Conservation of Information (COI). A Concept Paper on Virtual Organizations and Communities

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Abstract

As a work in progress, we have conceptualized virtual organizations and communities based on the conservation of information (COI). The literature indicates that applying social science to human or virtual organizations has been ineffective. Our approach is to unravel the fundamental interdependence between agent-based observation and action (an agent represents a human, machine or robot able to surveil its environment including itself and report on its observations). Tentatively, we propose that social theory parallels the quantum model, with the commonality between interdependence and entanglement, allowing us to borrow from quantum mathematics to develop a computational model.

I. Introduction

Virtual communities combine situational learning and evolution with action skills. However, researchers incorporating agent mobility into models of virtual communities with computational intelligence-machine learning (CI-ML) often draw more from personal experience with human behavior and community than from perspectives based on social theory. Among the reasons to avoid social theory for applications of computational intelligence to mobile agents is the present inability to solve evolving human problems with social theory (e.g., for military applications, see [5][18]; for the lack of a theory-based knowledge of effective decision-making, see [41]; and for our perspective, see the lack of an effective theory of organizations in [34], organizational performance in [26], and organizational metrics in [22].

We have attributed the weak state of social theory for computational modeling to the lack of a fundamental relationship between observation and action information [27]. For example, while it is common to find strong associations between self-reported behavior and self-esteem, arguably one of the most studied phenomenon in psychology, based on a meta-analysis with over 30 years of data, Baumeister and his colleagues [1] were surprised to find only a weak correlation between self-reported self-esteem and actual academic or work performance. Lawless and his colleagues [28] found no association between the knowledge of air-combat maneuvering held by combat fighter pilots and their results in air combat. And, for game theory, the first mathematical model of interdependence, Kelley [19] gave up after a career of troubleshooting the lack of an association between prior stated preferences and actual game choices, a problem that has kept game theory from becoming a predictive science [37]. This poor state linking computational social theory to actual human behavior has opened the way to develop and apply a new theory for human and artificial agent organizations not based solely on researcher or agent observations. Instead, we have concluded that for it to be effective, a computational theory of intelligence must include interdependence between agent observations and behaviors [28].

The general strategy in social science assumes that data to be analyzed statistically is derived from independent sources [20]. The goal for the analyst of social data is to remove or control the effects of statistical interdependence in data. Dawes and his colleagues [10] found similarly that, compared to the estimates by clinical subject matter experts (SMEs), actuarial data was more reliable and valid than expert witnesses of human behavior due to observer dependencies. Providing support, Tetlock [43] concluded that decisions by SMEs are no better than 50 percent of the time. Nonetheless, what makes our goal unusual is the opposite: instead of statistical techniques to remove observer dependencies, we plan to remove observer independencies to establish a science of interdependent systems and social processes (e.g., measuring deindividuation rates among the citizens of Burma imposed by the reigning military dictatorship may indicate geospatially and over time variability in the amount of power expended to oppress Burmese citizens). By extension, measuring the degree of interdependence among computational agents measures virtual community (Eqn. 5 & 6).

We have concluded that interdependence is fragile; measuring it produces only classical information; and it cannot be reproduced [30]. Interdependent beliefs are also conjugate. But the measurement of two conjugate beliefs creates a measurement problem reflected as COI tradeoffs (Eqn. 1).

To make room for a new theory of computational intelligence for mobile agents, the failure with human experience as a resource for building virtual organizations and virtual communities had to addressed. From our research, briefly, we have found that successful decision-making in human organizations was more likely to be practical and based on a competition of ideas (majority rule) using risk determinations by a handful of participants who drove the process to reach hard-fought compromises, but rending any rational perspectives arising from these decisions; in contrast, when a consensus view was purposively sought, it was often reached when decisions were less concrete and more likely to have uncertain effects by incorporating risk perceptions or illusions into the decisions ([29],[45]). Counterintuitively, we have also found for majority rules that after conflict was resolved with a compromise between protagonists, a consensus was quickly reached, which we have labeled an "action consensus".

We propose that these cognitive-action tradeoffs are characteristic of the conservation of information (COI) among four interdependent variables: Situational (localized) knowledge interdependent with plan execution; and energy expenditures from available resources interdependent with the duration of resource expenditures. For multiple interdependent events, we expect a competition to either focus attention and action, or fragment them among these four factors. Aware that the mind creates cognitive-motor maps of physical and social reality, we postulate that coherent thoughts reflect coherent maps of and actions in reality; and that incoherent thoughts reflect fragmented cognitive maps of and actions in reality (for robot generated consensus maps of their environment, see [44]).

