Multi-level Fusion of Hard and Soft Information

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***Abstract*—Driven by the underlying need for a yet to be developed framework for fusing heterogeneous data and information at different semantic levels coming from both sensory and human sources, we present some results of the research being conducted within the NATO Research Task Group IST-106 / RTG-051 on "Information Filtering and Multi Source Information Fusion". As part of this on-going effort, we discuss here a first outcome of our investigation on multi-level fusion. It deals with removing the first hurdle between data/information sources and processes being at different levels: representation. Our contention here is that a common representation and description framework is the premise for enabling processing overarching different semantic levels. To this end we discuss here the use of the Battle Management Language (BML) as a way ("lingua franca") to encode sensory data, a priori and contextual knowledge, both as hard and soft data.**

Keywords— multi-level fusion; hard and soft fusion; Battle Management Language; controlled languages; uncertainty representation/harmonization

I. INTRODUCTION

The exploitation of all relevant information originating from a growing mass of heterogeneous sources, both device-based (video, radar, etc.) and human-generated (largely expressed in natural language), is a key factor for the production of timely, comprehensive and most accurate description of a situation or phenomenon. There is a growing need to effectively identify relevant information from the mass available, and exploit it through automatic fusion for timely, comprehensive and accurate situation awareness. Even if exploiting multiple sources, most fusion systems are developed for combing just one type of data (e.g. positional data) in order to achieve a certain goal (e.g. accurate target tracking). This approach does not consider other relevant information that could be of different origin, type, and with possibly very different representation (e.g. a priori knowledge, contextual knowledge, mission orders, risk maps, availability and coverage of sensing resources, etc.) but still very significant to augment the knowledge about observed entities. Very likely this latter type of information could be considered of different fusion levels that rarely end up being systematically exploited automatically. The result is often stove-piped systems dedicated to a single fusion task with limited robustness. This is caused by the lack of an integrative approach for processing sensor data (low-level fusion) and semantically rich information (high-level fusion) in a holistic manner thus effectively implementing a multi-level processing architecture and fusion process.

II. PREVIOUS WORK

The general goal of multi-level fusion is making simultaneous use of sensor data processing techniques along with high-level processes working on symbolic elements of situation such as relationships, categories, etc. It seems clear that the ability to interconnect and make interactions among processes working at different levels will bring opportunities to address with success challenging applications. However, the interconnection of information fusion processes operating at different levels is a quite recent research topic in information fusion, with a limited number of research works being published until now. In the following, we highlight some related research that appeared in recently organized events around the multi-level fusion topic and close area of research.

An analysis of context operations to integrate JDL levels is given in [2]. Context has been identified as one of the key binding elements to integrate information at different levels [3]. The contextual knowledge can be adapted to adjust parameters of the algorithms at different levels (e.g. tracking, event detection, etc.), accordingly to the sub-areas of the observed scenario where this context can be applicable. Some analysis of possible extensions of JDL to address new requirements including contextual context are presented in [4], [5], and the problem of distinguishing the levels of different process in order to define interactions and potential advantages is recently considered in [6].

At the higher levels, an important input is soft data, consisting in human-generated information as text or voice. An example is the Tractor system [7], developed for text understanding in situation assessment problems. Analogously, soft data processing has been proposed in counter-insurgency examples, such as [8]. An important initiative to test with real data set is given by the fusing of soft textual information with hard signal information, called Mixed Initiative Soft Fusion Implementation Testbed (MISFIT) [9]. In this paper, the objective is putting together the content of hard data sources with soft sources (mainly texts in unconstrained natural language) trying to define a whole "machine-processable" representation.

In the ambient intelligence domain, multi-level architectures for the computation of contextual data at a smart home environment are presented in [10] and different methods at different levels of abstraction are addressed. So, belief functions theory is applied to measures included in stable abstractions, at the highest layer, and contextual data is exploited to provide adapted services. Other interesting area where multi-level integration has shown interest is in business intelligence and decision support products [11][12].

A fundamental aspect to inject high-level information is representation of uncertainty, as dealt later. As previous work, we can mention the analysis on absolute and relative conditioning rules for multi-level conditioning in a threat assessment problem [13][14].

III. MULTI-LEVEL FUSION

A. An example scenario

In order to illustrate the discussion of multi-level fusion concepts in this paper, particularly with consideration of device-derived and human-derived input from diverse sources we present a small example scenario. In particular, we wish to show how HUMINT can be combined with sensor-derived data.

