The URREF Ontology for Semantic Wide Area Motion Imagery Exploitation

Erik Blasch
Air Force Research Lab
Rome, NY, 13441
erik.blasch@rl.af.mil

Paulo C. G. Costa, Kathryn B. Laskey
C4I Center - George Mason University
Fairfax, VA, 22030
{pcosta, klaskey} @c4i.gmu.edu

Haibin Ling
Temple Universtity
Philadelphia, PA 19122
hbling@temple.edu

Genshe Chen
Information Fusion Tech.
Germantown, MD
gchen@intfusiontech.com

***Abstract*— *Current advances operational information fusion systems (IFSs) require common semantic ontologies for collection, storage, and access to multi intelligence information. One example is the connections between physics-based (e.g. video) and text-based (e.g. reports) describing the same situation. Situation, user, and mission awareness are enabled through a common ontology. In this paper, we utilize the uncertainty representation and reasoning evaluation framework (URREF) ontology as a basis for describing wide-area motion imagery (WAMI) analysis to determine uncertainty attributes. As part of the Evaluation of Technologies for Uncertainty Representation Working Group (ETURWG), both the URREF and a WAMI challenge problem are available for research purposes from which we describe the URREF, a exemplar schema to link physics-based and text-based uncertainty representations, and explore an example from WAMI exploitation for a common uncertainty demonstration.*

Keywords: *Component, Information Fusion, Performance Evaluation, Uncertainty Reasoning, Knowledge Representation, Ontology, Measures of Effectiveness.*

I. INTRODUCTION

Semantic ontologies [1] enable a framework for many applications such as command and control, emergency response, and information sharing [2]. Information sharing, and the inherent policies within an architecture, enable data to be fused into actionable knowledge. A key to information fusion is to reduce uncertainty that may come from many sources that require a unified, common, and standardized semantic understanding. Figure 1 [3], shows the relations between sensed and reported world information from which uncertainty representation and uncertainty reasoning are required for machine processing and user interaction, refinement, and understanding [4, 5, 6, 7].

The evaluation of how uncertainty is processed is dependent on the system-level metrics such as timeliness, accuracy, confidence, throughput, and cost [8], which also are information fusion quality of service (QoS) metrics [9]. Future large complex information fusion systems will require performance evaluation [10] and understanding of the connections between various metrics [11]. It is a goal of the *Evaluation of Technologies for Uncertainty Representation Working Group* (ETURWG) to formulate, test, and evaluate different methods of a semantic uncertainty ontology that is common, universal, and standardized.

Information fusion system-level metrics include timeliness (how quickly the system can come to a conclusion within a specified precision level), accuracy (where can an object be found for a specified localization level), and confidence (what level of a probability match for a defined recall level).Clearly, different choices in uncertainty representation approaches will affect the achievable timeliness, accuracy, and confidence of a system, and therefore must be considered when evaluating both the system's performance as a whole [12] and the specific impact of the uncertainty handling approach. Yet, when evaluating timeliness (or any other system-level metrics), one will likely find some factors not directly related to the handling of uncertainty itself, such as object tracking and identification report updates (i.e., Level 1 fusion) [13, 14, 15], situation and

