

Quantitative Aspects of Situation Management: Measuring and Testing Situation Management Concepts

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Addressing Information Fusion and Situation Management Concepts

The Data and Information Fusion domains have for some time addressed the issues involved with Situation Estimation and Situation Refinement as part of the characterization of the “higher” levels of fusion processing, meaning those levels of processing that deal with more abstract and complex world states of interest that people call “situations”. It is usually agreed however that at the moment at least the research in the Data and Information Fusion (DIF) field has by far been on the aspects of estimating single and sometimes multiple-object attributes from composite observational data, and usually from electronic or physics-based sensing devices such as radars and imaging systems, that is, on the so-called “lower” levels of fusion. As both the world and the technology have changed, and as research in the DIF arena has matured, there has been a considerable interest in directing the research to methods for estimating the higher state levels of DIF, usually called Situation Refinement and Threat or Impact Refinement, and related to “Level 2” and “Level 3” of the well-known “JDL” DIF process Model (Ref 1). Note that the “refinement” term is important, implying an awareness of the fact that the focus of DIF processing is almost always on dynamic events in the world; it also reflects the need for a temporally-adaptive, recursive state estimation process.

Not unexpectedly then, the research focus of the DIF community has been moving toward achieving the new capabilities necessary to develop such higher-level state estimates. In doing so it has been realized that there are various new challenges to deal with, such as:

- new types of sensing devices and systems to include small disposable and opportunistically-deployed sensors, mobile and ad hoc sensor networks and, rather recently, human-provided observations
- inclusion of a wide range of contextual data that can extend from basic topographic and terrain information to the full range of “PMESII” data (Political, Military, Economic, Social, Infrastructure, Information), as such data might influence the nature and processes of high-level state estimation
- highly-agile adversaries that stress and limit the ability to develop and rely on a priori type behavior models that form the usual knowledge bases that support deductively-grounded DIF processes
- entirely new types of conflict, labeled today as “asymmetric” and “irregular”
- conflict environments where there is great concern for collateral damage

among possible other factors. Indeed, the DIF literature shows the movement in this direction (e.g. Refs 2,3), to include a new monograph on this subject (Ref 4).

Further, the JDL DIF process model has always included a “Level 4” Process Refinement function that at least historically was intended to indicate that typical implementations of the fusion process would require adaptive processing operations of some type in accordance with whatever agile functionality might exist in the system prototype. What Level 4 (L4) operations might entail would be dependent on the DIF process or system boundaries and what resources were under the control of the L4 operations; for example if the sensors were manageable by and intended to primarily service the DIF estimation processes, then adaptive sensor management could be part of L4, and indeed a considerable amount of research has been directed to this control-like capability (eg Refs 5,6). However, it is judged that L4 functions can *always* be applied to the “internals” of the DIF process, since there is no question that the Common Referencing-Data Association-State Estimation core fusion operations are inherent parts of the overall DIF process and within the system boundary. Thus, L4 can include such operations as adaptive algorithm control, dynamic algorithm or process thresholding (e.g. for a detection process), or control over data base operations.

Information Fusion and Resource Management

However, the interfaces and interdependencies between and among DIF and the more general functions related to Resource Management have been rather vague, and have been argued about in the DIF community. In modern military ISR and C2 systems that have become so highly dependent on information¹, there is no questioning a close interdependency between any system information process and the management of system resources even to the “mission” level. If it is so that a DIF process is the core (or especially only) information-generating process to support resource management, then the functional connection is fully established. This is an important point; if there are important system-level information processes not involving any fusion operations, then the question of authoritative control over system-level resources has to be adjudicated as part of the overall system design. As we will see later, the Situation Management model properly allows for this in part, in defining both a “deliberative control loop” and a “subsumption-based”, sensing-to-action/resource-management control loop

However, there is an implicit question about how the fusion community views this connection to resource-management “in the large”, and importantly how its research activity is directed²; what can be examined to assess what the apparent view is on this point is the research literature. In doing so it is clear that the fusion community largely

¹ In part driven by defense research policies that have strived for “Information Superiority” and “Information Dominance”; while the policies might be questioned in general, here they are taken at face value.