A small military facility situated at the edge of a small town is bordered by a perimeter fence. A portion of the fence borders onto a small woods on one side, while other sides face onto open fields. Where the fence borders on fields, it is outfitted with an array of acoustic sensors which track activity outside the perimeter. Entrance to the facility is via a gate with a guard shack which is continuously staffed. There is also a routine human patrol along the perimeter. Within the compound itself there are various different surveillance motion sensors such as video and motion detection. One of the buildings on the facility is a lock-up for hazardous substances.

Because of its location close to the town, it is not unusual for there to be normal civilian activity outside of the perimeter of the fence. In particular along one portion of the fence there is a footpath used by local residents to walk their dogs. Children play in the fields and woods near the facility. At night wild animals living in the vicinity including deer and fox can be seen outside the perimeter.

Two weeks before the initial time of the scenario (t_0), a general notice was sent by intelligence that sources indicated that there was indications that an attack on a military facility would take place in the near future; the target facility was unknown, so all facilities were on alert.

The day before t_0 a hole was discovered in the perimeter fence near the woods; it is uncertain whether this is indicative of a potential attack or not, because there have been incidents in the past where the local children have caused minor damage to the facility (throwing rocks, digging holes, etc.). The fencing cannot be immediately replaced, and, since there is a danger of unwanted human or animal entry, a robot outfitted with various sensors (camera, motion detectors) is placed near the hole for surveillance purposes.

At night under cover of darkness, the acoustic sensors pick up a metallic sound from the perimeter fence which is initially identified with a high probability as wire cutters snipping fencing. This information is transmitted to a second robot which is sent to the coordinates of the possible entry to gather information, as the patrolling guard is on his rounds at the other end of the facility. He is also notified of the unusual reading and abandons his usual round to investigate the event.

In the meantime, motion detectors report movement, the synthesis of which indicates that something or someone is moving in the general direction of the HAZMAT storage facility. The IR camera on the robot which was sent for surveillance transmits the information that the moving object is large, probably human. Shortly thereafter the patrol arrives and verifies it is human and also reports that he observes the intruder drop something next to the HAZMAT facility and sends a report to that effect to the watch station at the guard shack who requests assistance. The robot is then tasked to investigate the object dropped by the intruder and reports a detection, via chemical sensor, that there is explosive present.

All communications within this scenario, whether between humans and robots, robots and sensors, is via BML (Battle Management Language) which we will describe in more detail in section III below.

B. "Multi-level" is not "hard+soft" fusion

The scenario described above shows the case of a significant amount of data collected over a time span of several days from multiple sources comprising sensor arrays, robots, and human observations. These data are meant to be received by a surveillance processing node able to fuse it and reason about possible suspicious activities. For the sake of simplicity, we are assuming here a single processing node therefore resembling a centralized architecture. The ultimate goal of the system is to assist human security operators by pointing out unusual patterns that might deserve further human analysis and validation. The amount of data is potentially very large as the scenario describes illicit activities that require several preparation steps several days before the actual breach into the monitored area is performed. In any case, such a system is supposed to be continuously running collecting both live signals from sensors and human observations. In addition to this live flow of data, the system is supposed to be able to take advantage of static information contained in repositories comprising: 1) a priori knowledge of the system (such as ontological knowledge supporting the general objectives and goals of the system), 2) contextual information relevant to the specific site and entities (and their possible relations) being monitored, 3) historical observations, that is significant past events that are logged into the system and build up as time passes forming the information the system has accrued so far during its operation.

The data and information just described and available to the system encompass a wide range of different pieces, going from positional data, to classification labels, to detection of events and situations, etc. The live stream from sensors is not assumed to be sent directly as raw signals to the processing node but messages are sent only upon the detection of simple events of interest [15]. This means that a first level of processing is performed by the various platforms in order to send formatted messages to the fusion node. However, the message maintains links to the original signals that can be accessed by the fusion node upon request.

To further clarify the nature of the data/information that the system is called to process, it should be noted that in our case here data is not only "hard" or "soft", that is coming from sensors or humans, but belongs to different JDL (and semantic) levels. As a matter of fact the level of the data and the type (hard/soft) are different dimensions and Table 1 exemplifies all four combinations that can hold.