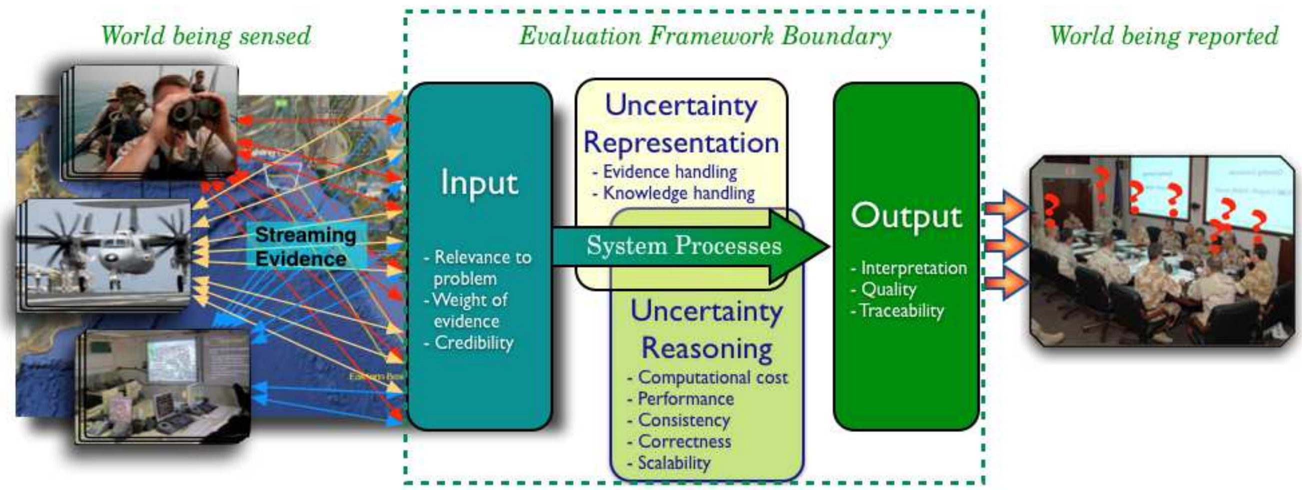

Figure 1 - Boundaries of the Uncertainty Representation and Reasoning Evaluation Framework [3].

threat assessment relative to scenario constraints (i.e., Level 2/3 fusion) [16], overall system architecture (e.g. centralized, distributed, etc.) [12], data management processes and feedback / input control processes (i.e., Level 4 fusion considerations) [17], and user-machine coordination based on operating systems (i.e., Level 5 fusion) [18], and others.

Key to the various Data Fusion Information Group (DFIG) [19] levels of information fusion is *evaluation*. For example, there have been efforts in comprehensive tracking [20, 21], object classification [22], and situation awareness evaluation [23] which focus on measures of performance (MOPs). Future evaluations will include high-level information Measures of Effectiveness (MOEs) [24] that include uncertainty characterization [25].

The ETUWRG has developed both an uncertainty framework ontology, but also has a series of use cases. One use case is that of *Wide-Area Motion Imagery* (WAMI) for developments in Level 1 fusion [26, 27, 28, 29]. Other computer vision working groups [30] are exploring semantic technology with datasets that are not necessary focused on uncertainty, but have a rich set of ontologies and datasets for collaboration and comparisons.

The paper investigates the URREF for WAMI tracking. Section II explores the issues of uncertainty characterization and Section III, the uncertainty evaluation framework. Section IV presents a WAMI tracking use case using the URREF for timeliness, accuracy, and confidence. Section V provides and discussion and Section VI conclusions.

II. The Uncertainty Representation Problem

The Information Fusion community envisions effortless interaction between humans and computers, seamless interoperability and information exchange among applications, and rapid and accurate identification and invocation of appropriate services. As work with semantics and services grows more ambitious, there is increasing appreciation of the need for principled approaches to representing and reasoning under uncertainty. Here, the term "uncertainty" is intended to encompass a variety of aspects of imperfect knowledge, including incompleteness, inconclusiveness, vagueness, ambiguity, and others. The term "uncertainty reasoning" is meant to denote the full range of methods designed for representing and reasoning with knowledge when Boolean truth-values are unknown, unknowable, or inapplicable. Commonly applied approaches to uncertainty reasoning include probability theory [31], expert systems [32], fuzzy logic, subjective logic [33, 34], Dempster-Shafer theory, DSmT [35], and numerous other techniques.