For knowledge-execution factors, coordinating one event interdependent with an event sequence in a business or military chain implies a center of gravity (COG) for a system interdependent with the distance between the frequencies of signals sent to coordinate the occurrence of a target event among a series of interdependent events. COG is either the physical centroid of a team [40]; organization; plan participants; or the landscape that is key to a plan. For example, in dealing with terrorist acts, it is "a Gaussian distribution centered … between key features and the event … [where the] terrorists prefer certain spatial features (consciously or not), such as buildings or streets near the target location" [15]. With c as a constant,

$$\Delta x_{COG}\, \Delta(1/\lambda)_{COG} \geq c, \qquad (1)$$

where Δx_{COG} is the uncertainty in locating the center of gravity (COG) of a target (key activity or plan), while uncertainty in the distance between a chain of interdependent events coordinated around a COG's sequence of events, including the target event, is $\Delta_i(1/\lambda)_{COG}$. Here $\Delta_i(1/\lambda)$ equals to $\Delta_i k$, the wave number. Equation (1) measures tradeoffs among the decisions made for the interdependent activities enacted in a virtual community.

In reaching organization decisions, we have found generally that majority rule was about four times faster than consensus rule. Similar to the reduced mass approach [13], we expect that the COG for a group discussion centers around the cognitive-action resistance weights of its protagonists (i.e., reactance or resistance to adopting the target plan or its associated chain of events is higher under cooperation). Let μ be the reduced mass of the COG for both majority and consensus rules. Then,

$$1/\mu = 1/m_1 + 1/m_2 \qquad (2)$$

With μ, we model two citizen groups, advising the Department of Energy on environmental cleanup of nuclear wastes at DOE sites, for which we have had experience. A majority rule group (MR) with 25 members requires at least 13 for a favorable decision, and a consensus rule (CR) group of 31 members requires at least 27 members for a favorable decision [26]. Assuming on average four protagonist in the MR group versus 27 in the CR group, and assuming they are of equal strength (an arbitrary 10 score for protagonists versus 1 for regular participants) produces a contrast resistance of about 3.48. This number is close to our field result of 4 based on an average of 2 hours for CR to make a decision versus ½ hour for MR decisions. Equation (2) measures decision resistance or belief fragmentation in a virtual community. In addition, we explored a variation of Grover's quantum search algorithm to measure decision resistance (i.e., $N_{consensus}/2 \div \sqrt{(N_{majority\ rule})} = 27/2 \div \sqrt{(13)} \approx 3.75$).

Revising Equation 1, with ΔE as resource uncertainty (the entropy associated with resources available to execute the target activity and its associated chain of events) and Δt as time uncertainty, gives [27]:

$$\Delta E \Delta t \geq c. \tag{3}$$

From Cohen [6] and Rieffel [36], we have revised Equation (3) to form Fourier transform pairs [30]:

$$\sigma_f^2 \sigma_t^2 \geq 4 \tag{4}$$

with σ_f as the standard deviation of the frequency distribution and σ_t as the standard deviation of the time distribution. Equation (4) assumes that the signals from an agent's motor controller sent to its motor drives can be treated with signal detection theory (SDT). It means that short duration signals are associated with broad frequency distributions or, conversely, that a narrow bandwidth is associated with a long duration signal.

For organizations, we had found that more effort (i.e., power) was expended under competitive than consensus rules. From another direction, human communities are built from multiple mergers of smaller organizations and communities. With multiple regressions and Fourier transform pairs, we have extended our results to mergers between organizations, finding an association between increasing market size and reduced volatility (i.e., beta[1]), implying that one reason for organizations to merge and grow in size is to marginally decrease the resource uncertainty in controlling a market [30]. More stable organizations respond at lower frequencies to market perturbations.

Our results match findings for the brain: the greater expenditures of energy (power) in the brain are associated with higher cognitive functions, leading to an increase in the ability to resolve mental maps of reality [17]; words spoken in anger expend about twice the energy of regular voice [26]; and when performing a complex military exercise, compared to experts, the brains of novices light up like a Christmas tree, indicating the increased energy wasted by novices compared to experts ([23]; see also [32]).

[1] Beta is the covariance between a target organization and the average of all organizations in a virtual community divided by the variance of the target.