TABLE 1. LOW AND HIGH LEVEL DATA VS. HARD AND SOFT SOURCES

	Low-level	High-level
Hard	Typically raw numerical data such as positional data provided by sensors.	Sensor or system outputs with high semantic value such as detection of events or situations which are typically underpinned by relations holding between the elements involved in the detected pattern (e.g. relations among detected entities, relations between entites and context, etc.).
Soft	Typically numerical information (e.g., figures giving number of observed entities) or text labels regarding entities.	Semantically rich observations typically couched in natural language.

In particular, what is referred to in Table 1 as "low-level" fusion comprises JDL levels 0-1, while "high-level" is considered level 2 and above.

It is clear then that the first step for this significant heterogeneity of static and inflowing data and information, both hard and soft, has to be couched by a common representation means in order to be exploited in a principled way thus allowing real multi-level fusion. As we will see in the following sections, these messages are encoded according to the Battle Management Language [1][19][20].

C. Analysis: real- vs. long-time, tactical vs operational

The JDL model proposes to decompose the information processing cycle into 4 or 5 levels depending on whether we consider the first proposed JDL model or a more recent version [4]. We will consider here the model with 4 levels. These levels are the following:

4 – Sensor management, Process refinement
3 – Impact assessment, threat evaluation
2 – Situation assessment
1 – Perception and object refinement

In an operational environment, the information processing includes many loops as shown in Figure 1and Figure 2.

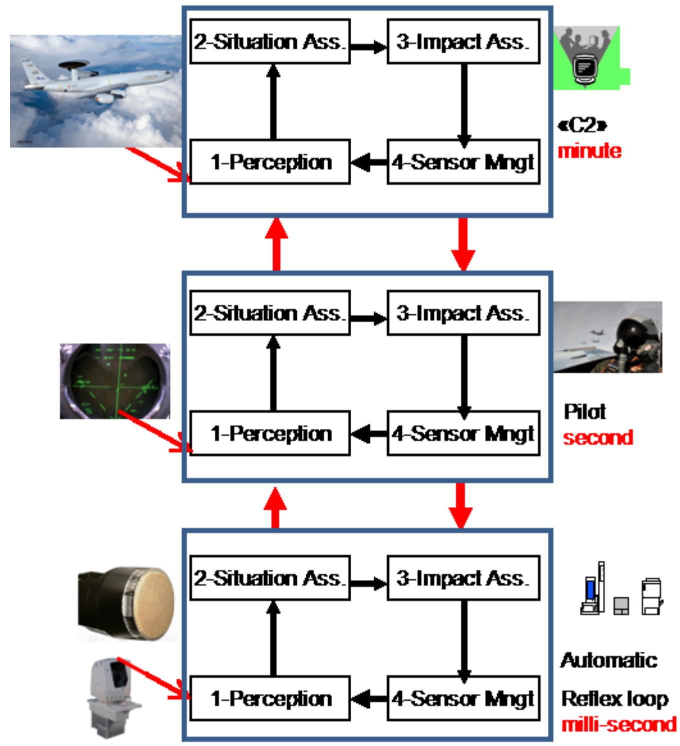

Figure 1. Air surveillance

Figure 1 gives a typical example of air surveillance with airborne sensors. There are three layers but there can be more if we include, for example, ground sensors. The first layer (at the bottom) is a reflex loop where all information is pure numerical. Information processing and decision making are automatic at this level. The semantic level of information is very poor (limited mainly to kinematics and sometimes, some identity attributes). It is important to note that at this layer the time to react is very short (ms). The second layer is at the level of the pilot. He observes the situation thanks to his screen (JDL level 1), he understands the situation (Level 2), and then, he predicts the enemy's action (level 3) and orients his sensor to have new information (level 4). In this layer the information is more elaborate (situation on the screen but also human information provided by pilots of others aircrafts. Here, the time to react is short (few seconds) but the human is in the loop and he is in charge of taking decision. The third level is at the C2 level, for example in an AWACS, the situation designed in this layer is the fusion of the situation provided by the lower level in many fighters plus the information provided by the AWACS sensors. In this layer the time to react is longer (few seconds to minutes).