To illustrate the challenges of evaluating uncertainty representation and reasoning in information systems, we consider below a few reasoning challenges faced within the World Wide Web domain that could be addressed by reasoning under uncertainty [1]. Uncertainty is an intrinsic feature of many of the required tasks, and a full realization of the World Wide Web as a source of processable data and information management services [3] demands formalisms capable of representing and reasoning under uncertainty such as:

- *Automated agents* (e.g., to exchange Web information)
- *Uncertainty-laden data*. (e.g., terrain information)
- *Non-sensory collected information* (e.g., human sources).
- *Dynamic composability* (e.g., Web Services).
- *Information extraction* (e.g., indexing from large databases)

These problems are all related with information fusion, involve both textual-based [36] and physics-based [37] data, and can be easily extrapolated to represent the more general classes of problems found in the sensor, data, and information fusion domain. A recent example of hard-soft fusion uses a controlled natural language (CNL) for data-to-decisions [38].

III. The Uncertainty Evaluation Framework

The uncertainty representation and reasoning evaluation framework (URREF) includes both hard sources (e.g. imaging, radar, video, etc.) and soft sources (HUMINT reports, software alerts, etc.) which requires integration for uncertainty MOEs.

Effectiveness relates to a system's capability to produce an effect. Many benefits of fusion include providing locations of events, extending coverage, and reducing ambiguity and false alarms. The goal for the IFS is to support users in their tasks whether providing refined information, reducing time and workload, or determining completeness, accuracy, and quality in task completion. Effectiveness includes *efficiency*: doing things in the most economical way (good input to output ratio), *efficacy*: getting things done, (i.e., meeting objectives), *correctness*: doing "right" things, (i.e., setting right thresholds to achieve an overall goal - the *effect*). The MOEs support system-level management and design verification, validation, testing, and evaluation. The URREF output step involves the assessment of how information on uncertainty is presented to the users and, therefore, how it impacts the quality of their decision-making process.

Key aspects of measuring effectiveness come from quality of service (QoS) metrics that can be utilized for hard-soft semantic information fusion [39, 40, 41, 42] Another perspective includes quality of information, or rather information quality (IQ), metrics to combine different types of uncertainty to an established quality. IQ metrics establish user semantic content as a schema or ontology [43] of uncertainty analysis such as a popular method of probabilistic ontologies [44]. Together, these metrics and representations support a formal theory of high-level information fusion [2, 45].

The URREF ontology, whose main concepts are depicted in Figure 2 below for the uncertainty of a Thing, is a first step towards building a semantic standard. The core of the ontology is the *Criteria class*, which drives the development of the elements of the subclasses (Section B). The Uncertainty Classes were either taken or adapted from the Uncertainty Ontology developed by the W3C's URW3-XG [1]. The ontology must also be used as a high-level reference for defining the actual evaluation criteria items that will comprise a comprehensive uncertainty evaluation framework. Other main class definitions include:

- A *source class* is the origin of the information. A physical sensor is one important example of a source; where natural language inputs from a human is another.

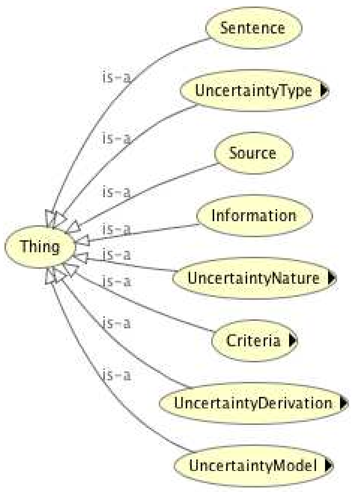

Figure 2 – The URREF ontology main classes.

- A *Sentence class* captures an expression in some logical language that evaluates to a truth-value (e.g., formula, axiom, assertion).
- A *Uncertainty Derivation* class refers to the way it can be assessed which is decomposed into:
  1) *Objective Subclass*: (e.g., factual and repeatable derivation process).
  2) *Subjective Subclass:* (e.g., a subject matter expert's (SME's) estimation).
- A *Uncertainty Model class* contains information on the mathematical theories for the representing and reasoning with the uncertainty types.

A. Uncertainty Type Class

Uncertainty Type is a concept that focuses on underlying characteristics of the information that make it uncertain. Its subclasses are Ambiguity, Incompleteness, Vagueness, Randomness, and Inconsistency, all depicted in Figure 3 below. These subclasses were based on the large body of work on evidential reasoning by David Schum [31].