² It can be argued that the fusion community is in part self-directed (especially as regards academic research that is not always driven by funding) and partly reactive to the requirements specified in solicitations for funding, so the broad research directions and philosophies in coupled fusion and resource management would seem to be a hybrid mix of such forces. It is not surprising then that this picture is unclear.

but not exclusively sees itself as an estimation-oriented community, developing the means to provide what it considers to be the best possible world state estimates to *support* any subsequent operation, included in which is decision-making. There have been several papers on the notion of a “Level 5” in the fusion process model, having to do with the human interface to and role in DIF processes, but these are position papers, and provide recommendations about the human as part of the DIF process, but not so much as regards the human as decision-maker.

The Situation Management community seems to have taken the role of extending the research boundary related to situational processes to be more proactively inclusive of the fusion-to-decision-making boundary, and to extend it to include controlling whatever effectors are necessary to bring the current (estimated) situation to a more desirable state. Quoting Jakobson (Ref 7) from what seems to be the latest definition of Situation Management, he offers “At a high level, SM is defined as a synergistic goal-directed process of (a) sensing and information collection, (b) perceiving and recognizing situations, (c) analyzing past situations and predicting future situations, and (d) reasoning, planning and implementing actions so that desired goal situation is reached within some pre-defined constraints.”

Boundaries Between Information Fusion and Situation Management

With SM involving decision-making and control of situations, which by implication involves some form of resource management, it is constructive to explore what the DIF to SM interfaces and interactions might be. We offer Figure 1 (in part from Ref 7) as a discussion piece on this point.

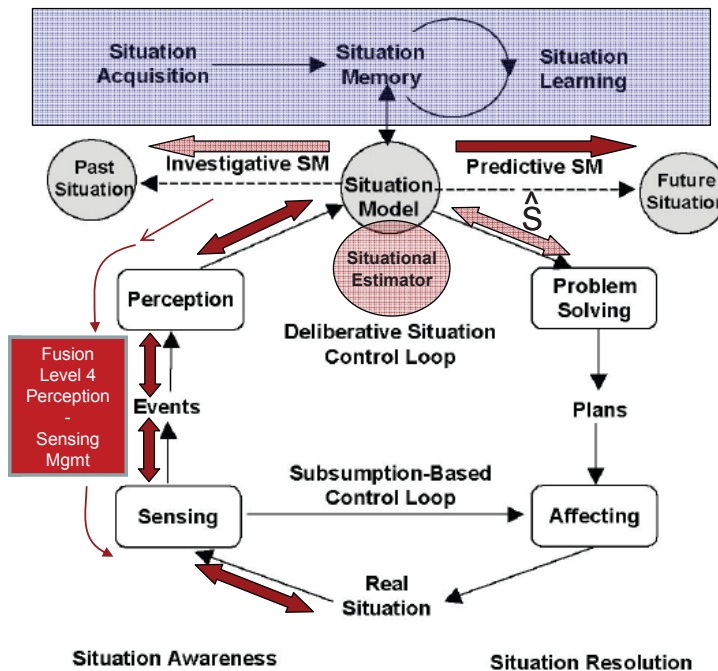


Figure 1 Composite Process Diagram of Information Fusion and Situation Management

The core of this figure is from Jakobson's description of SM (Ref 7), describing the closed-loop outer processes from Sensing to Affecting. The red colored arrows and text boxes show the traditional roles for DIF, which itself involves adaptive feedback, minimally to the sensing operations via a L4 process as previously described. Key to the DIF-SM interface is the situational estimate S_{hat} that provides one basis for the following problem-solving and decision-making of SM. (Much more is said on this interface below.) If this overlap is generally agreed-to, then there is a close interaction between DIF and SM in the sense of functionality and technology.

