A Framework for Dynamic Hard/Soft Fusion

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Abstract - ***We report on the ongoing development of a research framework for dynamic integration of information from hard (electronic) and soft (human) sensors. We describe this framework, which includes representation of 2nd order uncertainty. We outline current and planned human-in-the-loop experiments in which an "ad hoc community of human observers" provides input reports via mobile phones and PDAs. Our overall approach is based on three pillars: traditional sensing resources ("S-space"), dynamic communities of human observers ("H-space") and resources such as archived sensor data, blogs, reports, dynamic news reports from citizen reporters via the Internet ("I-space"). The sensors in all three of these pillars need to be characterized and calibrated. In H-space and I-space, calibration issues related to motivation, truthfulness, etc. must be considered in addition to the standard physical characterization and calibration issues that need to be considered in S-space.***

Keywords: Human sensors, uncertainty representation, information fusion

1. Introduction

The motivation for this research is the changing character of the observational reporting in irregular/asymmetric warfare cases where the observational capabilities and opportunities for traditional electronic ("Hard" henceforth) sensors is limited. This is especially related to the urban warfare case, but this is not the only application where soft data inputs can play a key role. New communications methods and links between military, local authorities, and others provide the opportunity to create a dynamic observation resource; in effect allowing humans to act as soft sensors. Information can be obtained from direct human reports as well as from open source information on the internet (e.g., MySpace, YouTube, Facebook, eBay, Craigslist, Wikipedia, Blogger, Photobucket and Flikr). Robert Lucky describes the concept of Internet based information [1]. Lucky states, "Meanwhile, those billion amateurs are taking pictures of everything on the planet and placing the images on Flickr and other sites. There are thousands upon thousands of pictures of every known place, taken from all angles and under all lighting conditions. Researchers are now using those pictures to create three-dimensional images and panoramic vistas." This information can significantly augment data obtained from traditional sensors such as unattended ground sensors, radar, airborne vehicles and others. Similarly, Burke et al [2] have described the concept of participatory sensing, in which a community of observers might be tasked to provide information for applications such as urban planning and pubic health.

While extensive techniques exist to combine data from traditional sensors ([3], [4]. [5]), little work has been done on combining human and non-human sensors. Clearly, humans do not act as traditional sensors and their accuracy, biases and levels of observation are quite different than traditional sensors. On the other hand, humans can provide valuable inferences and observations not available from standard sensors. A good example is the case where humans judge that a particular type of relationship exists between some entities. Virtually no hard sensor provides prima facia evidence of the existence of a relationship, since hard sensors are designed primarily to measure attributes and features of entities. A need exists to develop techniques for combining human supplied data with traditional sensor data. Issues include how to quantify the uncertainty of human data, how to model humans as sensors, how to task humans as sources of information, and even how to elicit information. Our research is addressing these issues and developing a demonstration of the capability to fuse human and sensor data in a dynamic network centric environment including open source information available via the Internet.

2. Information processing chain

The general processing concept and chain of information flow for incorporation of human reports with traditional sensor data is illustrated in Figure 1 (which shows only the soft data input on the left hand side). We are focusing on a tactical type of operation in which local sensors (e.g., ground-based sensor systems) are integrated with regional and national sources along with human reports in a tactical operations center (TOC).

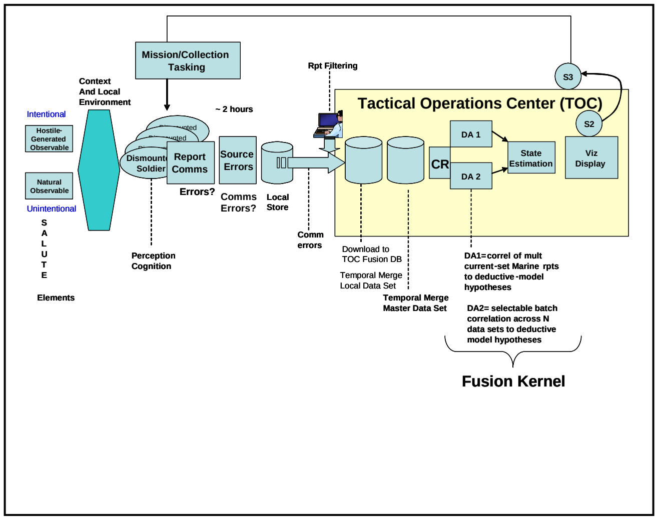

Figure 1: Notional Processing Change

Figure 1 shows:

