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Defining systems based on information exchange: structure from dynamics

F. Carvalho-Rodrigues[a], J. Dockery*[b,c]

[a]*INETI, Instituto de Tecnologias Informação and IST, Instituto Superior Técnico, 1699 Lisboa Codex, Portugal*
[b]*Defense Information Systems Agency, D8, Arlington, VA 22204, USA*
[c]*George Mason University, C3I Center, Fairfax, VA 22030, USA*

Abstract

We take the occasion of the workshop to examine a proposition that systems may be better defined in terms of interactions based on information exchange rather than on atomic elements. Although speculative, the paper is in the spirit of exploration within a workshop atmosphere. It is enough for us that the interactions be perceived to exist. On this basis, components become interactors, which signal each other through the exchange of information mediated by some interaction mechanism. At a minimum, interactions need only be imputed. Consequences for the appropriate definition of a system parameter based on our position are examined. Possible mathematical avenues are introduced. In the process, a connection with belief systems is explored.

Keywords: Information exchange; Workshop; Dynamics; Interactors

1. Introduction

In this paper we explore a definition for system parameters which eventually forces us to the conclusion that systems theory in some circumstances is a subset of information theory. The original impetus grew out of an attempt to use the concept of entropy as a basis for suites of system parameters. In that earlier work, we had already used Shannon entropy (H) to express the ability of systems to recover from damage absent from other compensating mechanisms.

$$H = -\sum_{i=1}^{n} p_i \ln p_i \text{ where } p_i \text{ is a probability} \quad (1)$$

* Corresponding author, Tel: +1 703 6076339; Fax: +1 703 6074100; E-mail: dockeryj@ncr.disa.mil.

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We explored what was termed casualty based entropy. In that case, the probability was computed as a ratio of damaged components, which were therefore removed from the possibility of interaction, to the total number of interacting elements present at the start of a time period (Carvalho-Rodrigues 1989, 1993a,b).

The work made use of the entropy curve of H versus p, which peaks for values of p around 35%. Our supposition was that even for values of damage around 10–20% the steep ascent of the entropy values signalled major system problems. In short, systems were more brittle than their components. We then asked what was unique about entropy that permitted it to model systems behaviour. We posited the following explanation. Entropy was crudely measuring the ability of components to exchange information through interactions. Removing or seriously damaging systems components decreased the system capacity to communicate information between components. To us, this indicated that interactions might be more fundamental to system properties than components.

We were eventually lead to a hypothesis that properly defined system description parameters must be resident only in the interactions of the systems and nowhere localized in the components. Only in this, albeit extreme, fashion could we guarantee that the proposed parameters would be tied to a functioning system. Moreover, they would unavoidably disappear when the system was devolved into components.

In subsequent explorations, entropy as the basis of additional system parameters was sought. To test this idea we drew up a list of potential, and perennial, (total) system parameter candidates. This list included cohesiveness, complexity, resiliency, redundancy, and reconstitution. The property of cohesiveness was selected as possibly being amenable to definition in terms of entropy. An 'excess' of entropy, relative to a standard lacking any special cohesive property, was advanced as a definition (Carvalho-Rodrigues, 1992). In this hypothesis, a fuzzy scale of weak to strong cohesiveness is used in place of absolute numerical values. We were driven in this exercise by a nagging suspicion that the usual list for system parameters could contain candidates, which might be manifestations of the same underlying mechanism. The results of this effort were ambiguous. We turned next to complexity since complex systems seemed to also involve the processing of information.

In fact, we were nearly hamstrung in trying to consistently define complexity. It seemed to exist in the eye of the beholder. The consequence of this was startling. It would make the definition of a system depend on the way in which information was processed. Special insights into this observation appear in a discussion of a painting by Kazimir Malevich called *Two Black Squares* (Carvalho–Rodrigues 1994). Rather than continuing an exploration of entropy and system parameters, we elected to re-examine the more fundamental question of what constituted a system.

2. A system is...

Several camps exist as to what a system really is. For us, the system characterizations listed in Table 1, although incomplete, were useful.

If there is a common thread in Table 1, it is that all entries seem to define a system in terms of its components, including those dealing in state transitions (the latter change the state of the components). In order to generate an alternative concept, we took the implications of our definition of systems parameters quite literally. This produces a definition based only on the perception of interactions, not always defined, which operate in some related fashion. We write this as a map from a set of interactions X into a defined system S. Thus,

P: $\mathrm{X} \rightarrow S$ where P is the observer's perception (2)

Before proceeding to speculate further, let us examine the implications of using perception. If we further write,

Table 1
Some common system concepts

Name	System concept
Algorithm replacement	A system is replaced by a computer model and judgments are referred to the model. Thus, the system is only as complex as its algorithm.
Input-output model	The system is a 'black box' whose properties are inferred from a comparison of output with input
Architecture model	A system is an ordered configuration of its elemental components
Stochastic	The system executes transitions with no history
State variable	A system is defined by transitions between states of its elements

$$m: S \rightarrow q \tag{3}$$

where q is some observable of the system and if we identify m with the Dempster-Shaefer belief measure, we have connected the general definition of a system to one which embeds the definition of a 'belief system'. In belief systems, the truth or falsity of a proposition q depends on the weight of information; or, in other words, the available information. Moreover, based on the work of Joslyn (1993), we have that m is either a possibility or a necessity measure if S is a random set. Summarizing, we write m: $(P{:}X) \rightarrow q$.

