# Visualisation Issues in the Context of Information Fusion

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Recent advances in information technologies have allowed military Command and Control systems to absorb and distribute large amounts of data that often exceed the information processing capabilities of human beings. One of the "technology enabler" that can be used to address this issue is data fusion, which can be defined as "the process of combining data to refine state estimates and predictions" [1]. Data fusion aims at reducing the complexity of the problem space by bringing together independent pieces of data to build "higher level" and more meaningful entities.

Automated data fusion can produce several direct benefits, by optimizing the processing (in terms of speed, amount of information processed and quality of the fusion products) and freeing the operator from tedious, repetitive and error-prone tasks so he can focus on situation analysis. However, the association, correlation and combination processes rarely result in a clear, unambiguous statement; more typically, the combination of uncertain, incomplete and even contradictory information will produce a large tree of hypothesis with various levels of uncertainty and likelihood. This applies to position and velocity estimates, and also to identity estimation and higher-level inferences (e.g. situation and impact assessment). The system designer then faces the issue of how to present the fused products to the operator. Between the two extreme options of presenting the entire hypothesis tree or displaying only the most likely hypothesis, there is potentially a range of solutions that can be more beneficial to the operator in terms of understanding the operational picture.

It has been said that "...the chief problem for information visualisation … is often finding an effective mapping between abstract entities and a spatial representation..." [2]. However, visualisation must be considered in the context of the overall human-machine interface (HMI), as it constitutes one of its many components; it is thus necessary to consider them simultaneously.

In this paper, we first review the generic data fusion process and describe issues related to the visualisation of its results. Then, a brief summary of Tagci, a novel HMI design method is provided, with justification for its potential use for data fusion applications. In particular, one building block of Tagci is described in more details as it is especially relevant to the monitoring of complex processes such as data fusion. Then, research issues that need to be addressed to further customize Tagci for data fusion applications are identified.

## DATA FUSION – PROCESS AND VISUALISATION ISSUES

Data fusion has been defined above as a process by which data or information is brought together to produce a global estimate of the current situation. This process is usually described in terms of the 4 functional levels introduced by the Joint Directory Laboratory (JDL) [1].

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Level 1, or Object Refinement (or Assessment), deals with the estimation and prediction of the kinematics and identity of individual entities, generally based on inferences from observations. Level 2 fusion is called Situation Assessment, and uses the individual object estimates to derive relationships between entities. Level 3 and 4, respectively Impact Assessment and Process Refinement, deal with the estimated threat and projected impact of the situation on mission objectives, as well as the appropriate allocation of resources (including the fusion processes themselves) in answer to the estimated impacts.

Another interesting representation of the fusion process is from the perspective of its main conceptual sub-processes, as described in [6]:

1) Knowledge Composition, where the evidence is prepared and structured for further information processing. For instance, correlation of input reports with existing tracks, or extraction of features from images belong to this sub-process. Higher-level example would be the generation of new hypothesis on the situation through pattern recognition, rule-based reasoning or clustering analysis.

2) Evidence aggregation, which accumulates evidence supporting a given hypothesis (e.g. the identity of a specific entity) through the combination of pieces of information. In most applications, Fuzzy Logic, Bayesian or Dempster-Shafer approaches are used in order to deal with uncertain and discontinuous pieces of evidence.

3) Decision, where the system states whether the collected evidence supports or not a given hypothesis.

Obviously, even though this point is not always acknowledged in the data fusion literature, each sub-process can be performed by a combination of human and/or synthetic agents. Furthermore, the outputs of each sub-process (including the “decision” stage) are often “soft” statements instead of “hard decisions”, and can therefore contain several hypotheses with associated belief or plausibility. These two considerations lead to a situation where data fusion can introduce several human factor issues in the system to which it is applied.

A typical data fusion scenario is the detection of a small number of airplanes by a few sensors: radar, Electronic Surveillance Measures (ESM), Interrogator Friend or Foe (IFF), and perhaps imaging sensors provided additional features. Fusion processes combine those pieces of information (position, altitude, speed, line of bearing, emitters, IFF answer, specific features) and produces a position estimate and possible target identity. This scenario however hides some implicit assumptions, and even from such a simple example one can readily point out several areas where the use of automated fusion algorithms will introduce important effects from a human factor perspective, in terms of information selection, function allocation and visualisation. A few areas of interest are given here for illustration purpose:

- Knowledge composition mechanisms will often produce uncertain results, such as a list of possible discrete statements with attached uncertainty. For instance, trying to infer a ship type from its length might yield a list of several possible ship types (frigate, destroyer…) with attached probability. Right from the start, one is faced with the problem of whether the operator should be presented the most probable value or the entire set of hypothesis, in which circumstances and under what format.
- Even when the information received could be seen as “absolute” (e.g. absence of answer to an IFF interrogation, inference of a target type from its emitters), results are generally incorporated with a nominal uncertainty to allow the system to recover from situations like processing errors or deception. One can readily see that when aggregating uncertain pieces of information, the end result will be a potentially large and fragmented “hypothesis tree”, containing a list of statements each associated to its own level of support. Clearly the operator cannot be presented this whole tree, but perhaps the

"most probable" statement is not sufficient in several cases. The situation can be further complicated, for example when output tree contains precise statements with low probability, as well as more generic statements (e.g. a list of 10 possible airplanes) with a high probability.