- That the problem starts in the real-world, in regard to whether errors of observation are attributable to only unintentional natural errors or to what we are calling "intentional" errors resulting from hostile deception
- That the observational errors, as for hard sensors, will be conditional on ambient observational conditions but also the observers state of mind
- That perceptual and cognitive errors will occur in the reports generated by the set of soldiers
- That errors will also result from whatever communication means are employed to relay those reports to the TOC
- That the incoming report-set may be (erroneously) reviewed by yet other humans in the TOC as a preprocessing/pre-filtering step
- That the resulting (still-raw but filtered) observational data will be processed by a data fusion system that:
    - Puts the data into a common frame of reference (CR=Common Referencing)
    - Associates the data to hypothesized objects, entities and to hypothesized situations (Data Association)
    - Generates fused state estimates for both the objects and situations and presents them to another human, probably the S2 (State Estimation)
- In this scenario, the S2 then likely advises the S3 who may modify the reconnaissance-squad tasking in real-time (analogous to Level 4 or sensor management) or direct a change in mission to deal with an emerging or imminent threat.

This concept can be expanded to include reports from local non-military personnel for operations such as humanitarian relief or disaster management. In such cases there is a possibly-high variation in the quality of the report input. All of these error factors and reliability factors should be accounted for in the data fusion process design.

3. Architectural concept

Figure 2 illustrates the key functions for a cyber infrastructure to support fusion of soft and hard sensors. There are three types of inputs shown at the bottom of the figure; (1) hard sensor data via sensor networks and platforms, (2) reports from ad hoc observers, and (3) input from the Internet. Each of these sources must be characterized and processed prior to fusion. The hard sensor data are traditionally processed via signal and image processing techniques, creating meta data such as feature vectors or state vectors (e.g., using feature extraction techniques, pattern recognition, and statistical estimation methods). Similarly, the human report information may be processed via knowledge elicitation techniques with meta-data generated to transform human data such as fuzzy or comparative relationships (e.g., "I observe an *activity* occurring *near* the Union building involving a *small group* of students…") into well-defined semantic terms and vector or scalar variables. In the previous example processing might use the observer's location, the a priori known location of the "Union building" and the fuzzy concept of *near* to compute a potential location and error ellipsoid to characterize the location of the reported activity. Finally, the Internet data is gathered via software agents or search engines. There is a parallel between the processing required to transform sensor energy collection (e.g., represented by signals or images) into useable information, transforming reported human observations and opinions into useful information, and transforming data mined from the Internet into useful information.

One aspect of our research is the development of the metaphor of "sensor tasking", "data and information elicitation" and "generation of meta-data" across these three types of information sources. Just as a traditional sensor must be directed to point in a useful direction (via the computation of "look angles" and sensor tasking), human observers may need to be directed or cued to focus their attention on key targets, events or activities. We are exploring these metaphors and identifying meta-data generation concepts. Interestingly, Wang and his associates ([6], [7], [8], [9], and [10]) have developed methods for automated processing of images to add semantic labels that characterize the image content. This provides the opportunity to link hard sensor data with

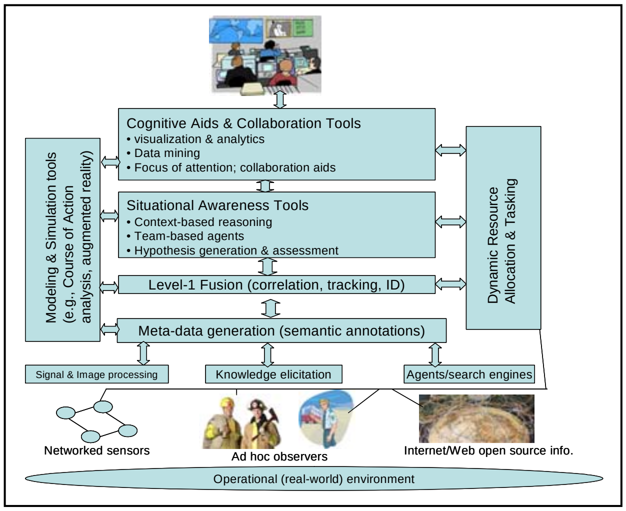

Figure 2: Architecture concept for linking sensor

human reports at the semantic level [11] and to incorporate contextual information.