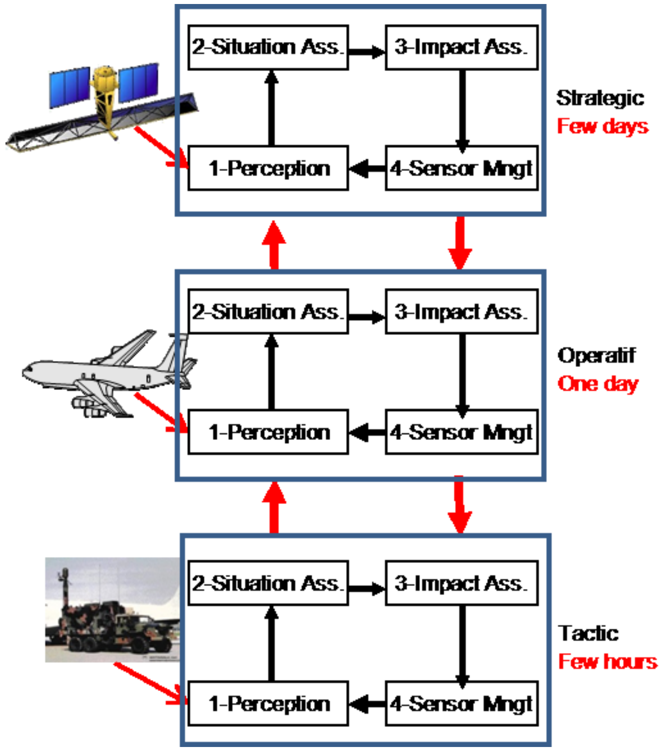

Figure 2. Battlefield surveillance

Part of the processing is automatic (fusion) and a second part is manual (track management). In this example the information in the first layer is vehiculated by an internal network to the aircraft. However, communications between layer 2 and layer 3 are done using Link 16. The local situations from the individual aircrafts are communicated to the C2 where they are fused. The fused situation is pushed back from the C2 to each aircraft and this situation is then considered as the reference situation.

Figure 2, gives an example of ground surveillance. In the first layer, the information is both numerical provided by sensors and verbal (human) provided by operators. The main part of the processing is done by operators. The time to react is much longer than in the first layer of Figure 1; it can vary from few hours to a day. The semantic of information is higher than the one of the first layer in Figure 1 because the information includes reports provided by human. In the second layer of Figure 2, the information roots are the lower layers and sensors, assigned to this layer, outputs. The information can be structured, with a data model like JC3IEDM (Joint Consultation Command and Control Information Exchange Data Model) Non-structured messages provided by humans with a very limited vocabulary and numerical data are also available and must be fused with the situation provided by lower layers. The third layer is similar to the second one but with a longer period of time. The language to carry the information between layers can be BML in the same way as the example in Section III.A. Figure 1 and Figure 2 depict only one loop in each layer. However, in a real scenario, there are many loops in a layer as it is show in Figure 3.

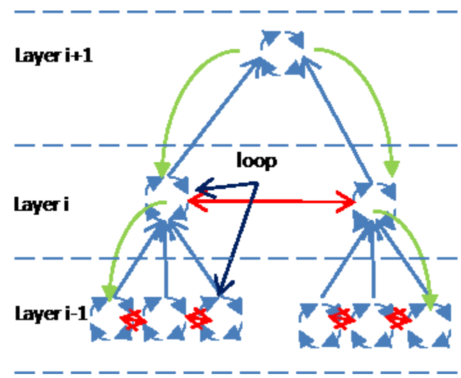

Figure 3. Processing loops between layers.

In a layer, the loops can communicate between themselves (red arrows) and can send the results of their fusion process to the immediate upper layer (blue arrows). A loop in a layer can also make the fusion of the received result from a lower loop and its own sensors output and send back the result to the lower layer (green arrows) as a reference situation.

IV. BML ENABLED FUSION

One of the major hurdles in fusing device-derived data, which is predominantly quantitative in nature and human-generated data, produced in natural language, is finding a representation which can easily and effectively handle data and information from all types of sources in a standardized manner. Within the context of our work, we are using Battle Management Language (BML), developed under the aegis of NATO and used for military communications (orders, requests and reports) [19].