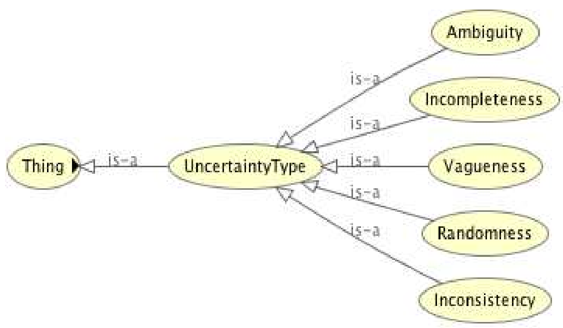

Figure 3 – URREF Ontology: Uncertainty Type Class.

B. Criteria Class

The *Criteria Class* is the main class of the URREF ontology, and it is meant to encompass all the different aspects that must be considered when evaluating information uncertainty handling in multi-sensor fusion systems. Figure 4 depicts the Criteria Class and its subclasses:

1) *Input Criteria:* encompasses the criteria that directly affect the way evidence is input to the system. It focuses on the source of input data or evidence, which can be tangible (sensing or physical), testimonial (human), documentary, or known missing.

- *Relevance to Problem* assesses how a given uncertainty representation is able to capture why a given input is relevant to the problem and what was the source of the data request.
- *Weight or Force of Evidence* measures how a given uncertainty representation is able to capture the degree to which a given input can affect the processing and output of the fusion system. Ideally, the weight should be an objective assessment and the representation approach must provide a means to measure the degree of impact of an evidence item with a numerical scale such as value of information [24].
- *Credibility,* also known as believability, comprises the aspects that directly affect a sensor (soft or hard) in its ability to capture evidence. Its subclasses are *Veracity*, *Objectivity*, *Observational Sensitivity*, and *Self-Confidence.*

2) *Representation Criteria:* encompasses the criteria that directly affect the way information is captured by and transmitted through the system. These criteria can also be called interfacing or transport criteria, as they relate to how the representational model transfers, passes, and routes information within the system.

- *Evidence Handling:* is a subclass of representation criteria that apply particularly to the ability of a given representation of uncertainty to capture specific characteristics of incomplete evidence that are available to or produced by the system. The main focus is on measuring the quality of the evidence by assessing how well this evidence is able to support the development of a conclusion. It has subclasses *Conclusiveness*, *Ambiguousness*, *Completeness*, *Reliability*, and *Dissonance.*
- *Knowledge Handling:* includes criteria intended to measure the ability of a given uncertainty representation technique to convey knowledge. Its subclasses are *Compatibility* and *Expressiveness* (which is further divided into the subclasses *Assessment*, *Adaptability*, and *Simplicity*)

3) *Reasoning Criteria:* contains criteria that directly affect the way the system transforms its data into knowledge. These can also be called process or inference criteria, as they deal with how the uncertainty model performs operations with information. It has the following subclasses:

- *Correctness* measures of the ability of the inferential process to produce correct results. In cases where there is no ground truth to establish a correct answer (including a simulated ground truth), the representation technique can still be evaluated in terms of how its answers align with what is expected from a gold standard (e.g. SMEs, documentation, etc.).
- *Consistency* assesses of the ability of the inferential process to produce the same results when given the same data under the same conditions.
- *Scalability* evaluates how a representational technique performs on a class of problems as the amount of data or the problem size grows very large. Scalability could be broken down into additional sub-criteria.
- *Computational Cost* computes the number of resources required by a given representational technique to produce its results.

same concepts with different names. For example, accuracy sometimes is used as a synonym of precision; sometimes the terms are used with different meanings. Indeed, accuracy and precision can be inversely related. As one makes the granularity coarser, one can expect that the system will have a better accuracy. Precision can also be used to determine bounds on the certainty of the reported result.