Now then if SM is to "manage situations" then a goal-state for the "corrected" or "controlled" situation must be able to be defined; call this S_{desired} . For many military or security problem cases, we see this as a problem in itself, since this needs to be done quite quickly in the face of a broad range of possible real-time situations. Further, note that S_{hat} is not the "true" situation in the world but a fused estimate, equal to $S_{\text{true}} + \text{error}$, or $S_{\text{true}} + \epsilon$. SM would then seem to be focused on setting $\Delta S = S_{\text{hat}} - S_{\text{desired}} = 0$ by taking whatever actions that (to some degree of predictability) move the current situation in the direction of S_{desired} .

Measuring Differences in Situations

It would seem that the entire SM process begins with a determination that the current situational estimate S_{hat} (from fusion) is different than that desired. This naturally raises the question of how this difference can be measured. In turn, this relates to how the situational states are represented, a topic beyond the scope of this paper. But we offer a few thoughts on this question.

At CMIF, we have had good success representing situations as graphs. If this is the chosen representation, then regarding the measurement of differences requires defining notions of similarity in graphs. There is a body of literature on this involving both graphical-science methods that examine isomorphism, edit distance, maximum common subgraph and minimum common supergraph methods, as well as statistical comparisons using network centrality metrics. Another possible literature to examine is that (limited) work on association metrics for high-level fusion (essentially a mirror problem to the similarity question). One example of such association metrics is given in Ref 8 where the Level 2 association metrics included a group distance measure, a cardinality distance measure and "gap metric angle measure" that signified differences in entity composition; the final metric was an area metric that measured the degree of overlap or interaction between groups. These metrics include the effects of uncertainty, based respectively on the Gaussian covariance for the target kinematics and the likelihoods drawn from a Bayesian taxonomy for reporting classification information.

This brings us then to the relationship between decision-making, course of action selection, outcome consequences, and goal states. We see an analogy between Problem-Solving—Plans—Affecting in the Fig. 1 characterization of SM to a process involving Option Generation—Option Assessment—Course of Action selection—Resource

Selection/Optimization—Implementation, which then gets reexamined in the fashion of what one could call “Situation Effects Assessment” (done via DIF), not unlike Battle Damage Assessment subsequent to combat operations.

To examine the information (S_{nat}) to Affecting process, we draw extensively on the research of Marshall Yovits and his colleagues, carried out originally at Ohio State University.

Marshall Yovits and Relationships Between Information and Decision-Making: A Review of His Work and that of his Colleagues

In a theory that traces back to 1969 (Ref 9), Professor Marshall Yovits and his colleagues, originally while at Ohio State University, develop an approach to gauging the effectiveness of information provided to decision-makers for decision-making. In this major subsection of the paper, we follow and review his work closely, as we largely agree with his ideas; this section is thus in a sense a paraphrasing and summarization of several of the works of Yovits and his colleagues.

Notions of the value of content of information have been developed by Shannon (Ref 10) and others but Yovits inquires as to the pragmatic value of information specifically for decision-making support. They offer the following “generalized information system model” of Figure 2, and argue that virtually all situations involving the flow of information in a decision system can be described by this model. In this model, an important aspect is that the decision-maker uses information in order to decide on courses of action that eventually generate various observables. The courses of action choices are the result of a model of the decision situation that he is concerned about; this model may be a very poorly structured or poorly understood but is nevertheless the foundation for his choices. Adaptations to this model are the result of comparing the resultant observables of the chosen actions to those predicted or anticipated by his current model