BML was created as an unambiguous language which allows automatic processing of statements, including information gathered by both humans and by devices, therefore making it an ideal vehicle for fusion. It is a controlled language [17] based on a formal grammar, Lexical Functional Grammar (LFG) [18] from the field of computation linguistics. While the original goal of BML was to facilitate the exchange of orders and requests between C2 systems of various NATO countries, it was later expanded to include various types of reports [20]. These report types include not only HUMINT information on own and enemy activities, but also status reports, location reports, task completion reports, etc. While such reports may be generated directly in BML via an interface, there has been considerable work on the automatic analysis of natural language text (HUMINT, OSINT, etc.) and conversion into BML [21]. Furthermore, BML statements can be generated uniformly even when underlying natural languages are different [22], easing cross-border communications.

The next step from communications between human players on the battlefield was the extension of BML to include communications with robotic forces [23], including swarms, drones, and unmanned vehicles. Because the robotic forces are outfitted with sensors of various types, BML report types were developed (e.g., sensor readings) [24] or extended (e.g., location report). The BML statements are generated by middleware or by algorithms reporting data or results.

The end result is that all information flowing between humans and devices in the area of endeavor can be represented in the same standardized automatically processable format. The difference between a location report from a human patrol and a location report from a robot will be essentially identical: only the identity of the report (mechanical or flesh and blood) will be different [25], and also their associated uncertainties (see Section IV.D)

This means that the fusion algorithms working upon received data need only to "understand" (i.e., be able to parse BML statements for the relevant data needed) and to be able to produce their results as BML statements for use within the complex system of humans and devices to support multilevel fusion.

It should be noted that BML is a standardized representation of complex information which preserves that information in context, generally that of the "5 Ws": who, what, where, when and why. The information contained within a BML statement may be considered comparable to an arguments list from one function to another within a programming language. There is other work in controlled language which, at first glance, appear to be similar to BML. However, there is a significant fundamental difference in, for example, Controlled English (CE) and BML. CE in contrast to BML focuses on the extraction of information in order to perform reasoning upon that information using logical constructs [26][27]. BML simply presents information in context, in a system-independent, standardized allowing the algorithms used by other processes to access all or part of this information as needed. Thus, BML statements can be parsed by CE and converted to CE format for further analysis and reasoning.

A. BML in action

Using the scenario described above (Section IIIA) the original HUMINT report (warning) has already been converted into BML for fusion processing. As a result, the "perimeter breach" threat model has been activated but has not reached critical mass (i.e., is "humming" in the background). A patrol registered the first fence break-in via BML, as the patrolling soldier has been fitted with a tablet fastened to his arm with a BML interface for reporting. This statement has been processed automatically by the system and the warning level in the threat model has climbed slightly, but is not yet registering actual danger (the hole may have been the work of local children, who have pulled pranks before). Then the acoustic sensor array picks up noises, which are conveyed to the low-level fusion algorithm which identifies the sound as a metal-on-metal, likely wire cutters, at a location calculated by the algorithm and that algorithm delivers its results to the system. This time the threat model kicks up to a higher threat level and begins to transmit warnings of a possible perimeter breach along the fence to the human (guard) at the guardshack. At the same time, the system issues an automatic order to the closest patrol robot to proceed to the location identified by the acoustic sensor array algorithm, and likewise sends the (BML) notification to the (foot) patrolling guard who also proceeds to investigate. When the robot approaches the specified location, its motion detector / IR camera (whatever) verify the presence of movement and a large object, possibly human, and again the system is notified so that the threat model kicks up yet another notch (i.e., the "yellow" warning turns to "orange"). Stationary motion detectors located on various buildings register movement, each movement is processed and from that the probable direction of the movement is identified by another algorithm as being in the direction of a sensitive facility and that result is sent via BML to the system and distributed to the humans (guard and patrol). The patrolling solder verifies via his forearm-tablet using BML that the "large object" detected by the robot are two humans inside the perimeter fence who are carrying something toward the building which the motion detector algorithm has identified as the possible target and the threat model moves to "red alert" mode and an automatic transcript of the system proceedings is forwarded to the next level of contact within the command (to HQ or whatever). Once the threat level has reached the point that this information goes up the line, the up-line center would receive real-time information forwarded by the local system (which consists of men and machines).

When fusing information from ontologically different sources, uncertainty of information, obtained from the particular sources, plays an important role. When, additionally, these sources produce information on different processing levels, the importance of the uncertainty raises significantly.