- *Interpretation* refers to the degree to which the uncertainty representation and reasoning can be used to guide assessment, to understand the conclusions of the system and use them as a basis for action, and to support the rules for combining and updating measures.

The above concepts are being explored within the ETURWG, which is making use of this ontology (shown in Figure 4) to support the development of uncertainty evaluation criteria for a set of information fusion use cases. The interested

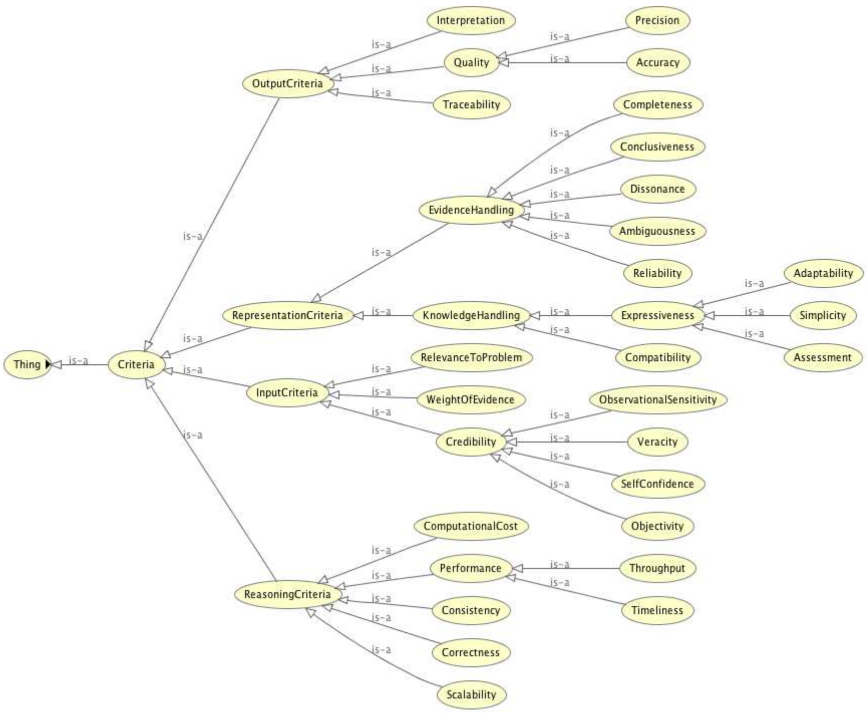

Figure 4 – URREF Ontology: Criteria Class.

- *Performance* includes metrics to assess the contribution of the representational model toward meeting the functional requirements of an information fusion system. Other system architecture factors also affect these metrics. This criterion is divided into subclasses *Timeliness* and *Throughput*.

4) *Output Criteria* relates to the system's results and its ability to communicate it to its users in a clear fashion. It has the following subclasses:

- *Quality* serves to assess the informational quality of the system's output. It includes *Accuracy* and *Precision* as subclasses. It is common to see in the literature the

reader should refer to the group's website for more specific details (http://eturwggmu.edu). Note that the URREF ontology is not supposed to be a definitive reference for evaluation criteria, but simply an established baseline that is coherent and sufficient for its purposes. This approach privileges the pragmatism of having a good solution against having an "ideal" but usually unattainable solution. For instance, a definitive reference would involve having universally accepted definitions and usage for terms such as "Precision." This is clearly infeasible. The approach also takes into consideration that more important than naming a concept is to ensure that it is represented clearly and distinctly within the ontology so to ensure the consistency for such applications as hard-soft fusion.

To assure utility and acceptability of the URREF ontology, most of its concepts have been drawn from seminal work in related areas such as uncertainty representation, evidential reasoning, and performance evaluation. The ontology has built on the URW3 uncertainty ontology [1]. Also, the structure and viewpoint adopted in the ontology development have been tuned to addressing the uncertainty evaluation problem and its associated perspective (e.g. how information is handled within a fusion system). Next, we present simultaneous tracking and identification application using the URREF.

