
# Fusion Processes and Situation Control

***Abstract***—The ISIF community has a long heritage in research directed to situation assessment. That research traces to the earliest days of the International Society of Information Fusion (ISIF) to include the first few conferences. Well thought out ideas and models of situation analysis/situation assessment/situation projection processes were developed across the international community. Companion efforts grew out of the Cognitive Situation Management (CogSIMA) community in the context of cognitive situation control that are complementary to the ISIF papers. However, continued maturation and integration of those ideas toward designing and developing prototype integrated fusion processes have not been realized. This paper offers some additional ideas that we call an expanded framework for situation control that will require such integrated and managed processes. At its heart, the paper is a call for the ISIF community to move away from functionally isolated research, and to develop a more systemic view of its research that will offer opportunities for more impactful roles in the research community.

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## PERSPECTIVES ON SITUATION ASSESSMENT

There is an extensive body of literature on the topic of estimating situational states in applications ranging from cyber-defense to military operations to traffic situations and autonomous cars. In the military/defense/intelligence literature, "situation assessment" seems to be the *sine qua non* for any research on surveillance and reconnaissance, command and control, and intelligence analysis. Virtually all of this work focuses on assessing the situation-at-the-moment; many if not most of the estimation techniques are based on data and information fusion (DIF) approaches, with some recent schemes employing artificial intelligence (AI) and machine learning (ML) methods. But estimating and recognizing situational conditions are processes often couched in a decision-making, action-taking context, implying that actions may be needed so that certain goal situations will be reached as a result of such actions, or at least that progress toward such goal states will be made; that is, situations are generally not being estimated just to be observed. This context thus frames the estimation of situational states in the larger context of a control-loop, with a need to understand the temporal evolution of situational states, not just a snapshot at a given time. Estimating situational dynamics requires the important functions of *situation detection*, *situation recognition*, *situation understanding*, *situation prediction, and situation comparison* that are also central to such an integrated estimation + action-taking control process architecture. The varied processes for all these combined capabilities lie in a closed-loop "situation control" framework, where the core operations of a stochastic control process move the situation to a desired goal state; see an earlier paper on this topic [1] and a longer version of this paper in [2].

## SYSTEMIC VIEWPOINTS

The issues described above are DIF system-boundary issues in the systems-engineering sense. Much DIF research is couched in the sense of DIF as a value-adding but isolated process: e.g., how many papers on tracking, the most-studied function in the community, address the details of and synergies with multisensor operations or other system-level functions? Proportionally, very few, and virtually all rely on the sensing system somehow producing observations that satisfy the Mutual Exclusion criterion[1], among other assumptions about observational data. This paper suggests that more systemically expansive research is needed in the DIF community and is a paper that looks at some of the interdependencies among DIF situation-estimating processes and decision-making. Minimally, the DIF "Black Box" should be extended to synergies with Sensing and with Response Systems, and with Humans. In adversarial and many civilian situations, the core purpose of DIF will be to deliver information needed for optimal action-taking of some kind; fusion for disaster-response is a good example [3], involving situation assessment to enable coupled life-saving operations as a major purpose.

We propose several additional functionalities for this closed-loop control process as an expansion of some prior work on the situation-control topic and include remarks on the integration of some control-theoretic principles. Some remarks are also made on the state of the art of the schemas and computational technologies for situation detection, recognition, prediction, and understanding, as well as the roles for human intelligence in this larger framework. Our intent in this paper is to expand the framework of situation control in terms of our views of several other component processes briefly described herein, and in discussing these additional processes, to relate them to research and capabilities in the DIF domain.