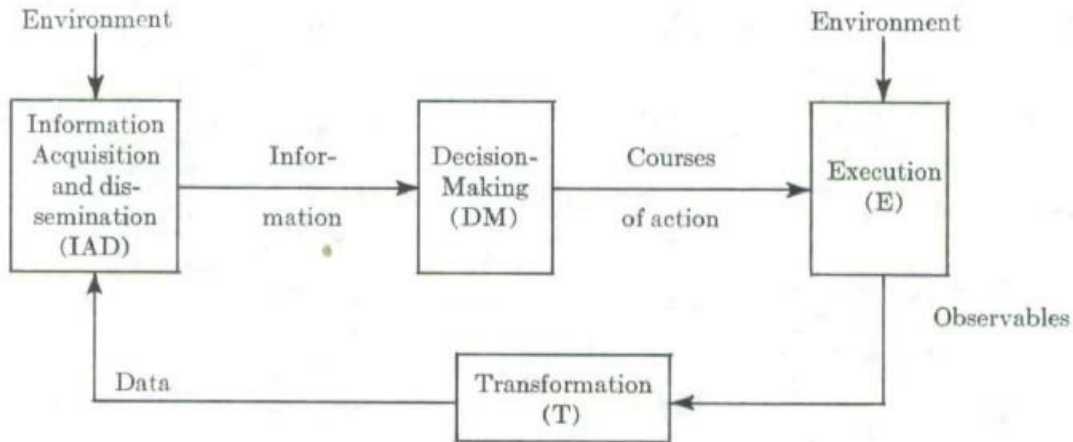


Figure 2 The Generalized Information System Model of Yovits (Ref 9)

Ideally, the decision model must accurately represent the structural and relational aspects of the “system” or decision-problem that he is addressing. The approach assumes that the situation in which the decision-maker (DM) finds himself is unique to him, i.e. there is no prior precedent. The DM needs to develop a model of the overall decision problem and craft the best decision possible regarding a course of action. The decision problem model has, in Yovit’s approach, a set of “decision elements”. These elements include:

- a set of courses of action,
- a set of possible decision outcomes,
- a decision goal or set of goals,
- a function which relates decision outcomes to goal attainment,
- and a set of states of nature, or current situation estimates

Note that the model allows for sets of each element; clearly there will be choices among multiple possible courses of actions (COA’s; we equate these to decisions), and clearly there can be various possible outcomes of any given choice of course of action. It is also possible that a set of goals could be under consideration, i.e. that there could be a one-to-many mapping from a given course of action to various goals. And finally, any given decision will be contextually-dependent on the overall situation or “state of nature”. A notional worst-case decision-making condition then would be when the only action for the DM is to select from a set of alternative COA’s, i.e. when there is no helpful additional information about the other elements. Note that this means there is no relational knowledge about the decision problem, meaning that the DM also has no basis for learning from experience.

Assuming the DM has some (imperfect) structural and relational knowledge about the decision problem, this means there exists an “executorial uncertainty”, an uncertainty about what any COA will produce as an (observable) outcome. (Note that a role for an Information Fusion system then is also to provide the observables or fused estimate of the

outcome resulting from any given COA.) Yovits also points out that, in the same way as for the decision problem, there is a modeling problem for fully understanding a goal-set. Here too the DM needs structural and relational information among the goals in the goal-set, and may not be totally clear about this model, yielding a “goal uncertainty”. He notes that even if the basic goal structure is relatively clear, the DM may be uncertain about the relationship between the various decision outcomes and how they yield given levels of goal attainment; that is, he may be uncertain as to how to assign values to the various outcomes in terms of the degree to which they help toward achieving a goal.

Yovits continues in discussing additional uncertainties that surround the DM’s problem, in asserting an “environmental uncertainty” that characterizes the uncertainty (again having structural and relational components) in what he calls the “states of nature”, which are the conditions within which the activities set in motion by the decision will operate; we see this as equivalent to a “situational state”. Assuming that this state was created by a Level 2 (or 3) fusion process, it will have an inherent uncertainty associated with its estimated value; that uncertainty equates then to Yovit’s environmental uncertainty. Collectively then, in Yovit’s model we have six types of uncertainty: three categories of uncertainty—goal, executional, environmental—each having a structural and relational dimension—the joint uncertainty represents the overall uncertainty in the DM’s conceptualization of the decision problem space. This categorization is shown in Figure 3 (from Whittemore and Yovits in 1973, Ref 11):