IV. EXAMPLE – WAMI

Characterizing the uncertainty in IF processes is not a new research topic. An example is the Semantic Web as part of the Web Ontology Language (OWL) (http://www.w3.org/TR/owl-guide/). OWL operational semantics support message formats (e.g. XML schema) and protocol specifications for an ontology knowledge representation. With a knowledge representation, uncertainty reasoning can be determined from the message format.

A. Schema

A *schema* for image processing is shown in Figure 5 for the Cursor on Target (CoT) program [46]. As detailed, the schema provides target type and identification (ID) allegiance, time stamps, and coordinate locations (much as the DFIG level 1 object assessment information of object track and ID information). While the schema is simple, and worked well [47], for purposes of information transmission, processing, exploitation, and dissemination, future developments could include uncertainty fields from the URREF ontology. It is important to research which semantic content is most relevant for operational information fusion management and systems design.

```
<?xml version='1.0' standalone='yes'?>
<event version="2.0"
    uid="J-01334"
    type="a-h-A-M-F-U-M"
    time="2005-04-05T11:43:38.07Z"
    start="2005-04-05T11:43:38.07Z"
    stale="2005-04-05T11:45:38.07Z" >
  <detail>
  </detail>
  <point lat="30.0090027" lon="-85.9578735" ce="45.3"
              hae="-42.6" le="99.5"  />
</event>
```

Figure 5 – Cursor on Target Schema [46]

In order to determine what ontology content can be added to such a message passing schema, there are three issues (1) what, (2) how much, and (3) which ones. For the case of physics-based (video) and textual-based reports, we need to determine what semantic content could be useful. One simple case is that either a human analyst can report a “friendly” in the uid field, or a machine tracker could extract the information from the video to update the uid field of “friendly”. One example of “friendly” could be from extracted text and video exploitation of a blue vehicle. What is obviously missing from the CoT schema is some notion of uncertainty with the measurements and information as to the confidence, timeliness, and position accuracy. While the entire URREF cannot, and should not, be considered for the schema updates, as a message passing service for the ontology, the first issue is to calculate possible uncertainty metrics that could go into the schema.

B. Metrics to Suppor the URREF Semantic Ontology

For the metrics available in the Cursor on Target Schema, we seek uncertainty measures of confidence, accuracy, and timeliness, as related to uid, time, and point; respectively.

- Credibility / Confidence: evaluates the ability to discern an object based on a known target. Classification is the target match, while identity is target allegiance. If targets are of known entities, it can be assumed that the targets not classified could pose an ID uncertainty. Using a Bayesian approach for this example, we determine the relative probability from the likelihood values of the object, versus of target clutter $\ell_{O|c}$, where c_j is for $j = 1, \ldots, n$ clutter types:

$$Pr_{O|c} = \frac{[\,\ell_{O|C}\,]}{\Sigma_{c_j \in C}\,[\,\ell_{O|c_j}\,]} \tag{1}$$

  Using plausibility, uncertainty is everything unknown

$$U_L = 1 - Pr_{O|c} \tag{2}$$

- Timeliness: evaluates when the system knows enough information to make a decision versus when it was collected. For the purpose of this analysis we simulate the deadtime for an *input time delay* (TD_i) for a decision i, as related to the user achieving a control decision [48]. Likewise, in the action selection requires time as modelled as an output time delay (TO_i). The updated state-space representation is:

$$\begin{aligned} \dot{\mathbf{x}}(t) &= -A\,\mathbf{x}(t) + B\,\mathbf{u}(t - TD_i) \\ \mathbf{y}(t) &= C\,\mathbf{x}(t - TO_i) + D\,\mathbf{u}(t) \end{aligned} \tag{3}$$

  To determine the estimation parameters of A and B, as well as the output analysis of C and D, we model the importance of the information processing as related to the cognitive observe-orient-decide-act (OODA) functions. Uncertainty is defined as the decision time difference of arrival:

$$U_T = \mathbf{x}(t - TO_i) - \mathbf{x}(t - TD_i) \tag{4}$$

- Accuracy: evaluates how the real world track estimates from the measurements compare to the ground truth. For the purpose of this analysis, the real world is reduced to a specified track estimate x_M, as related to ground truth x_T. Using a root-mean square error, we have:

$$U_L = \sqrt{(x_M - x_T)^2 + (y_M - y_T)^2} \tag{5}$$

Accuracy can be determined versus the ability to track a target exactly : 1 - U_L. Other aspects could include track purity for track-to-track association [49] for situation awareness including:

- Specificity: evaluates how much of the real world clutter is reduced such as reducing the false alarms. While we do not simulate, we can deduce from the track confidence.