## INTRODUCTION

The concept of a "situation" can be thought of as describing a portion of a real-world that is of interest to a participant in

[1] One measurement per single target per sensor.

that portion of the world; see "Situation Estimation" for some details. An understanding of a situation is needed and useful toward guiding or assessing the need for possible assessment and action of the participant in that situation. Action of a participant may also be needed to possibly alter the situation if it is in an undesirable state (assuming resources capable of affecting the situation *in known ways* are available, and that a *goal state* can be specified), or for the participant to alter his position in the situation. For a human participant, the mental faculties of human cognition, such as consciousness (awareness), reasoning, formation of beliefs, memory, adaptation, and learning, frame the functional aspects of a process of *cognitive situational understanding*, related to the notion of "sensemaking" (see, e.g., [4], [5], [6])[2]. Acting on the situation, however, leads to the need for a process of *cognitive situation control (or management)*, as well described in various of Jakobson's papers [7]–[10] that, in part, motivated this work and provided its foundation. We build on and recognize Jakobson's work especially in [10]. We also recognize and draw on Roy's Fusion 2001 paper on Situation Analysis that also brought forth many of the ideas discussed herein [11]. Similar ideas were also described in Lambert's 2001 paper as well [12]. In our *Frontiers* publication [2], we offer an expanded view of the issues discussed here, including aspects of cognitive/neural situational understanding.

## SITUATION ESTIMATION

Our abstraction of the notion of a situation is as "a set of entities in a set of relations". If this characterization is acceptable, then situation estimation (SE) involves inferencing about the *existence of relations* across entity sets. Philosophers have generally agreed that "relation-making characteristics" derive from *certain types* of "monadic" properties of entities, e.g., the heights of people form the *basis* of possible relations ("taller-than", etc.). In this view, such properties *enable* inferencing about the existence of relations. These shared properties that enable the existence of relations are called the "relata" (of relations), or "relative-making characteristics" [13]. This line of thought also suggests *that relations are the result of a process* of some type of comparison, i.e., [14], "an act of reasoning". Further, sensors and associated processing (feature/attribute extraction) provide "relata" or *entity properties* that would *support* reasoning from which inter-entity relations could be asserted, but sensors *do not* provide "observations" of relations; those need to be inferred from the relata, as just stated. Importantly, situation estimation is also complicated by the *combinatorics of relations* among entities and entity-sets in complex real-world cases; sets of relata and sets of entities impute these inherent combinatorics. We have not seen much continued research focused along the lines of these remarks, yet Roy [11] pointed out as far back as in Fusion 2001 the need to develop estimates of *sets of relations* among entities in a process he called "Situation element contextual analysis", as part of his situation analysis model. That contextual analysis "… thus develops a description of *all sorts of relationships* among situation elements: physical (is composed of), spatial, proximity, temporal, structural, organizational, perceptual, functional (involves/requires/provides), functional (e.g., supply, communications), process (performs the process of), causal, informational source/recipient, influence source/recipient, sequential dependency (occurs conditional upon), temporal dependency (occurs when), etc.", from [11]. Research directed to the complex machinery needed to estimate the component relations and relation-sets and their integration remains fairly absent in the fusion community at large.

### SEMANTIC LABELING, MODELING, AND ONTOLOGIES

The entities at higher levels of DIF processing are not just the physical objects but can be actions, events, behaviors, and other things that may be of concern. Specifying the appropriate Level 1 entities requires looking ahead to Levels 2 and 3 because these inferencing/estimation processes are *interdependent*. In turn, these entities can have combinatoric sets of relations to each other, as just mentioned, but now across fusion Levels. Some type of semantic labeling of the entities and their relational constructs must be established to have a "language" with which to discuss and label DIF-produced estimates of situational conditions.[3] There are various ways to address this language requirement: examples are the use of a situation modeling language, e.g., [15], or the use of an ontology, e.g., [16], [17]. The situation modeling approach typically employs a graphical language for situation modeling (such as Frames), allowing the expression of primitive situations and complex situations involving the composition of situations (with temporal or other constraints when required). In an ontological approach, along with the entity ontology, a relation ontology is also needed so that the specifics of a labeled, specific situational state can be assembled from these components. That assembly requires a higher level of abstraction in inferencing. Thus, a situation detection or recognition process will need to be supported by an ontological foundation where entities, relations, and *labeled situational states* are coupled to the fusion and recognition processes that will have to assemble the recognized, labeled situational state by exploiting this framework and all of the relata. Steinberg [18] offers one example of the inferencing machinery for these operations, building on the situation logic processes of Barwise and Perry [19]. These processes also need to account for the various uncertainties in the integrated observational and inferential processes. Jousselme et al. [20] provide an overview of the principal typologies of uncertainty employed in situation analysis and inferencing and suggest that addressing reasoning and uncertainty in situation assessment will require frameworks having capabilities to integrate qualitative and quantitative pro-