4. Extreme events laboratory

We are designing and implementing a distributed cyber infrastructure to facilitate the design and conduct of experiments involving a combination of traditional sensors and humans acting as soft sensors. The facility is termed an extreme events laboratory (EEL) due to the types of applications such as crisis management related to environmental disasters, terrorist events, or other events. The facility will include three main components; (1) a central command, control and analysis facility housed in the Information Sciences and Technology building (see http://ist.psu.edu/ist/iststory/page2.cfm?intPageID=1066), (2) a van acting as a mobile command center, and (3) mobile devices such as Nokia 800s, personal data devices (PDAs), cell phones, or laptop computers used by students and staff acting as human observers. Selected ground based sensors such as video devices will also be incorporated into the EEL. The cyber infrastructure for this campus-wide facility will utilize web-services concepts and be developed for open-source utilization. Initial software prototypes have been implemented to demonstrate secure communications and connectivity between mobile devices and the Penn State IST 3-D full immersion display facility.

5. Human in the loop experiments

We are currently designing human in the loop experiments to evaluate the effectiveness of developed knowledge elicitation techniques (e.g., methods used on hand-held devices to solicit observational data, as well as methods for combining soft and hard sensor data). The approach will use a "living laboratory" concept developed by McNeese and his associates ([12], [13], [14]). The concept involves a sequence of iterated steps including:

- *Ethnography studies* – field based study of cognition in the field to understand the issues related to a particular domain or application; these studies involve working with analysts or end-users to understand the specific issues related to decision making, human observations, types of data and inferences sought, etc.
- *Cognitive systems engineering* – formal methods are used to elicit information from end-users (including structured interviews, observing group dynamics, etc.). Special tools assist in characterizing and understanding the problem domain. One in particular involves development of fuzzy cognitive maps to lay out reasoning concepts [15].
- *Development of scaled-world simulations* – In order to evaluate the evolving concepts, scenarios and test sets are developed using a scaled world simulation. The scaled world (modeled using a computer simulation called neoCities) allows creation of a miniature command and control and decision support environment for the application of interest. Small teams or individuals can be used to emulate the decision-making and analysis process of the larger real-world problem. Student teams, for example, can be used as human subjects to evaluate the effectiveness of tools such as collaboration aids, visualization tools or advisory agents.
- *Design of support tools* – Based on the results of scaled world simulations, new or modified tools can be implemented to improve the effectiveness of individual or team-based situational awareness and decision making. If successful, these tools can be introduced back into operational environments.

6. Characterizing uncertainty

The latest U.S. Defense Department Quadrennial Defense Review (QDR) advocates a range of new initiatives for focusing defense research "to prepare for wider asymmetric challenges and to hedge against uncertainty over the next 20 years" [16]. As events in the Middle

East have shown, asymmetric challenges (e.g. the improvised explosive device (IED) problems) are such that in spite of efforts to study and analyze adversarial tactics, techniques and procedures (TTP's), the deductive model foundations reflecting such behaviors are fragile and quickly obsolesce. We call this type of modeling and analysis environment a "weak knowledge environment", and one important part of it is the means to account for the higher levels of uncertainty in the knowledge frameworks that form the basis for approaches to Information Fusion techniques.

The quantitative essence of the problem involves dealing with "uncertainty in the uncertainty" or "second-order uncertainty (SOU)" in the asserted levels of uncertainty associated with adversarial behavior models, as typically elicited from Subject Matter Experts (SME's). Among the key issues are: effective methods for reliably eliciting probabilistic or other uncertainty measures from SME's, representation strategies for SOU's of different type, and propagation/calculations involving SOU's as, for example, in propagating SOU's in Bayesian Networks.