		UNCERTAINTY ABOUT:		
		Execution of courses of action	Goals	Environment
UNCERTAINTY ABOUT:	Structural components of the decision model	structural-executional uncertainty	structural-goal uncertainty	structural-environmental uncertainty
	Relationships among the structural components	relational-executional uncertainty	relational-goal uncertainty	relational-environmental uncertainty

Figure 3 Yovit’s Classification of Decision-making Uncertainty (Ref 11)

and is shown diagrammatically in Figure 4, again from Ref 11:

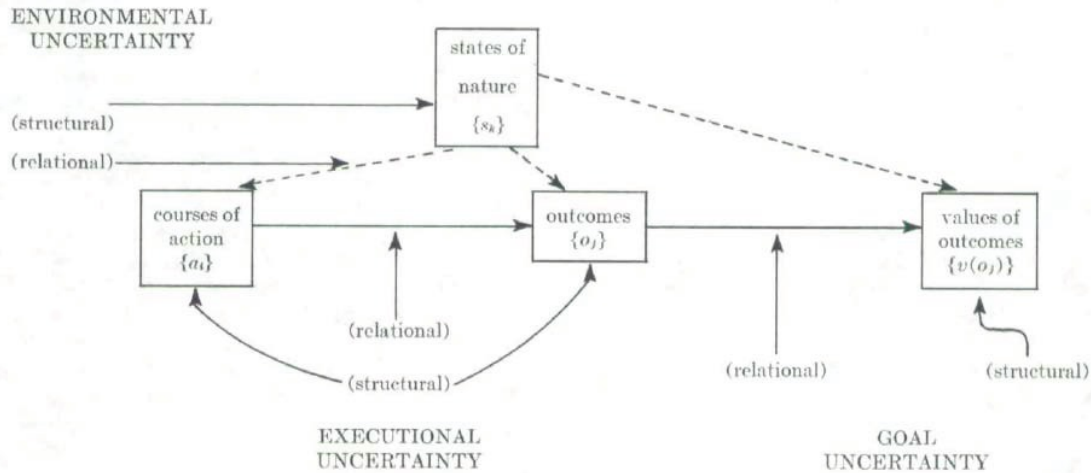


Figure 4 Notions of Uncertainty in Decision-Making (from Ref 11)

Making Decision about Courses of Action

Upon facing his own construct of the decision problem, the DM will craft a set of possible alternative courses of action, and develop a decision strategy that will select one of the alternatives. To keep consistent with Yovit's notation, call the set of alternatives $\{a_i, a_j, \dots, a_m\}$; note that m changes from case to case of each subsequent decision problem. Associated with the course of action set is a set of possible outcomes; call these $\{o_i, o_j, \dots, o_n\}$; note that n also changes from case to case. The likelihood that the execution of course of action a_i will result in outcome o_j is denoted in the Yovits notation by the subjective probabilistic estimate ω_{ij} . Also, each outcome can be assigned a value of the degree to which it moves the situation to a desired goal state; this value can be denoted by $\{v(o_i)\}$. Finally, we consider the possible "states of nature" or in this discussion the situational states. Continuing to follow Yovits we denote these as $S = \{s_i, s_j, \dots, s_r\}$, where r is again a case-to-case variable. The probabilities of occurrence for the various states of nature can be denoted by the subjective estimates $P(s_i), P(s_j), \dots, P(s_r)$.

The decision elements A (the specific choice of course of action), the associated desired outcome O , and the related values of ω_{ij} and $v(o_i)$ are all state-of-nature or situational-state-dependent. Courses of action which seem quite reasonable under one situation may be totally nonviable under another; similarly, a decision outcome which is very possible in one situation may be quite impossible in another. We can thus modify the notation a bit to indicate this situational dependence by using ω_{ij}^k instead of ω_{ij} , and $v_k(o_i)$ instead of $v(o_i)$. Still following Yovits, we then have the decision model depicted as the matrix in Figure 5:

Relative Values							
Outcomes		$v_k(o_1)$	$v_k(o_2)$...	$v_k(o_j)$..	$v_k(o_n)$
Courses of Action		o_1	o_2	...	o_j	...	o_n
a_1		w_{11}^k	w_{12}^k	...	w_{1j}^k	...	w_{1n}^k
a_2		w_{21}^k	w_{22}^k	...	w_{2j}^k	...	w_{2n}^k
.	
.	
.	
a_i		w_{i1}^k	w_{i2}^k	...	w_{ij}^k	...	w_{in}^k
.	
.	
.	
a_m		w_{m1}^k	w_{m2}^k	...	w_{mj}^k	...	w_{mn}^k

Figure 5 The Decision-Maker's "Decision State" (after Ref 11)

which is the basis for whatever decision rule the DM invokes; note that the model accommodates any type of decision rule. An example provided by Yovits in which the DM chooses to maximize the expected value of a given action (i.e. toward goal-accomplishment) would to choose A such that

$$EV(a^*) = \max \{EV(a_i)\} \quad [1]$$

where

$$EV(a_i) = \sum_{k=1}^r P(s_k) \sum_{j=1}^n \omega_{ij}^k v_k(o_j) \quad [2]$$

The Contribution of Information

Yovits argues that the value of information is in its ability to reduce any of the various uncertainties involved in this model. Moreover, information can change either or both of the structural or relational components of these uncertainties. Further, this model allows for a formal analysis of the effects of learning (and can suggest learning rules) in regard to the uncertainties, whether it be on a sequential, decision-to-decision basis, e.g. where we adapt ω_{ij}^k and $v_k(o_j)$ as

$$\begin{aligned} [\omega_{ij}^k]_{t+1} &= [\omega_{ij}^k]_t + \Delta \omega_{ij}^k \\ [v_k(o_j)]_{t+1} &= [v_k(o_j)]_t + \Delta v_k(o_j) \end{aligned} \quad [3]$$

reflecting what we have learned at time t . Now then, regardless of what decision rule a DM is utilizing, the distribution of the $P(a_i)$, which is dependent upon *all* the components of the generalized decision model can be said to define the *decision state* of the DM. In turn, this function can then serve as a basis for defining a pragmatic information measure that is both a measure of information amount and information value, and that indicates how $P(a_i)$ changes as a function of these information parameters. If we say that the DM has enough structural insight such that his list of a_i at any moment is exhaustive, then according to Ackoff (Ref 12, cited Ref 11), a measure that reflects the degree to which the DM's particular $P(a_i)$ set is insightful as compared to a random guess of any a_i is given by

$$\sum_{i=1}^m \left| P(a_i) - \frac{1}{m} \right| \quad [4]$$

Note that if the DM's decision rule picks any a_i arbitrarily, then $P(a_i) = 1/m$ and this expression = 0. Note too that if one of the choices is dominant and it's $P(a_i) = 1$, then the expression takes on a maximum value of

$$\sum_{i=1}^m \left| P(a_i) - \frac{1}{m} \right| = \left(1 - \frac{1}{m}\right) + (m-1) \left|0 - \frac{1}{m}\right| = 2 - \frac{2}{m} \quad [5]$$

This leads Yovits to suggest that a reasonable measure of the degree to which a DM is insightful can be given by

$$V(DS_t) = \frac{\sum_{i=1}^m \left| P(a_i) - \frac{1}{m} \right|}{2 - \frac{2}{m}} \quad [6]$$

By normalizing to the maximum value we see that V takes on the range (0,1). Yovits then sets the probability of a DM making any particular choice dependent on the relative value of that choice compared to the total value possible across all currently-nominated choices, or

$$P_i(a_i) = \frac{EV(a_i)}{\sum_{h=1}^m EV(a_h)} = \frac{\sum_{k=1}^r P(s_k) \sum_{j=1}^n \omega_{ij}^k v_k(o_j)}{\sum_{h=1}^m \sum_{k=1}^r P(s_k) \sum_{j=1}^n \omega_{hj}^k v_k(o_j)} \quad [7]$$

Then, the value of any decision state can be computed by substituting this formula into the above for V(DSt); note that for convenience the time subscript is not shown in the above equation but it should be noted that these probabilities are computed at “decision time”.