[2] Sensemaking is not the same as understanding; sensemaking involves interplay between foraging for information and abstracting the information into a representation called a schema that will facilitate a decision or solution (http://www.peterpirolli.com/Professional/Blog__Making_Sense/Entries/2010/8/16_What_is_sensemaking.html).

[3] The Level 1 state estimates have a relatively simple set of semantic labels drawn from common language and not needing formalisms of ontology, or at least less so. Those labels provide enough semantic specificity from which to engineer solutions to required processes; e.g., what a "track" is and how to form an estimate of it–this is not the case for Level 2 and 3 processes.

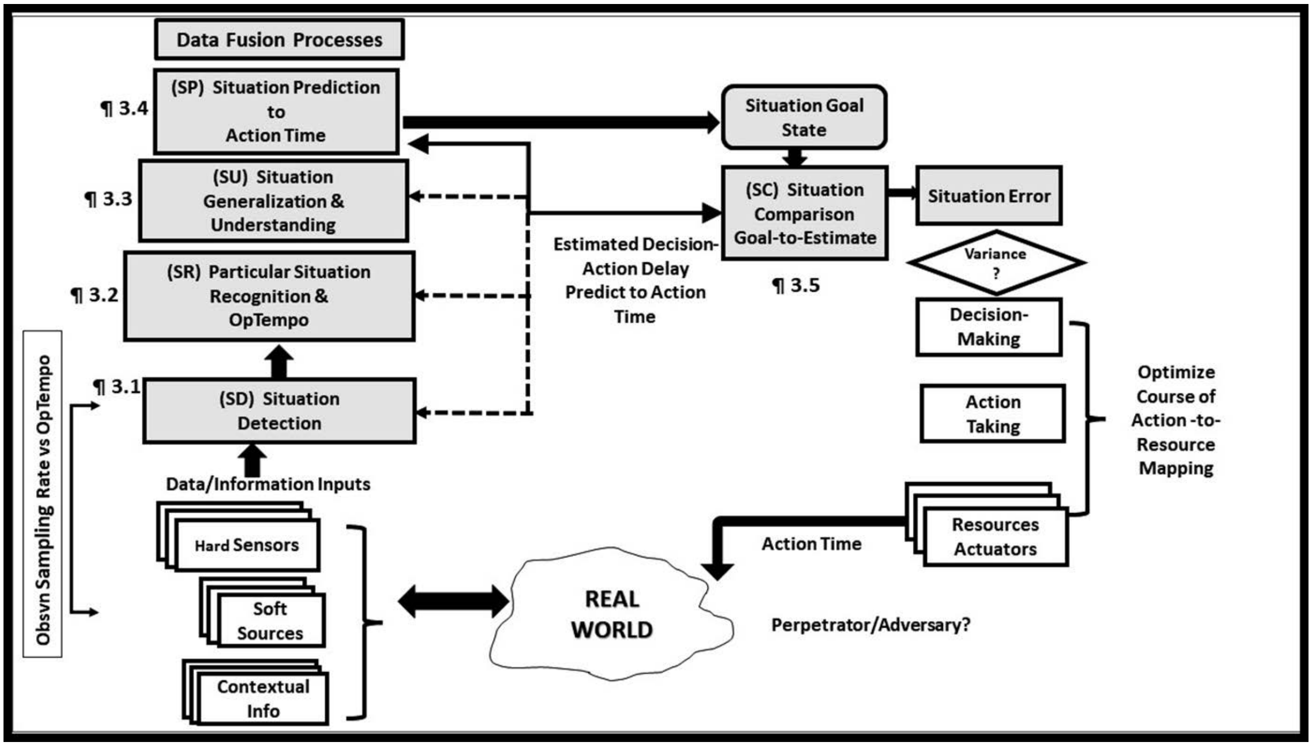


**Figure 1**
Fusion processes in situation control.

cesses. The modeling and relational specificity described here would also be needed if labeled training data were to be used in an AI/ML-based approach to situation estimation. There has been a fairly large number of publications that offer representational schemes for situations, some labeled as ontologically-based, but those models have not been broadly applied (see [16], [21]–[26], that are just a sampling).

## PROPOSED FUNCTIONAL EXPANSION OF THE BASELINE FRAMEWORK: OVERVIEW

While Jakobson provides a sound initial foundation for a process description of situation control, we suggest various enhancements of this process description; our discussion is linked to Figure 1 below. The paragraph titles below are shown in the figure for clarity in following the discussion. Fusion-based situational processing begins with the flow of inputs from hard and soft sensors or sources and from incorporation of contextual information, in the lower-left of Figure 1.

### SITUATION DETECTION (SD)

Our view of detection relates to prior knowledge and the aspect of observing the occurrence of something or some part of something that is known *a priori* (elsewise the process is discovery); integrated detection and discovery processes may very likely be needed in some applications, as bounded by prior knowledge but we do not address that issue. For a state such as a situation, an entity-relation complex, detection may relate to observing or measuring some parts of the relational complex. Thus, to detect a situation requires deciding if any entity or relation of a situational complex is of equal value for asserting the detection of the entirety of the situational state. On the other hand, if a situational complex is of large dimensions, detecting small components might lead to many false alarms. Construction of a detection methodology therefore requires setting thresholds and labels of a) numbers of things that need to be detected, and b) which of those things are most indicative of an evolving situational state. Notions of detection probability and probability of false alarm are present here in the same way as for a hard or soft sensor. There are various papers in the literature on this topic, e.g., using Bayes Nets and Fuzzy Logic for Situation Detection but it is rarely presented in the context of an integrated system approach or as a detection theory for situations.

