutionary biology and psychology as well as the neuro sciences and epigenetic robotics (cf. [6],pp.2ff; [18]). The structure showing intelligent behavior is here understood as a dynamic state based on ongoing interactions with a dynamic environment. The environment triggers the structure and the structure feeds back onto the environment. The structure generating the behavior is constantly changing by 'growth' and 'learning'.

In this analysis it is not possible to define structures independently of an environment. And [6] clearly states that the quality of the responding structures depends on the quality of a precise definition of the 'adaptive problem' which has to be solved in the environment (cf. [6],p.3).

In the terminology of systems engineering is such an 'adaptive problem' the problem $\mathcal{P}$ which has to be translated during requirements engineering in an appropriate behavior model $\mathcal{M}_{\mathcal{S}-\mathcal{R}}$ which includes $\mathcal{M}_{\mathcal{I}}$. The qualification of a system $\mathcal{M}_{\mathcal{SYS}*}$ as intelligent is a *derived* statement that presupposes the adaptive problem to be solved. It is learned from nature that an adaptive problem can trigger numerous different structures in solving the problem.

4 Intelligence as an Open Concept

Turing, one of the fathers of AI, decided not to identify intelligence with a certain structure. Instead he classified a system as intelligent or not by judging the observable behavior in an imitation game[38]. If the observable behavior of a system cannot be distinguished from that of a human then the system is classified as intelligent. The description of the imitation game can be mapped into the terminology of this paper by saying that the observable behavior of a real system $\mathcal{M}_{\mathcal{SYS}*}$ (a machine or a human) is measured with the behavior model $\mathcal{M}_{\mathcal{S}-\mathcal{R}}$ of the testing person's knowledge.

The following assumptions are made: (i) In general, it is accepted that the behavior $\mathcal{M}_{\mathcal{S}-\mathcal{R}}$ of biological systems is a *natural point of reference* for *generating* *intelligent structures* $\mathcal{M}_{\mathcal{BIOL}}$:

$$\mathcal{M}_{\mathcal{S}-\mathcal{R}} \Longleftrightarrow \mathcal{M}_{\mathcal{BIOL}}$$

(ii) Whatever *intelligent behavior* $\mathcal{M}_{\mathcal{I}}$ is, for a natural standard, it is assumed:

$$\mathcal{M}_{\mathcal{I}} \subseteq \mathcal{M}_{\mathcal{S}-\mathcal{R}}$$

(iii) To make $\mathcal{M}_{\mathcal{I}}$ useable, a set of *basic intelligent units* $\mathcal{M}_{\mathcal{BIU}}$ is defined where each single unit $m \in \mathcal{M}_{\mathcal{BIU}}$ allows for the definition of an experimental procedure with a clearly defined task τ and a clearly defined outcome $goal(\tau)$. The combination of the basic intelligence units is called an *intelligent profile*:

$$M_{IP} = \{m | m \in M_{BIU}\}$$

$$M_{IP} \subseteq M_I$$

The above assumptions establishes the concept of intelligence as an *open* concept, which can be expanded by experience.

A $\mathcal{M}_{\mathcal{IP}}$ can be reproduced by different generating structures. Thus, with $M_{IPA} = M_{IP.1} \cup ... \cup M_{IP.k}$ a situation can be encountered where

$$M_{IPA} \Longleftrightarrow M_{SYS.i}$$

and $M_{SYS.i}$ is one of the system models, which can fullfill the tests with the intelligence profiles, and where every system model $M_{SYS.i}$ has a different structure compared to an $M_{SYS.j}$ with $i \neq j$.

Something that is called *the singularity* possessing *superhuman intelligence* is envisioned in [40]. A clear definition is not given for the singularity nor for the enhanced intelligent behavior in [40]. In the light of the framework presented in this paper, it is an interesting question whether there could exist in the future a system $M_{SYS.sing}$ which is more powerful with regard to possible intelligent behavior M_{IPA} than any human person $M_{SYS.hum}$.