So that some elementary consequences of the introduction of measures into this treatment can be considered, we include some basics of fuzzy measure and belief measures taken from Klir and Folger (1988). A fuzzy measure assigns to a set X a degree of membership in the unit interval [0,1]. In the context of belief systems, that membership is equivalent to our belief that the weight of evidence supports that inclusion. If g is the measure then it must satisfy the following axioms:

A1. $g(0) = 0$ and $g(X) = 1$;

A2. $\forall A, B \in X, A \subseteq B \rightarrow g(A) \leq g(B)$

A3. $\lim_{i \rightarrow \infty} g(A_i) = g(\lim_{i \rightarrow \infty} A_i)$ where either $A_i \subseteq A_j$ or $A_j \subseteq A_i$, $\forall i,j$

When g satisfies the following additional axiom, it becomes a belief measure (Bel).

A4. $\mathrm{Bel}(A_1 \cup A_2) \geq \mathrm{Bel}(A_1) + \mathrm{Bel}(A_2) - \mathrm{Bel}(A_1 \cap A_2)$ which can be generalized for $i = 1, n$.

Note that when

$\mathrm{Bel}(A_1 \cup A_2) \geq \mathrm{Bel}(A_1) + \mathrm{Bel}(A_2)$ with $A_1 \cap A_2 = \emptyset$

the belief measure becomes the probability measure. Associated with the belief measure is a dual called the Plausibility measure defined as $\mathrm{Pl}(A) = 1 - \mathrm{Bel}(\bar{A})$. The following inequalities hold:

$$\mathrm{Bel}(A) + \mathrm{Bel}(\bar{A}) \leq 1 \text{ and } \mathrm{Pl}(\bar{A}) + \mathrm{Pl}(\bar{A}) \geq 1$$

These quantities can also be related to entities called the 'Possibility', and its dual the 'Necessity'.

What are the implications of these measures for systems definitions which incorporate the fuzzy concept of perception as a vital element? A partial answer is as follows. If two definitions compete, context will determine when they are possibly equivalent. One can also accept or reject on the basis of plausibility or necessity. The same holds true for weighing the evidence for the existence of an imputed interaction. It is seen to depend on the degree of belief.

3. Consequences of perception

With Eq. (2) we commit to a definition of a system which depends solely on the way in which information is processed concerning the set of defining interactions. As a semantic nicety, we introduce the concept of *interactors*, by which we mean those system elements which reveal information about the interactions. We must leave open at this juncture whether or not the interactors are the same as the standard conception of system components. The following four tables introduce some of the concepts which follow from either our preoccupation with interactions or our focus on information. In the tables, we distinguish virtual systems as those which our current understanding of the physical world will not support. For example, the nightly interactions of Osiris, Isis, and Ra sufficed as a model of the heavens for the history of ancient Egypt. Although now recognized as myth, that system persisted intact for thousands of years as a complete explanation of the observables.

From Tables 2 and 3 we are able to organize conflicting views of the same system. (Entries were somewhat arbitrarily chosen to illustrate our contentions.) In Table 2 for instance, some common terms used to describe information are listed with their systems implications. In Table 3, general statements about interactions are used to infer aspects of system parameters.

In Table 4 are listed some major system concepts, together with our evolving system explanation as information changes our context for

Table 2
Some information descriptors

Information related entity	Corresponding statement about the perception of a system
Information base	Whether or not a system is inferred will depend on the existing knowledge base. Whether or not the imputed system is virtual or real will depend on the quality of the base.
Processing rate	The ability to analyze the available information at various rates is predicted to influence the perceived existence of a system.
Information filters	The existing cosmology, into which the system must fit, will influence the acceptance of it as a suitable explanation.
Data or information language	If the language is metaphorical, you will get analogues; if mythic or mystical, you will get virtual systems; if algorithmic, you will get computer models; etc.
Error correction	It will determine the resilience to facts.
Rate of information change, collection and collation	These determine the 'half life' of the system without major changes.
Sophistication of observer	Whether or not the set of interactions is believed to be a system will depend on how untutored the observer is. An example is found in a case where a forest dweller trades places with a city dweller.
Screening out noise or extraneous or non-essential information	This determines whether we focus on the 'right' interactions, and no others.

understanding. Finally, in Table 5 for classes of systems we list the evolving interaction archetype for that class as a growing wealth of information made improvements possible.