One of the hurdles for the analysis of uncertainty of information derived from multiple types of sources, and in particular, when fusing device-based and human-based information is how to harmonize the uncertainty in order to make it appropriate and useful. Much of the uncertainty in device-based data can handle by knowledge of calibration, previous performance, environmental factors, etc. Uncertainty in human language may be based upon perception, intention and, motivation of the source and as well as the interpretation of the words themselves by the receiver of the information, factors which may be much more slippery to determine.

In such case information uncertainty must undergo scrutiny, being examined on many points. Also the uncertainty representation should be a subject of extensive analysis in order to guarantee that: *If one source is "better" than others then uncertainty representation has to be able to indicate that.*

B. Expressing uncertainty in BML

C2LG introduces a possibility to examine information provided by a source on many points. Namely, each report line is tagged with "Certainty" attribute, which consists of three constituents: one mandatory: "Credibility", and two optional: "InformationSource" and "Reliability" [1].

"Credibility" expresses the degree of the trustworthiness of the information reported as evaluated by reporter [1]. By definition, it may be either: "reported as fact", "reported as plausible", "reported as uncertain" or "indeterminate".

$$Cr = \{\text{RPTFCT, RPTPLA, RPTUNC, IND}\} \quad (1)$$

"InformationSource" denotes the type of source from which the reporter obtained the information [1]. By definition it may be one of several values such as "eyeball observation", , "human intelligence," "refugee" or "prisoner of war". This value allows the identification of whether the information is first party or third party, which has an effect on the certainty of the information in the statement. For example, "eyeball" indicates that the reporter has personally observed the reported event, whereas other values indicate that the information was obtained via other informants and may therefore be less reliable. It also allows the factoring in of a "class" weighting, for example, when in the theatre of operations information from refugees tends to be quite reliable, one may factor this into the certainty of the information received from such individuals.

$$IS = \{\text{EYOBSN, refugee, POW}\} \quad (2)$$

"Reliability" expresses the degree by which source can be trusted according to the reporter [1]. By definition it can be either: "completely reliable", "usually reliable", "fairly reliable", "not usually reliable", "unreliable" or "reliability cannot be judged".

$$R = \{\text{A, B, C, D, E, F}\} \quad (3)$$

C. *Exploiting BML representations for uncertainty management*

"Certainty" information expressed in BML may be used effectively in order to manage uncertainty in multi-level fusion system. "Credibility", "InformationSource", and "Reliability" attributes provide a descriptive view of vagueness of both: the source and the information it is providing. Even though some of the relationships among these different constituents of "certainty" may be easily drawn based on logic or common sense, e.g. "*…if "InformationSource" is set to EYOBSN eyeball observation it is unlikely that "Reliability" will be given as D (unreliable)…*" [1], it is important to have them defined explicitly.

In order to define the precise relationships the most convenient way is to convert them into numbers, and then to establish the necessary dependencies.

1) Transforming labels into numbers

For two of the attributes (*Cr* and *R*) transformation of qualitative descriptions, expressing information uncertainty into quantitative ones may be easily achieved by selecting appropriate number intervals (for each of the attribute values), and then simple assignment of medians of these intervals to the particular labels, e.g. for (1) it may be as shown in Table 2. Note that "InformationSource" attribute cannot be transformed in such a way due to the fact it refers to different observation means, not to the degree of trust.

TABLE 2. EXAMPLE OF LABEL-TO-VALUE TRANSFORMATION OF THE "CREDIBILITY" ATTRIBUTE

Labels	**RPTFCT**	**RPTPLA**	**RPTUNC**	**IND**
Intervals	0.75-1	0.5-0.74	0.25-0.49	0-0.24
Values	**0.875**	**0.625**	**0.375**	**0.125**

Fortunately, this attribute is highly correlated with "Reliability" attribute, which undergoes the mapping mentioned above. Therefore even if "InformationSource" is omitted while assessing quantitative uncertainties it does not matter due to the fact that its meaning for manageable uncertainty resides mainly in reliability of the source it is indicating.

2) Modification of uncertainty

While discussing label-to-number transformation of the uncertainty attributes a question may be raised: Why medians, not maximal (or minimal) values, have been taken as representatives of the particular value intervals? The answer is that this kind of solution enables easy modification, both: increasing and decreasing their values in the subsequent stages of information processing.

The above mentioned modification may have two origins: intrinsic and extrinsic. The intrinsic origin may be conditioned by specific algorithms of quality degradation, mostly as a function of elapsing time. The extrinsic origin may result from fusion when additional information is available. In both cases precise determination of the uncertainty changes can be performed only if appropriate process specification is delivered.