- Situation Completeness: evaluates how much of the real world the system knows. For the purpose of this analysis the real world is reduced to a specified region of space (the volume of interest, VOI) during a given time interval (the time interval of interest).

C. Wide Area Motion Imagery Example

For the ETURWG, a use case is available for the purposes of semantic investigation. WAMI has gained in popularity as it affords advanced capabilities in persistence, increased track life, and situation awareness, but it also poses new challenges [50, 51] such as low frame updates (timeliness).

Leveraging developments from computer vision [52, 53, 54, 55], methods are being applied as part of the ETUWG [27-29]. The persistence coverage affords such methods as multiple object and group tracking [56, 57, 58], road assessment and tracking [59, 60], contextual tracking [61, 62], and advances in particle filtering [59, 63]. Because of the numerous objects and their movements, there are opportunities for linear road tracking, but also there is a need for nonlinear track evaluation [64] such as the randomized unscented transform (RUT) filter [65] for accuracy assessment. These issues will be important for future work.

We utilize the results from a WAMI tracker for track location accuracy, the pixels on target for classification for target identity (e.g. credibility), and the timeliness to make a decision. We are tracking four targets with an on-road analysis with a nominated target of interest, as shown in Figure 6. Vehicles turning off road are not considered as part of the user defined targets of interest. Note: the entire Columbus Large Image Format (CLIF) WAMI image collection has been presented in previous papers with discussions with the entire video data set (see the ETURWG website).

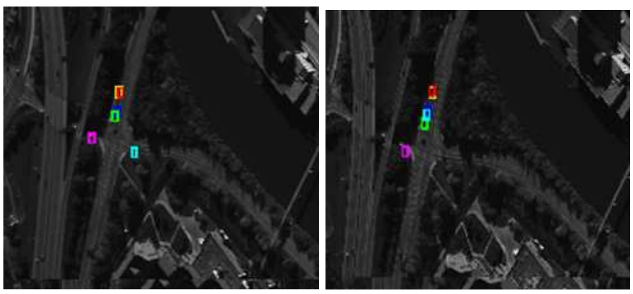

Figure 6 – WAMI Tracking.

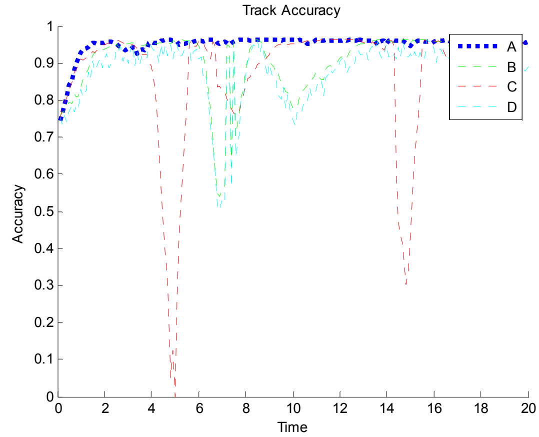

Figure 7 – Target Accuracy

Figure 7 plots the target accuracy (which is the inverse of the typical plots that show the target tracking error). Figure 8 combines the track accuracy in a unified display plot showing the target confidence (uid) and the accuracy. The confidence is shown as solid lines and the timeliness presented as the black humps where the time intervals are shown as: orient (t = 2.5-5), observe (t = 5-10), decide (t = 10-13) and act (t =13-18) time steps.