The Value of (Fused) Information

It should first be noted that the perspective Yovits takes regarding informational value (and that we agree with) is a “pragmatic” or effectiveness-oriented view, meaning how it affects the value of the DM’s decision-state as described above. We also are focused on cases where the information provided is that that comes from a fusion process; note that such information is estimated information with some estimated error. Note too that “pragmatic” information is quite different than the technical or information-theoretic view of information (concerned with the accuracy of the communication of symbols), or from the semantic view that focuses on how well the communicated symbols convey the intended meaning.

If we agree that the value of information relates to its impact on the value of the decision state, then, using the above, we can say that such contribution can be measured by

$$I(D) = V(DS_{t+1}) - V(DS_t) \quad [8]$$

which says that the value of information is related to the change it imparts onto the decision state of the DM. Note that this measure is a function of the estimated situational state and also a function of time. Note too that the same fused information will have a different impact to different decision-makers at any time or to the same decision maker at different times.

Following Yovits in a 1974 paper (Ref 13), another view of the value of information can be developed. Equation [2] describes the expected value of a given course of action. Considering the expected value as a statistic, its mean and variance can be written as

$$\mu = \frac{[\sum_{i=1}^m EV(a_i)]}{m} \quad [9]$$

and

$$\sigma^2 = \frac{[\sum_{i=1}^m [EV(a_i) - \mu]^2]}{m} \quad [10]$$

Yovits suggests that the information *contained* in a decision state is related to what is usually called the coefficient of dispersion (aka variance-to-mean ratio), given by, from Eqs [9], [10]

$$\frac{\sigma^2}{\mu^2} = m \sum_{i=1}^m \{P(a_i)\}^2 - 1 \quad [11]$$

which he directly labels as an information measure,

$$I = m \sum_{i=1}^m \{P(a_i)\}^2 - 1 \quad [12]$$

Note that this information measure has a minimum when $P(a_i) = 1/m$, i.e. when all decisions are equally likely (when the DM is totally confused), and a maximum when one $P(a_i)$ is 1 and the others 0, yielding the maximum value of $(m - 1)$. It is also a function of time in the same sense as the alternative expression of Eq [8]. Using this development, the contribution of the fused information would be

$$I(D) = I_{t+1} - I_t \quad [13]$$

Exactly how this information changes the DM's choice preferences is highly individualistic; this is an individual learning process. However, it is likely that some types of information will help improve the DM's insights into the various dependency relations that his choices employ such as the execution uncertainty or the relative values of outcomes, as suggested in Eq[3]. In one of Yovits' 1981 papers (Ref 14), he describes one approach to how a DM might learn over time to adjust his expected values of a given course of action.

Experiments to Measure Decision-making Effectiveness (still from Yovits, et al)

Yovits continues in his research to define DM Effectiveness (DME) and then to characterize how experiments would be made within his theories and models to conduct measurements of DME and to validate the models. DME is defined conceptually as the degree to which the COA chosen with probability $P(a_i)$ by a DM achieves some proportion of the maximum performance provided by (presumably) a different choice of COA. Thus, Yovits puts

$$DME = \sum_{i=1}^m P(a_i) EV^*_i / (EV^*_k)_{\max} \quad [14]$$

where EV^*_i is the (unknown to the DM) expected level of the value (toward goal achievement) of selecting a_i , and $(EV^*_k)_{\max}$ is the (also unknown to the DM) expected level of the maximum value toward goal achievement that would have been provided by the “best” COA choice “ a_k ”. Note that in the case of Situation Management then, DME measures the DM’s performance toward achieving the goal of ΔS going to 0.