In general, one may deduce that intrinsic degradation pace depends on the particular source, which can be reasoned from "InformationSource" attribute. This may perform a sort of application of this attribute that even though it is not directly mapped like "Credibility" and "Reliability" it affects the quality degradation pace. It is worth of notice that the quality affection may refer to "Credibility", which is a requirement very often stated in specifications for C2 systems, as well as to "Reliability" if appropriate amount of statistic data is collected.

3) Decision defer

One of the basic reasons for uncertainty management is decision-making. Thus, the uncertainty information is important not only due to the fact it enables to "glue" other pieces of information properly or deal with intrinsic and extrinsic modifications, but also directly allows the operator of the fusion system to make decision upon it.

Sophisticated algorithms of data association may produce seemingly useful information, however if it is to be utilized effectively its certainty (expressed in terms of the introduced measures of "Credibility" and "Reliability") must be above the predefined thresholds. In other cases decision should be deferred.

4) Multi-statement

The basic role of BML as Battle Management Language is to enable the preparation, transmission and receiving of the reports and commands.

It aims more at communicating with short and concise messages rather than encompassing the full analysis of the tactical situation.

From the perspective of fusion system architecture it conducts hard-decision fusion due to the fact that a report in itself, even though it is tagged with uncertainty information, performs a form of decision.

In order to enable soft-decision fusion with usage of BML multiple reports from the same source must be sent. Then, global uncertainty constituents must be calculated based on the respective partial ones, obtained directly from the report messages.

However, this is not a standard regime of BML usage, and probably will be used only on middle-levels of fusion systems.

D. Harmonisation of multi-source BML information

When integrating complex fusion subsystems one has to be aware that information which is up to the fusion process may be of different processing levels. In the practical term that means that 'a common denominator' is required in order to establish the contribution weights properly with respect to their informational incomes, and uncertainties of information they are providing.

Having "Credibility" and "Reliability" attributes expressed in numbers together with paces of degradation of each one of them, one may assume to have in their hands a well defined "common denominator". For example if one source provides information with an error smaller than another "Credibility" of such information should be relatively greater. On the other hand, when two sources provide information of the similar "Credibility", and one source performs a complex system while the other is a radar, the "Reliability" of the first one may (but does not necessary have to) be greater than the other's but the pace of information degradation of the first one is expected to be much slower than the other's.

In the above case, harmonization of the uncertainty information may be achieved by appropriate processing of "Credibility" and "Reliability" values of the participants of the fusion. There are diverse techniques which can be applied starting with weighted averaging, through probabilistic arithmetic, and finalizing with evidential techniques.

However, the most problematic seems to be the transformation of uncertainty information to the numerical forms of "Credibility" and "Reliability". In subsection C.1) it was presented how values of these two attributes may be retrieved based on their label substitutes. Nevertheless, in case of specific low level fusion subsystems there is a need for defining "Credibility" and "Reliability" based on estimation errors and possibly on covariance matrices. On the other hand, considering the reverse conversion, BML may be regarded as a bottleneck in communication between tracking systems, due to the obvious fact that conversion from "Credibility" and "Reliability" to tracking covariances will never be flawless.

BML as a communication medium among different fusion centers probably will never be flawless in terms of information transformation (especially uncertainty information). As *lingua franca* it must be a subject of some compromise and in most cases transforming information from a certain original protocol to BML and back to the original protocol it will never lead to the same information. However, that is not the point. One may accept this loss if in return gets some additional information from different system. That makes BML a powerful tool, due to the fact it enables information enhancement by its exchange. Even though the resulting information in some cases is not as precise as in the source subsystem, it is far more adequate due to the synergy with other subsystems.

V. CONCLUSIONS

In this paper we have discussed a the use of BML as a *lingua franca*, that is a common communication mechanism to interface fusion processes at different levels and dealing with data and information coming from both human and device based sources. An illustrative example has been developed to show the capability to integrate information from multi-level hard and soft sources, and we have discussed also how uncertainty could be encoded in the corresponding messages. Further work will be directed to the algorithmic exploitation of the messages generated for a surveillance scenario being developed within the NATO Research Task Group IST-106 / RTG-051 on "Information Filtering and Multi Source Information Fusion".

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