2. Proposed Social Decision Model (SDM):

Using natural computation, we plan to model and study consensus and majority rules in making decisions. In our study, we plan to use recombination operators [11]. For these operators to be able to drive the evolution of machine control algorithms based on Darwin's survival-of-the-fittest [46], we will use binary tournament selection based on a competition between pairs witnessed and evaluated by other machine agents. This is the same basis of political campaigns common to democracies, found to best educate undecided (neutral) voters among the public [7] [however, we have not yet resolved how to employ neutral agents]. Based on Shannon information theory [8], the reason is straightforward: cooperation reduces the information available to observers; competition increases it. The joint uncertainty $I(x_1,x_2)$ between two agents is

$$I(x_1,x_2) = I(x_1) + I_{x1}(x_2) = I(x_2) + I_{x2}(x_1). \tag{5}$$

Equation (5) is the uncertainty in one variable combined with that in the other after removing knowledge of the first. $I(x_1,x_2)$ ranges between $I(x_1)$ or $I(x_2)$ at the minimum when both are equal but one controls the other (enforced cooperation), to $I(x_1)$ plus $I(x_2)$ when both are independent (competition). The information transmitted, or $I_T(x_1{:}x_2)$, between two agents is:

$$I_T(x_1{:}x_2) = I(x_1) + I(x_2) - I(x_1,x_2) = I(x_2) - I_{x1}(x_2). \tag{6}$$

Equation (6) measures the amount of uncertainty that one variable interdependently reduces in the other. The constraint ranges between [0, min$\{I(x_1),I(x_2)\}$] as x_1 and x_2 range between independence to interdependence (i.e., conjugate). With the perspective of Shannon information, interdependence increases when cooperation occurs in a system, business chain, but also under competition when two or more opponents are coordinating their activities around a common objective (e.g., courtroom). Equation (3) will measure pre-decision information among virtual agents; Equation (4) will measure decision interdependence.

Measurement. We speculate that better decisions occur when the self-interests of expert agents (e.g., defense attorneys and prosecutors) are maximized [12]. If we assume that dialectics are composed of polarized views (180 degrees apart; i.e., A is true, $\neg A$ is false), producing a random outcome and a greater chance of conflict, orthogonal views are composed of independent (alternative) views, implying value associated with orthogonal belief systems (modeled with the dot product between two beliefs, A and B; from [14]). Maximally orthogonal beliefs offer several advantages [4]. From our perspective, we postulate that the primary reason is the ability to model interdependence, which we have asserted in the past is similar to the entanglement between qubits (where a qubit is a linear superposition of 0 and 1 bits of information). As noted earlier, interdependent beliefs are conjugate, and the measurement of one of two conjugate beliefs creates a measurement problem for the remaining belief. Measuring one belief conjugate to another produces Von Neumann entropy (the Von Neumann entropy becomes the Shannon entropy only for orthogonal states) in the measured belief and the maximum Shannon entropy in the other; i.e., Von Neumann entropy goes to zero as one belief becomes fully known, the other becomes random, approaching one [8].

In classical science, a system's state is specified by its observable properties at any one point in time (statics) or evolution over time (dynamics). Measurement copies a system's properties. In classical science, there are no entangled states. In general, n-bit systems require n times as much information as single bit systems. For interdependent systems, however, full descriptions are not possible, only the measured observation of results from interactions constrained by the probabilities inferred for future outcomes. Interdependent state spaces are Hilbert spaces with 2^n dimensions, such that a superposition occurs for 2^n n-qubit states. Measurement disturbs the association between a system's conjugate interdependent variables, forming a tradeoff between information gain and disturbance. Our plan is to monitor entropy at the individual, organizational and community levels.

Neutrals. In our social decision model (e.g., juries, citizen advisory boards, etc.), neutrals decide outcomes. Neutrals serve other important functions. Social tension is maximized under polar opposite views, increasing the opportunity for conflict. The presence of neutrals reduces the probability of conflict [21]. Futures markets work by employing investors who are neutral to the overarching topic they are investing in but not neutral to making a profit [29]. And neutrals are where most new learning and evolution take place [30]. But again, how we plan to employ neutral agents is not solved.

Feedback. All things being equal, SDM (e.g., jury) should lead to marginally better decision-making, but no guarantee exists that it will be better. We speculate that the key ingredient is feedback. Feedback is the primary mechanism that distinguishes democracies, especially those with limited and counterbalancing centers of power [16], from those using censorship (autocracies) in exchange for stability [31]. The result with feedback in a democracy is an increase in accountability and trust [25]. For our model, individual agents will be controlled with evolutionary algorithms [47]. For virtual organizations and communities, while we have not resolved our plans with control, we plan to follow Csete and Doyle's model ([9]; see Fig. 1).