If it is assumed that the human brain embedded in the body is structurally equivalent to a universal Turing machine (UTM) [39] then the system $M_{SYS.sing}$ could principally not be more powerful than a human $M_{SYS.hum}$. As a real system $M_{SYS.sing}$ could possibly operate *faster*, have a *larger memory* and have a *better machine table*, making it relatively better than a $M_{SYS.hum}$. Besides this, it cannot be excluded that the human body, including the brain, could evolve in a way which will be comparable to $M_{SYS.sing}$. It is possible that human culture could evolve to the point that enables all individual human brains to operate like one big brain.

5 Interdisciplinary Context

Within engineering processes there is always a temptation to forget about the fact that the phenomenon of intelligent behavior has a long and rich tradition in human culture and sciences beyond engineering as such.

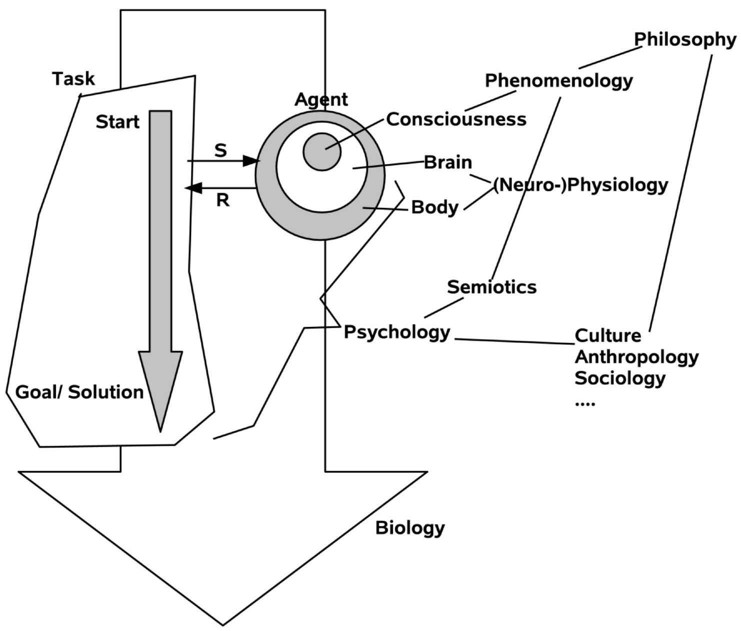

Fig. 2. The Phenomenon of Intelligence and the Main Contributing Disciplines

As one can see in figure 2 there exists a dense network of disciplines, which all are dealing within their subject area with the phenomenon of intelligent behavior. Each of these disciplines has contributed a lot in the past. And what we have learned from Philosophy of Science is that the different 'views' which are exercised by these disciplines are irreducible to each other. A phenomenological approach (cf. e.g.[36], [32]) can not be replaced by a purely behavioral approach –and not vice versa– and a behavioral approach can not be replaced by a (neuro-)physiological approach –and not vice versa–. These irreducibilities induce the necessity to develop individual domain theories which have to be mapped onto each other. But truly cross-disciplinary mapping theories are yet missing. One reason seems to be that we not yet have domain theories of some maturity.

5.1 Artificial Neural Networks

One way to structure the field of computational intelligence into important subfields is to look at the way that the system function of the intended artificial intelligent system will be modeled. A clearly identifiable case is the subfield of artificial neural networks (ANNs) [2], [22]. Starting with the general dependency

$$M_{BIU} \in M_I \subseteq M_{S-R} \Longleftrightarrow M_{BIOL}$$

where the natural biological systems are considered, it is known from evolutionary biology, e.g. [11], [24], [35], that the actual structures of biological neural networks are the result of long-term development processes which have been driven by the necessity to solve certain tasks in certain environments. Therefore, to understand the meaning of a biological structure M_{BIOL}, it is necessary to understand the behavioral context M_{S-R} which has to be mastered. If biological systems are accepted as a natural standard for intelligent behavior, it is logical to use prototypes of a biological structure and within them the biological neuronal networks NN as a starting point for research and development of possible behavioral structures [17]:

$$M_{BIU} \in M_I \subseteq M_{S-R} \Longleftrightarrow M_{NN}$$

Starting with the real brain, an abstract model of a neuron network ANN is derived with M_T as a special behavior model corresponding to M_{ANN}:

$$M_T \Longleftrightarrow M_{ANN}$$

Then one has to show to which extend M_T overlaps with M_I. Thus if

$$M_T \cap M_{IP} = M_{IP} \Longleftrightarrow M_{ANN}$$

then we can say that an artificial neural network is behaviorally equivalent to a biological system with regard to the chosen subset M_{IP}.