### SITUATION RECOGNITION (SR)

Given that a situation has been detected, situation estimation processes can begin toward estimation of the existence of some *Particular Situations*. In some works, these processes are asserted to be "the" Situation Estimation process. But we choose to call this the Particular Situation, arguing that it is just that, the collection of situational elements at any given moment, for a dynamic evolution process that has some time to completion. In the same way as for SD, methods for SR have to decide on the issue of "completeness" and set notions of thresholds toward asserting the existence of any particular situation. An issue that arises here is the degree to which particular situations in the situation ontology are similar to each other. If the "truth" situations specified in the ontology are not sufficiently disparate, labeling of particular situations will be yet more difficult because of overlapping similarities.

### ESTIMATING SITUATIONAL RATE: "OPTEMPO"

We introduce a new requirement for DIF that we have not seen in the literature: the estimation of a factor that will be very important in determining the process context for Situation Management and Control: the assessed rate at which the situation is unfolding; that is, the *Operational Tempo* ("OpTempo") of the situation. This factor needs to be estimated early in the SR process and weighed in relation to both the scanning/sampling rate of the observational resources, the prediction interval, sensor resolution factors, and in fact the viability of the overall DIF process (again indicating the need for systems-level thinking). If the situation is unfolding at a rate faster than it can be feasibly observed (or perhaps acted upon), forming dependable situation estimates going forward will be very difficult, and situational predictions will be equally hard.[4] OpTempo can be roughly thought of as related to the hard sensor Nyquist-type sampling rate to capture sufficient information for estimation. This balance changes the dependencies of the Learning/Understanding process (see below) between *a priori* knowledge and real-time observational data; uncertainties in the consequent estimated situation will also be affected. Estimating situational OpTempo should therefore be a fundamental requirement of the SR function, as it is a critical process design and management parameter, setting the overall "clock" for this control process. The notion of OpTempo is also in the fashion of a meta-metric, since any situation will be comprised of multiple component multi-entity relational processes unfolding at varying rates (the combinatorics mentioned previously). Note too that there are optimization issues lurking here, as regards defining how optimal co-employment of bounded observational resources (OR) and situation processing (SP) will be managed across these process needs. That is, there will be competition between the use of OR and SP computational resources for situational state development and for co-estimating its evolution-rate/OpTempo that will for example require temporal comparison processes to be developed.