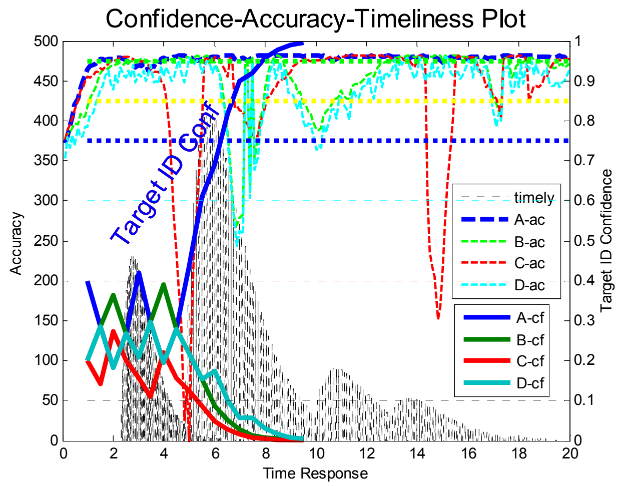

Figure 8 – Confidence-Accuracy-Timeliness Results.

Using the above information, we combine the credibility /confidence, accuracy, and timeliness (CAT) for a semantic notion of fused uncertainty in Figure 9 (where the normalized values are $U_T = U_C + U_T + U_A$). Together, the combined uncertainty could be a ontology field in an updated CoT schema to give the user a quality assessment of a machine processed semantic representation of uncertainty.

V. DISCUSSION

Figure 9 shows a case for a unified uncertainty estimation and is meant for discussion. Given the choice to utilize the URREF ontology, there are issues associated with choosing an ontology representation that can work within a message passing schema. If only one field was available, say ut, then is it appropriate to normalize the uncertainty and combine for purposes of the schema? For this case, only one target was nominated (like the CoT program), from which we see that the combined evidence supports a reduction in uncertainty; namely decreased track error, increased plausibility and hence ruling out the uid error, and the timeliness in decision making.

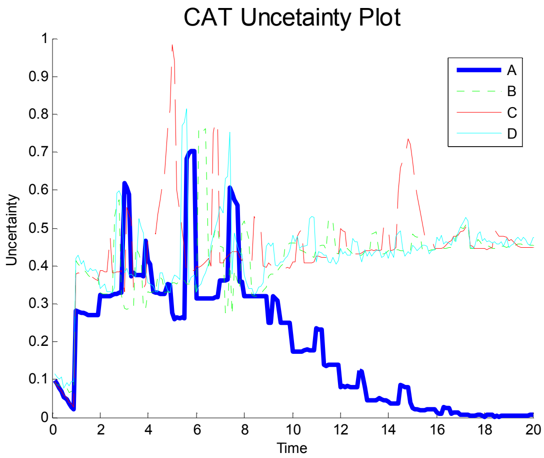

Figure 9 – Objective Semantic of Uncertainty.

VI. CONCLUSIONS

Characterizing the uncertainty is important in information fusion (IF) processes. Evaluation of IF systems presents various challenges due to the complexity of fusion systems and the sheer number of variables influencing their performance. Developing the operational semantics will include issues of representation, reasoning, and policy which need to be considered for command and control [66]. Representing uncertainty has an overall impact on system performance that is hard to quantify or even to assess from a qualitative viewpoint. The ETURWG technical considerations unearthed many issues that demand a common understanding that is only achievable by a formal specification of the semantics involved [67, 68].

In the paper, we utilized the current URREF ontology in relation to an established schema (Cursor on Target) to support the development of a specific use case for wide-area motion imagery (WAMI) simultaneous tracking and identification. We also presented a visual analytic method for uncertainty metrics and analytics. Future work includes group tracking, activity analysis, hard-soft fusion, and contextual understanding.

More specific requirements to evaluate a set of use cases and associated data sets designed by the ETURWG are accessible through our webpage [http://eturwg.c4i.gmu.edu]. Although it is clear that the URREF ontology is not a definitive reference for all types of information fusion activities, it has proven to be a discussion towards a common framework.

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