In general, it is clear how an M_{ANN} can be derived by starting with individual neurons (N) as basic building blocks and relations between the neurons ($CON \subseteq 2^N \times ... \times 2^N$). A behavior is defined on the structure ($dyn : 2^N \times ... \times 2^N \times CON \longmapsto 2^N \times ... \times 2^N \times CON$). This is a formal model of an artificial neural network

$$ANN = \langle N, CON, dyn \rangle$$

With regards to an evolutionary process, this construction is embedded into a dynamic process where the evolving neural structures are constantly evaluated against the challenging adaptive problem $\mathcal{P}$.

Until today there is no common agreement which kind of an abstract ANN-model is a “good” abstraction. Is it necessary to have nearly one-to-one models of neurons and networks to generate a certain behavior or is it sufficient to use simplified elements e.g. McCulloch-Pitts, etc.?

5.2 Computational Semiotics

Across all disciplines there is a strong agreement that the ability to communicate with symbolic systems is a clear case for intelligent behavior[12], [21]. Besides many disciplines like phonetics, linguistics, psychology of language, ethology, acoustics and others contributing to the studying of symbol usage $M_{SYM} \subseteq M_{S-R}$, it is the discipline of semiotics, which has “symbol” and “symbol usage” as its main subject [29], [9]. It seems plausible to assume that the following holds

$$M_{SYM} \cap M_I \neq \emptyset$$

Thus, symbol usage can overlap with intelligent behavior.

Semiotics has more than one founder and every founder brings its own flavour into the field. This comes as no surprise as symbol usage is by its own a truly cross-disciplinary phenomenon.

By examining Peirce [30], one is confronted with a *phenomenological* approach in semiotics. It offers a rich terminology to handle questions of meaning. One is quickly lost in the phenomenological space without a clear relationship to behavior and how to control the soundness of the described phenomenological structures. This is caused by the fact that the space of *phenomena* $PHEN$[3] is the space of the consciousness $M_C = M_{PHEN}$. Because there are also other phenomenological theories around, it remains a question to which extend $M_{PEIRCE} \subseteq M_{PHEN}$ holds. Another unanswered question is to which extend it is true that $M_{SYM} \Longleftrightarrow M_{PEIRCE}$. The relationship between M_C and M_{NN} is unsolved too.

Despite its open methodological status, the Model of Peirce inspired some computational models [20]. The constructors of these computational models usually don't reflect on the methodological issues of this approach.

Alternatively, by examining Morris [28], which represents mainly the *behavioral* approach in semiotics, one is closer to the known behavioral models of psychology and ethology, and Morris contributed a lot to associate M_{SYM} with M_I $M_{SYM} \Longleftrightarrow M_{MORRIS}$. Because he didn't make use neither of phenomenology nor of neural networks, and he did not work out an explicit formal theory, it is difficult to say what kind of model he has developed [16]. Morris shares this 'fuzziness' of his model with behavioral psychology in general (see below).

The relationship between Morris and Peirce is until today not explicitly established. For a methodological analysis see [15].

There is also some overlapping between computational semiotics and computational linguistics. This is outside the scope of this paper.