### NATURAL AND ADVERSARIAL ENVIRONMENTS

In any setting involving situation state estimation, an early question has to do with whether the setting is a natural one where phenomena are driven by natural causes or whether the setting comprises a two-sided, adversarial context. The case involving adversaries can be related to the case of "Information Warfare", where the two sides are manipulating information, the bases for perception and inference, to their advantage. The larger purpose of these operations is to manage adversarial perceptions by structuring the information available to an adversary to be compliant with intended perceptual constructs. Another topic related to deception is denial of information by covertness, camouflage, jamming, and other means. Deception and denial strategies work because of exploitation of reasoning errors, cognitive limitations, and cognitive biases [27]. It can be argued then that another early function for SE is to assess and filter out any adversarially related data or states and make an early assessment of the quality and reliability of the data ("garbage-in/garbage-out"). For both natural and adversarial cases, situational models will need to be posed as bases for framing all situational estimates. Thus, as can be said for all DIF processes, process design will require making choices on issues of Data Quality; this is also a factor not seen very much in the SA literature; see [28].

### SITUATIONAL UNDERSTANDING (SU)

While the particular situation estimate may be helpful to certain analytical or even decision-making purposes, in many applications, it is desirable or possibly necessary to know or estimate the *class or type of situation* the particular one is an instance of. One notion of understanding can be said to relate to an ability to "generalize from the particulars". Generalization allows the recognition of the similarities in knowledge acquired in one circumstance, allowing for transfer of knowledge onto new situations. A challenge now receiving considerable attention with the new thrusts into AI is to understand how humans are able to generalize from very limited sampling, as well as the issue of "transfer learning". In defense contexts, this type of generalization is often directed to gaining or asserting a "mission" context for the particular situation (the mission class that this situation is an instance of). For example, surveillance is a mission class, comprising phases such as ingress, tactics such as evading, and actions such as attacking; a type of taxonomy of mission-to-situations could help in the generalizations proposed here. Generalizing then allows estimation of a broader type and can also trigger layered estimates (e.g., particular-to-mission-to-tactics-to-strategic). Such broader, generalized views require application of prior knowledge, tacit knowledge, and contextual influences. Ideas along these lines are also seen in [11], where he asserts a need for a "Situation element interpretation" process that similarly focuses on forming a higher, generalized view of the fused results. Generalization can be done by exploratory excursions from the particular situation at the moment as a kind of extended induction, and also by methods drawn from argumentation. Similar techniques are employed in Sensemaking models where "Foraging" is a process that searches for related data and for plausible extensions to the current data set, related to "inductive generalization". Following [29], methods of elaboration and reframing are frequently employed by humans when people are confronted with, or discover, new information from developing situations. Other methods that may offer ways to generalize could come from Bayesian network-based probabilistic generative frameworks that, for example, employ Allen's interval relation network to represent local temporal dependencies in a generative way. These probabilistic generative methods may offer some possible approaches toward "generalizing from the particulars". Probabilistic generative methods have been successfully employed in data fusion-based classification and may offer methods extendable to Level 2 situational understanding. Generalization is also a rather pervasive topic in psychology. In [30], Austerwell et al. discuss the issue of learning how to generalize, which suggests that generalization requires postulating "overhypotheses" or constraints in effect on

[4] This same concern certainly applies at Level 1 (L1) fusion and again is often not an issue coupled to L1 tracking and classification operations because, in much of the community research, they are not couched in the systemic sense as influencing or controlling sensing operations. In the same way as for the Mutual Exclusion issue, "adequate" sensor sampling rates are typically assumed.