An immediate question is whether individual DM’s are being tested and examined or some group of DM’s, to characterize some average-type performance; the experimental procedures described are quite different since the averaging mechanisms and calculations are quite different. For example, if an “average” DM’s performance is trying to be studied, Yovits sees the need to define what he calls a “trial” in the following way:

“On the average a DM will sample all COAs in proportion to their perceived probabilities of occurrence. We will define a “trial” then as one single execution involving all COAs, each being executed percentagewise according to its probability of selection. Thus, a trial is representative of many selections involving all COAs. Therefore, we can consider the result of a trial as the weighted average of the results obtained by the selection of all alternatives.”

This approach requires defining and modeling the “average DM”, using procedures suggested by Yovits in Ref 15. The experimental procedure for studying these effects is presented by Yovits in Ref 16. For an individual DM, experimentation proceeds on a sequential COA-by-COA basis; selecting any single COA at a time is called “a choice”, as distinct from a trial. Each timewise run-through of a scenario is called a sub-experiment and a number of repetitions is then an experiment, yielding mean performance.

Note that Eg [14] requires defining, for simulation-based (or other) experimental purposes, the “truth” conditions of the effects of different COA choices under different situational conditions. Yovits does not address this issue very much in his works and while it is something difficult to do if what is being affected by the COA’s is benign, the question is yet more difficult when trying to achieve $\Delta S \rightarrow 0$, especially if adversarial factors need to be considered.

Optimum Dynamic Resource Management

The selection of a specific COA essentially defines a type of task to be carried out. Depending on how COA’s are defined, the specific resources to carry out the tasks may not be part of the COA specification (we think usually not). So a next step in the overall SM process could involve determining first what resources can feasibly conduct the task, and then of those feasible, which are best or optimal. As we have experienced, this can lead to a requirement to solve a complex optimization problem. In our approaches, we first define an objective function (or functions), and the constraints defined by the task(s) that want to be done. This sets up a mathematical programming-based optimization problem that has to be solved, and whose solution defines the resources to be employed in carrying out the COA task. The objective functions involved provide another basis for additional quantification of the overall SM process.

Reflexive Control

In the case of SM when adversarial aspects are involved, another possibly applicable concept of control might come from Reflexive Control. One definition of Reflexive Control (RC) is given by Thomas (Ref 17) as “a means of conveying to a partner or an opponent specially prepared information to incline him to voluntarily make the predetermined decision desired by the initiator of the action”. Conceptually this could be extended to include “specially crafted actions” that influence the opponent to take the desired action, and thus (inadvertently) move toward the situational state desired by the controlling agent. Reflexive control is a subject that has been studied in particular in the Soviet Union and Russia for nearly 40 years, so it is hardly new. Although it has been studied for a long time, a new Russian journal (“*Reflexive Processes and Control*”) was launched as recently as 2001. In terms of modern military thinking, RC well precedes Information Warfare but it is clearly related to it, and is sometime spoken of as equivalent to “perception management”. From a control-theory point of view, RC is about altering the “plant” model, ie the system process model, something not usually done in conventional control theory.

To draw analogies to Yovit’s goal-oriented approach (and to the goal-oriented nature of SM (Ref 7)), RC can also be thought of as a method for altering an adversaries goals. Ionov, in Ref 18, describes four basic methodological categories for RC:

- Power pressure, which includes: the use of superior force, force demonstrations, psychological attacks, ultimatums, threats of sanctions,..and others
- Measures to present false information about the situation, which include: concealment (displaying weakness in a strong place), creation of mock installations (to show force in a weak place), abandoning one position to reinforce another,...and others
- Influencing the enemy’s decision-making algorithm, which includes the systematic conduct of games according to what is perceived as routine plans, publishing a deliberately distorted doctrine, striking control system elements and key figures,...and others
- Altering the decision-making time, which can be done by unexpectedly starting combat actions, transferring information about the background of an analogous conflict...and other

Summary

This paper has offered some additional thoughts on the nature of the overall Situation management process, and a set of ideas on what can perhaps be measured throughout the process, and how to conduct experiments to quantify the performance of any given SM process prototype. The ideas are largely conceptual but have some specificity in a few areas. All of the ideas should be further studied and have been put forward to stimulate additional discussion thought to be needed in the SM community.

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