5.3 Computational Psychology

Psychology was rooted in philosophy and based on introspection in the beginning. After the development of experimental methods and the rise of empirical sciences, introspective methods became more and more obsolete in psychology. Large parts of psychology converted at the beginning of the 20th century to a behavioral approach, banning introspection as an unscientific method [5], [27]. During the course of experimental psychology, it became clear that the theoretical explanation of advanced behavior cannot be done without rich enough formal models explaining the data. Furthermore, it became clear that the more advanced models are not feasible without computational support, e.g. advanced experiments with perception or cognitive tasks, especially with memory. This new symbiotic relationship between psychology and computer science caused many new methodological issues [19].

[3] Outside Phenomenology, philosophers use the term *qualia* instead.

The general intention of experimental psychology is given by the formula:

$$M_I \subseteq M_{S-R} \Longleftrightarrow M_{PSYCH}$$

where M_{PSYCH} is an explaining structure able to produce the behavior under investigation. To embed psychology in an evolutionary perspective, it is necessary to model the changes of the behavior too. In a strictly behavioral approach one does not make use of neural M_{NN} or phenomenological M_{PHEN} structures. From a methodological point of view [37] [4]) this exclusion is not necessary. Psychology could use either neural models

$$M_I \subseteq M_{S-R} \Longleftrightarrow M_{PSYCH.NN}$$

– representing the paradigm of *Neuro-psychology* – or even phenomenological models

$$M_I \subseteq M_{S-R} \Longleftrightarrow M_{PSYCH.PHEN}$$

– representing *Phenomenal psychology*–. But because the neural and the phenomenological type of theory have completely different measurement domains MD_{NN} and MD_{Ph} they are inherently irreducible to each other[4]. It could be an interesting case to develop a phenomenological based theory of an artificial consciousness and embed this theory in a neural model as generating machinery for the consciousness as well as for the observable behavior. It seems that these exciting theoretical possibilities have not been really exploited.

Psychology was one of the first – and more or less the only – contributor of behavior based concepts of intelligence, e.g. behavioral learning theory [10] or *IQ-Theories* [8], [34], [41].

In IQ-Theory one is defining the term *intelligence* indirectly by identifying a set of typical problem-solving procedures $M_{IQ} \subseteq M_{S-R}$, which are assumed to be possible indicators of "generating intelligent structures". These M_{IQ} are indexed by certain age-cohorts together with some "standard performance parameter". Every member of such an age-cohort solving these M_{IQ} within the given standard performance parameter will be qualified as possessing "normal intelligence generating structures", and all the others which are better or worse are qualified as more or less intelligent. The important point here is not the final numbers (like to have an IQ of 70, 100, 130...) but the *identified set of processes* M_{IQ} which are used to measure the performance of a user exposed to these[5].

Despite the huge amount of data gathered by experiments, explicit elaborated models of intelligence are rare and mostly very limited. A general empirical based theory of behavioral based intelligence is not known yet.

[4] Simple examples how one can formalize phenomenological theories has been described by one of the authors in [15].

[5] In the realm of IQ-Theorizing you can also find strategies which try by statistical assumptions to compute from the data several kinds of hidden factors which are then identified as the real factors of intelligence [42]. This reminds to the above described tendency in AI to turn from behavior to structure.

Another interesting approach is given by theories of computational anthropology, [3], [33]. Investigating the extend to which genes are contributing during evolution to culture, one can more and more identify mechanisms rooted in behavior, imitation learning, and communication independent of the genetic machinery which allow kinds of knowledge and learning beyond the individual level. This explains the extraordinary adaptive flexibility of the human species as well as the observable rapid changes in behavior by whole populations. These complex patterns of behavior have also to be included in the definition of intelligent behavior.

6 Future Steps

This paper is the result of many years' work of interdisciplinary research and engineering in the field of computational intelligence with explicit interactions to neighbouring disciplines. The authors experience this general lack of commonly accepted standards what intelligent behavior is as a real obstacle. Although it is possible to find interesting solutions for special problems it is in such a situation not possible to improve the field of intelligence in a fruitful and sustainable way. The biggest problem seems to be, that the installation of a standard of intelligent behavior cannot be done by the field of computational intelligence alone. Something like an international interdisciplinary council for the organization of an open process for the establishment of a standard for intelligent behavior seems necessary.

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