- Another topic of concern is the dynamic nature of the outputs of the fusion processes. When the variable impacted is continuous (e.g. the airplane speed or altitude), variability might not be dramatic, but the effect is not as subtle on discrete variables (e.g. Friend or Hostile). The possible reasons for variability are numerous (e.g. wrong correlation of an input report, variances in speed and acceleration caused by a radar's intrinsic measurement error, identity propositions based on the tracker's speed and acceleration, etc.), and the side effects in the systems can be important, in particular if the results of the fusion process feeds another process like threat evaluation and engagement calculations. Here again, the issue lies more at the operator's cognitive level than in the algorithms themselves.
- The immediate output of an identity fusion system is typically not displayed directly to the operator, since it is oriented towards algorithmic efficiency more than user needs (e.g. a list of all the platforms in the reference database that are compatible with a given track). Those results are therefore expressed ("mapped") in terms of meaningful elements of information such as Allegiance, Country of origin, Lethality, platform type, etc. Of course, the choice of the proposition set by itself constitutes a human factor issue, but those generic statements will also be affected by all the factors described above: lists of values with attached uncertainty, variability of the result, etc. Again, there is a need for a careful analysis of the way a list of discrete and uncertain values need to be presented to an operator in a given context.
- A recurrent theme when dealing with Identity fusion is "conflicts management". Conflicts happen for instance as a result of incorrect reports, deception or simply bad correlation (e.g. high positional uncertainty coupled with high target density and/or low report rate). As an example, detection of 2 incompatible emitters from the "same" target could be resolved by creating a second track. In principle, conflicts are well-managed by fusion algorithms – but it doesn't mean they should always be. Clearly the resolution of the conflict will become a function allocation issue; in some cases it should be handled by the system as an expected situation, perhaps with a warning, in other cases it should be considered a show stopper – sometimes in the same system.
- The "tracking" process itself can also introduce a number of human factor issues, even though it is generally studied as a totally autonomous process in the data fusion literature. Depending on the system, an automatic tracker might be the best option (e.g. defence against air targets), while in others the system should probably benefit from a high level of intervention from the operator (e.g. land surveillance with low report rates). In this case, the operator could interfere directly within the fusion process itself (by forcing correlations, adding pieces of evidence, creating "clusters" of entities, rejecting pieces of information, etc.). This issue also brings higher issues such as monitoring of the fusion processes.
- Integration of data from unstructured sources (e.g. HUMINT, voice transmissions, video streams, visual observations) brings another challenge, since they typically need to be combined with digital information directly by an operator. Situation Assessment (SA) algorithms, normally associated with higher level inferences and typically a lot more context-dependant, are also challenging since they typically produce "cues" or "propositions" that cannot be used at the same level and with the same confidence as the outputs from level-1 fusion. Those certainly need to be looked at from an operator interaction perspective.

From the above example, we see that data fusion opens a number of questions related to human factors, in areas such as function allocation and level of automation, as well as the selection (and presentation) of the fused information in a HMI. The answer to those issues will typically be highly context dependant, and will therefore require a thorough analysis of each specific system during design phases from a cognitive perspective.

If we see data fusion as essentially an information producer, acting as a process that builds structured information out of available data of information elements, it seems logical to think that the key to understand fusion requirements and function allocation for a specific system is through the decision maker's (as well as his team's) main Information Requirements. Those in turn can be deduced from the goals of the system. In some systems, the designer will be helped by doctrinal considerations; for instance, in the Intelligence world, a "fusion node" (e.g. a command post) will typically be fed by Information Requests from other nodes, in particular Commander's Critical Information Requirements (CCIRs), which will be converted into Priority Information Requirements and other specific flavours of Information Requirements by the Intelligence staff. Details of the CCIRs will vary depending on the context, the mission, and the role of the specific node inside the "information gathering" hierarchy.

For those reasons, we believe that a System Design methodology appropriate to analyse data fusion requirements in a military context should ideally provide a simple mechanism to convert the decision maker's goal and requirements to the corresponding information elements required; the methodology should work out of generic tasks, in order to reduce the scope of the activity but also accommodate the multiple goals of the decision makers; and it should connect to established software design methods in order to feed the development and validation loop of an actual system. The next section describes such a mechanism.