the hypothesis domain to be nominated. Some assert that such overhypotheses are innate but Austerwell et al. argue that they can be learned. In either case, the generalization framework is said to be Bayesian-based. Generalization has also been studied in [31] that suggests an exponential metric distance between the stimuli as a basis to assert similarity, and in [32] that discusses the overhypotheses issue. If *a priori* models of general/mission-level situations of interest can be formulated, then notions of "degree" to which the current, particular situation matches that model can be estimated. As situational elements are of natural graph form (nodes as entities, arcs as relation-models), graph-based methods can be applied toward assessing the degree to which the current situation is close to a generalized class of situation. Gross et al. [33] explore such an application and study various ways to make probabilistic-type comparisons between such graph structures.

### SITUATION PREDICTION (SP)

The main requirement for a DIF-based situation prediction (SP) process is driven by another system boundary issue, in cases where the DIF SE processes are linked to action-taking and associated decision-making operations; see [1] for an early paper on this topic. This interdependency is driven by the need for synchronizing action-taking such that the action is being taken on the best-estimated situation *at the time of the action*. If that synchronization is not achieved, the acting resources will be acting on an incorrect situation and/or the incorrect entities. This issue also relates to the OpTempo issue; if the situation change rate is slow, some degree of mismatch in SP-action-taking synchronization may be tolerable, and also errors in SP are more tolerable. The opposite is true if the OpTempo is high. Further, as for most prediction, projection, or extrapolation processes, the difficulty and accuracy of such processes is linked to the temporal degree of projection (how far ahead) and the rate of observation and input of any data that the projections depend on; this is not just sensor/observational data but contextual and soft data as well. Some resources that act on situations may be more or less time-sensitive, and this also changes the SP requirement. Thus, synchronization across several interdependent processes may be of concern in this context; a mission goal-based analysis of these dynamics is needed to guide overall processing.

The degree to which an SP needs to predict ahead is related to the expected delay in the combined time it takes to a) decide to act and b) the action-time of any actionable resources. Presuming decision-making precedes action-taking, these projection requirements can also depend on the *type of decision-making style* being employed (see also [1]). That is, it is well-known that there are many variants of decision-making processes that humans and machines may make (see [34]), and so this projection-time estimate may also need to know the decision-making modality being employed.

### SITUATION GOAL AND SITUATION COMPARISON (SC)

At some point in time or as part of an ongoing process, an assessment of whether the situation is satisfactory or not is typically carried out; this requires a specification of some desired or goal situational state that is the basis for comparison to real-time estimates. We note that the existence of a goal state is crucial to the overall process, and the placement of comparative operations. It is possible that Goal-to-Estimated SCs could be done quite early in these operations, such as at the moment of Situation Detection or Situation Recognition. Such comparisons, no matter where they occur, are the triggering process for decision-making if the situation is not somehow acceptable. But executing this step thus requires a process for SC. Goals may also change over situation development time, and thus multiple comparisons may be required, in a somewhat ongoing process. However executed, the SC process yields what could be called an "error signal" as would exist in any control process, as Jakobson [10] also points out. We assert that this error signal will have stochastic properties, since the estimated situational state, and perhaps the goal state as well, will have stochastic-type error factors embedded in the calculations. The error signal requires assessment as to whether any action is required, and so there is a question as to "degree" of error, and if the error is stochastic, issues of variance in this error variable will factor into the severity assessment. For example, if that error has "three-sigma" variance, no action may be decided, as the situation error estimate is poor. We see almost no research addressing these concerns.

## SUMMARY

This article is intended to create discussion in the Information Fusion (IF) community about taking broader and systemic views of fusion process designs and addressing the consequently more-systemic impacts of such views on process designs. Here, we have probed into the Level 2 Situation Estimation space with some ideas on this type of thinking and about impacts to IF-based process designs. A main motivation here is toward realization of new opportunities and challenges for the IF community, and that addressing such challenges broadens the impact that this community can have across a very wide range of applications. We need to step away from functionally isolated data fusion R&D.

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