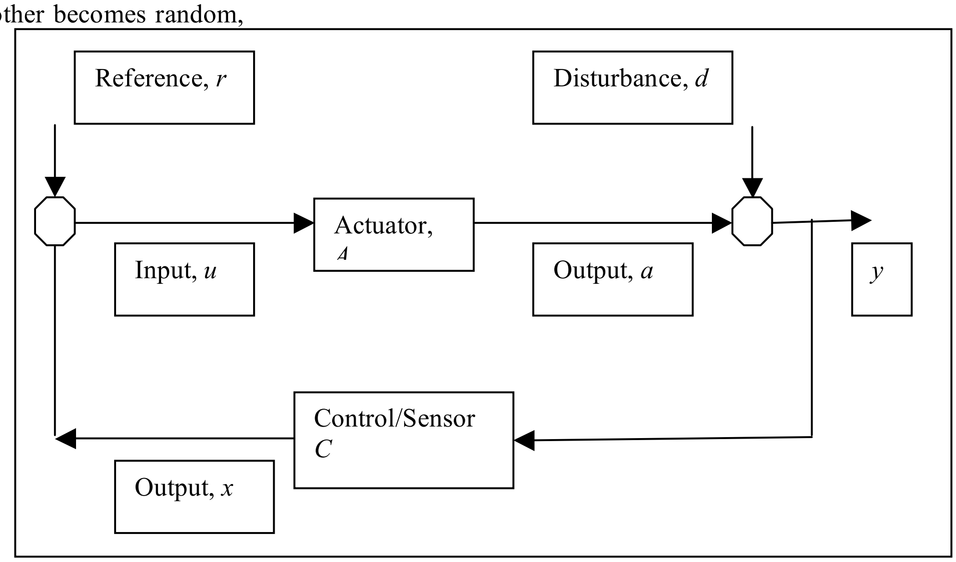

Figure 1. A notional control system is illustrated (from [9]). In general, positive and negative feedback, *F*, apply under static or steady state conditions; with *S* as the deviation from perfect control, log |*S*| applies to the dynamic case. The goal of a control system is to amplify reference *r* independent of disturbance *d* (where *r* = mission, plan or goal). Working as a low-pass filter, controller *C* removes short-term oscillations to follow long-term average trends. That makes *A* a pure integrator with gain *g*. The goal for a system's *C* is achieved when *F* is negative and -1/*C* >> 1, in the limit making |*S*| -> 0. With Log |*S*| as control fragility, when log *S* < 0, dynamic control is achieved; in contrast, when log *S* > 0, *d* is amplified.

3. Works in progress: Ensemble model

As of yet, we do not have a strategy for combining the results into an ensemble. Good classifier performance with training data designed to learn an underlying distribution has often not performed well with data not seen during training. In a review, Polikar [35] concluded that combining classifiers into an ensemble generalizes better by reducing the risk of selecting a poor classifier. This becomes important when decision boundaries among different data classes are complex, as we expect them to be for mobile agents. Ensembles of linear classifiers can learn complex nonlinear boundaries. Our plan is to contrast consensus and majority rules to data fusion processes. We will attempt to do this by increasing diversity of classifiers with decision boundaries different from those of others. Similar to a low pass filter, our plan is to combine a diversity of weak classifiers into a stronger classification system.

Our algorithm is incomplete at this time. But because the mean is simple to use and found to be effective [35], we plan to build from means to standard deviations and then to fitted Gaussian distributions for the data. This would permit us to introduce Fourier pairs to explore patterns of frequencies and wave numbers, Δk, where Δk equals $\Delta(1/\lambda)$. In addition, to speed up runtimes, we plan to use a control system that combines simulation and reality [46]. A similar control system was found by Bongard and his colleagues [2] to be effective at path disambiguation for robots.

4. Summary

Natural computation models will permit us to test field data and model the organizations that produce this data. We propose to test the data and organizational models with artificial agents evolved using biologically inspired natural selection [11] and social methods of decision-making (e.g. jury or "voting" ensembles). Based on our field research, we predict longer decision times and more oscillations under consensus rule (CR) than majority rule (MR). We expect CR to model serial sequential individual decision processes. Surowiecki [39] gave evidence and case studies of why human ensembles (crowds) often outperform individual experts. Earlier, Opitz and Maclin [33] empirically showed that ensembles often outperform individuals, with theoretical support provided by Brown [3] and Tang [42].

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