## TAGCI – AN HMI DESIGN METHOD

A method called Tagci, the French acronym for Generic Architecture and Tasks for HMI Design was developed in the process control domain [3]. Briefly, Tagci prescribes that the monitoring and control of a complex system (and data fusion, with its large number of interconnected variable, dynamics, conflicting goals and risk, certainly qualifies as a complex system in itself) can be represented as a structure of generic tasks. Generic tasks are "basic combinations of knowledge structures and inferences strategies that are powerful for dealing with certain kinds of problems"[4]; they are used in Tagci to derive the information requirements for an operator to accomplish his tasks. Those tasks are:

- detection of a threat to an operating goal,
- transition (taking the system [1] from an operating region to another),
- diagnosis (identifying the source of a threat to an operating goal),
- optimization (fine tuning of the system to enhance the achievement of an operating goal within an operating region), and
- compensation (bringing the system to a safe state in case of anomaly).

By themselves, those tasks describe how an operator (or more generically, an agent) operates a complex system or process. A useful property of generic tasks is that one can define logico-temporal constraints on their ordering. For example, detection must precede compensation or diagnosis tasks; further, detection must

[1] Here, "system" may refer to the data fusion process itself, provided it is sufficiently complex, or to the "process" (i.e., specified military domain, in the current context).

be constantly active to ensure that relevant goals continue to be achieved. On the other hand, transition tasks are carried out upon demand.

Since the operator understands and acts on the process through models, there is a natural relationship between the various models and the generic tasks. An analysis has shown that it is possible to map the generic tasks to specific process models. Of particular interest to data fusion is the detection task, to which is associated a type of goal hierarchy known as a goal tree success tree (GTST) [7]. The GTST provides the information required to support the detection, diagnosis and compensation tasks. Goal hierarchies have also been shown to be able to support the detection and part of the handling of expected and unexpected abnormal situations. The following Figure shows the relationship between the detection and compensation tasks and the GTST.

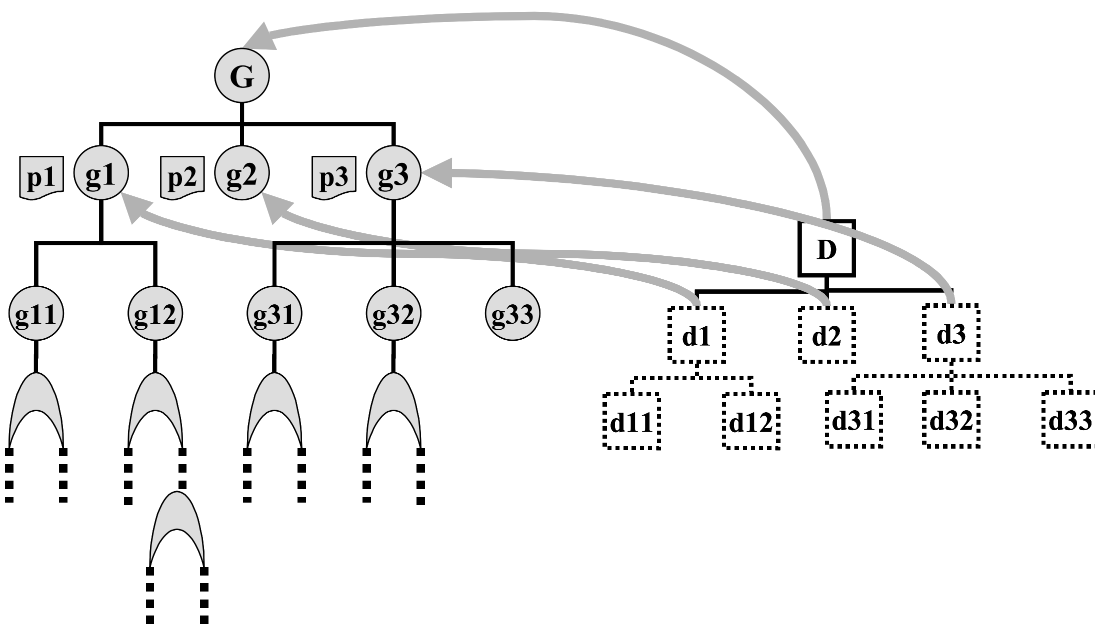


**Figure 1: Relationships between the GTST and the Generic Tasks.**

The left hand side of Figure 1 shows the GTST. The top part is the goal tree, which comprises the set of all domain goals that are needed to achieve a mission. The main goal (G) can be decomposed into sub-goals (respectively, g1, g2, and g3). There is an implicit AND gate between the goals and sub-goals of any given level. The bottom part of the GTST is the success tree, where success paths (connected by an OR gate) lead to the achievement of the sub-goals that in turn lead to the achievement of their parent goal(s). Compensation plans (noted p1, p2, p3 in Figure 1) can be found next to their associated sub-goals (which does not exclude it being present for the main goal). Compensation plans essentially hold pre-determined strategies to deal with threats to a given goal.