So what can we say about complexity now. The work of Chaitain (1987) came to mind. For him, complexity is the number of lines of an algorithm which describes the computer model of the subject system. For others, it is sheer number of components. Based on entries in Table 3, we would regard both viewpoints as just two contextual dependent manifestations of an informational interaction. Basically, we have elected to classify complexity as a box in an n-axis matrix whose axes reflect context.

An interesting test arose when we attacked the problem of creating a system to solve a technical problem. This required us to first perceive potential relationships; and then, through the insertion of interactors, actualize them. Our particular example relating fire detection in a forest to speed of response required just such initial visualization

Table 3
Interaction descriptors

Interaction statement	Corresponding implication for system parameters
Absolute number of interactions	Probably sets an upper bound on complexity.
Number of different, or same, kinds of interactions	Probably affects computation of complexity and redundancy respectfully.
Number of interaction types affecting an interactor	Probably affects the perception of cohesiveness.
Number of equivalent interactions	Probably affects the computation of resilience and adaptability and also redundancy.
Language of expression for the interactions	Related to the question of whether or not the relationships (real or virtual) can be expressed.
Range of the interaction	Probably affects the perception of subsystems and system boundaries.
Hierarchy of interactions	Probably affects the perception of subsystems.
Existence of 'spare' interactions	Probably affects ability to repair and reconstitute the system after damage — implies the existence of stored instructions encoded in the interactions

Table 4
Example mega-systems

System example	System explanation
Solar system	Egyptian Ptolomey Copernican/Newtonian Einsteinian
Biological	Earth-air-fire-water Humours Space-time-mass-energy DNA
Evolutionary	The Flood Gilgamesh epic Darwinian Ecological Gaia
Cosmological (time)	Mythic: Navaho, Mayan, Zuni Newtonian Big Bang
Societal	Hunter-gatherer Agricultural Mercantile Innovation/industrial Military/industry Innovation/service/trade/industrial

and perception. This latter process imposed the system on the elements by making them interact through interactors in the form of sensors, and fusion of sensor data.

Table 5
Sample system interaction drivers

System class	Interaction archetype
Communications	Paths Terrestrial roads Maritime Aerial Information highways
Power	Muscle Draft animals Steam-petrochemicals Nuclear

4. Similarities

Clearly our examples favor a viewpoint that system models evolve with information acquisition. On this basis, a question of similarity between equivalent systems descriptions based on information can be asked.

As an extreme case, take a mythic view of the diurnal cycle and a Newtonian model. First, one can ask what is the similarity between the two system models? Then one can ask for the similarity between each system in a comparative sense; and between each and objective reality. The immediate answers are 'none', 'none', and 100%.

Are there other answers as well? Work by Dockery and colleagues (Dockery, 1993; Barry, 1994) in the area of modelling an understanding virtual reality were applied in an exploratory vein. That work is in turn based on work by Ruspini (1992) on modal logic and possible worlds. Ruspini makes use of a similarity measure, which is a kind of accessibility measure involving possibility and necessity of the truth of propositions in accessible worlds. We have already predicted relations based on possibility and necessity as a consequence of belief systems.

Possibilities are interesting because they need not sum to unity. This means that additional possible hypotheses can be entertained without disturbing existing ones. Necessity **N** is the dual of **P**, and is written as [1 − **P**]. Ruspini's development proceeds by asking about the accessibility of worlds in which all truths are maintained (**N**), and also worlds in which at least one truth is maintained (**P**). A similarity function is introduced which measures the 'stretch' between the two possible worlds. We view the difference between two possible systems in terms of such a stretch. Such thinking addresses the issue of complexity definitions which equate complexity with the number of equivalent definitions. Let us see if Ruspini's ideas permit additional similarity comparisons.

Operationally speaking, the mythic system is probably easier to explain and comprehend, given the prevailing belief system of the Egyptians; than the Newtonian view. In fact, the mythic explanation is not complex to a tutored (or untutored) observer inside the prevailing belief system. Out-side that belief system it is another story. The whole belief system is seen to be highly complex and at complete odds with our current information base. Should we re-examine the score? Two answers are possible depending upon which belief system you are in. From the mythic side, the result is 100% (mutual comparison), 100% (mythic reality), and 'none' (Newtonian reality) because one does not question the ways of a God who happens to also choose Newtonian mechanics. Starting from modem side, the score is 100% or 'none' depending upon your strict adherence to an operational viewpoint for the first entry followed by 'none' and 100%. Lest the reader reject the conclusion for similarity of 100% between the two think of the modern day manager who has been heard to bellow: 'I don't care if it works by magic.'

We think our information based approach to system definition could be useful for understanding how both information was processed and interactions were perceived in earlier cultures. We would be operating, as it were, inside an alien belief system.

What started as investigation of entropy became a search for a more fundamental understanding of systems in terms of belief structures. This in turn allowed us to propose insights into systems explanations which evolve as information accumulates.

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