The right hand side of the Figure shows the detection task; this generic task is carried out by an operator (or any intelligent agent) to determine if the goal is achieved. The top level detection task (D, in the Figure) can thus be associated to the top level goal; this task can also be partitioned, if it is sufficiently complex that doing so would reduce the risk of a design error in the HMI. Those tasks are used to derive the information and control needs of the operator. It should also be obvious that with this framework, diagnosis becomes a recursive application of a detection task, down the goal tree.

Aside from the definition of a strictly technical content for the HMI, Tagci also integrates important human characteristics. One such characteristic is the fact that operator will sometimes monitor a process through a “management by exception” strategy where he relies on various exceptions (e.g., alarms, indicators) to alert them to an active anomaly; he may also use a “management by awareness” strategy where he is actively engaged in the monitoring of key process variables in an attempt to prevent anomalies [8]. Both types of behaviours occur naturally and may sometimes even cohabit, depending upon individual operator styles and process conditions. In terms of HMI design, recognizing those two types of behaviours, and taking into consideration typical HMI design constraints (e.g., limited display real estate) permit to identify design rules. For example, one such rule dictates that indicators supporting management by exception must always be shown, while indicators supporting management by awareness must always be available.

Further, the initial version of Tagci includes design rules that support the selection of some simple visualisation components and guidance on how to “compose” individual displays to best support the operator.

As discussed previously, one of the main issues with the visualisation of fused data is the selection of what to display to the operator (e.g., only the most likely hypothesis, all of the hypothesis with their associated certainty factor). The detection task from Tagci provides a potential answer to this problem through its reliance on the goal hierarchy with which it maps. For example, lets assume that a display must be designed to support an operator in assessing whether a certain goal is achieved (i.e., ensure no hostile presence in zone X). Then, rather than providing a list (full or partial) of hypothesis to the operator, one can use Tagci (after having selected the system of interest, which be a data fusion process, a set of processes, or even a complex arrangement of resources) to:

- Identify the goal hierarchy; this can be done using well known methods of function decomposition methods, and bind fused data (complete or partial) to the various goal, sub-goals, etc., for which they are relevant. Depending on the availability of data, the goal tree will be quite shallow or deep.
- Build a task model using the generic task framework as a model; where appropriate, capture any operator strategy into the task model.
- Match the task model to the goal hierarchy, that is, determine for each detection task, which set of sub-goals must be evaluated.
- Use Tagci’s design rules to associate visualisation components to various detection tasks, and to set up the navigation between those visualisation components. The design rules take into account the management by awareness, and management by exception strategies described previously.

Using Tagci should enhance traceability of the HMI design and, more importantly, improve the performance of the “operator – data fusion” system. It also changes the way data fusion process is considered; the algorithms remain, but the operator becomes more involved into the process. However, this involvement needs to be mediated in such a way that his workload will not increase.

To achieve these results, some research issues must be dealt with; those issues are discussed in the next Section.

## RESEARCH – ADAPTING TAGCI FOR DATA FUSION APPLICATIONS

Tagci has been developed initially for process control applications; even though process control shares several dimensions with data fusion, differences remain. There is thus a need to demonstrate that the generic tasks and models that are currently part of Tagci are satisfactory for monitoring and controlling data fusion processes. In particular, it will be necessary to examine how to best support the intervention of the operator into the data fusion process. Currently, in Tagci, this is addressed mostly through the transition and optimisation generic tasks, with faults or failures being dealt with compensation tasks. There is a need to extend the detailed design rules to better support the HMI designers.

A related issue is to try and identify operator strategies that are useful to enhance the outcome of the work. If such strategies could be built into Tagci's generic tasks (refetted to earlier as the "plan"), the GTs would then become very powerful components around which to define the HMI.

The visualisation components used in the current version of Tagci are rudimentary; in particular, they deal with simple binary (on – off) and continuous variables (e.g., trend graphs). There is a need to define a set of primitive visualisation components that would be better suited to support the monitoring and control of a broader set of data (e.g., HUMINT, imagery).

In spite of those research issues, we believe that Tagci can lead to better HMIs, that will in turn lead to better "operator – data fusion" systemic performance.

## CONCLUSION

This paper has identified several human factors issues associated to the use of data fusion techniques and process. Among those issues, the presentation and visualisation of the results has proven to be especially difficult to tackle. It has thus been argued that a solution to this issue is to leverage a novel HMI design method known as Tagci. The main characteristics of Tagci,, that are relevant to data fusion, have been described and justifications have been provided about its use as an appropriate HMI design method.

It is expected that benefits in terms of traceability and performance will be derived from the use of Tagci. Research issues, dealing mostly with the optimization of Tagci, have also been identified.

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