Llinas and his colleagues in the Center for Multisource Information Fusion (CMIF) (http://www.infofusion.buffalo.edu/) have studied such problems under three separate programs funded by both the U. S. Air Force Research laboratory and the U. S. Army Research Office. However, much remains to be done to achieve a better understanding of the SOU issues noted above. One example of the newness of this area of research is that the Society for Imprecise Probability: Theories and Applications (SIPTA) was only just formed in 2002, and is the focal international society for research into SOU and related topics.

On one of their projects CMIF scientists researched the design of a hybrid inferencing scheme using both a Bayesian Network (BN) component and a Fuzzy Logic (FL) component. The research involves exploring particular strategies for elicitation of both probability and possibility values from SME's, and also studying the consistency of such elicited values. Following Monti and Carenini [17], an elicitation approach is being employed based on the Analytic Hierarchy Process which allows the measurement of the degree of inconsistency in elicited values.

These issues apply to the BN case and the elicitation of probabilities but also to Fuzzy Logic and the elicitation of possibility values, and can apply to yet other modeling forms requiring some values of uncertainty to be provided. Both inconsistency in elicited values and knowledge uncertainty on the part of the SME are situations leading to the need for SOU-based techniques. For example, one reconciliation approach to inconsistent values from qualified SME's is to use an interval representation that spans the provided values; intervals are just one representational strategy for SOU's. A particular challenge for soliciting and representing uncertainty and SOU from human observers are the persistent cognitive biases described by Piatteli-Palmarini [18].

Ideally, all inputs to an information fusion (IF) process are assigned an uncertainty by the input source or by a model of the uncertainty characteristics of that input source. Another point in the overall IF processing chain where uncertainty enters is in the foundational knowledge models that support the inferencing or state estimation processes of IF. Broadly speaking, most uncertainty representations for these various applications have to date employed single, precise-valued forms. It is realized of course that the IF community has also employed both the Dempster-Shafer and other characterizations of uncertainty, which are two-valued or interval-based representations. Thus, there has already been a mix of uncertainty representations in the collective works of the IF community, although the precisely-values, probabilistic frameworks have dominated the IF literature.

Addressing the SOU topic requires understanding the foundational arguments related to probability, because any imprecise probability can only come from relaxation of the Kolmogorov additivity axiom of probability. A way to show the range of generality of these representational forms is described in [19]. The second predominant way to represent second-order uncertainty is as a second-order probability. An excellent review of the debates about and the theoretical basis for second-order probability as a representational form is given in [20].

The literature thus seems to focus on two probabilistically-based strategies for representing second-order uncertainty: the imprecise probability form and the second-order probability form. A logical next question is whether there are techniques for propagating these forms through inference processes that can exploit and operate on them. CMIF has been studying these methods on two of their research grants but again this is a topic requiring extended research to develop effective, formally-correct, and practical techniques for use in operational information fusion systems. Our goal is to develop tested prototypes of methods for effectively integrating SOU representational forms and propagation techniques into Information Fusion applications for asymmetric problems.

7. Knowledge elicitation

Knowledge elicitation refers to the general problem of obtaining information from human observers or experts; this may include soliciting information about their cognitive processes, beliefs, methods, observations and the uncertainty associated with their beliefs and observations. Extensive research has been performed in this area. An excellent introduction is provided by O'Hagan et al [21]. For this discussion, we divide the problem into two related areas; (1) elicitation of general information about a cognitive decision process (e.g., methods to perform knowledge engineering to understand how an analyst processes data, makes inferences and decisions for a general problem such as situation analysis), and (2) dynamic elicitation of specific information related to the observations and beliefs about a particular instance of a problem. The first area is analogous to the original concept in expert system development of creating a knowledge base of facts, rules, scripts, frames or analogical representations of the inference process to describe how an expert such as a maintenance technician, physician, or intelligence analyst processes data to make inferences. McNeese et al ([22], [23], [24], and [25]) have conducted knowledge elicitation as part of their living laboratory research methodology for applications ranging from crisis management centers, to 911 police centers, emergency management personnel and image intelligence analysts. They have developed formal methods to conduct this elicitation process including structured interviews, in situ observations of domain experts, introduction of sample problems and stimulating questions, and post analysis. The representation techniques have involved the use of fuzzy cognitive maps to assist in representation of the knowledge [15].

The second area of knowledge elicitation concerns how to elicit information from observers about an evolving situation, event, or activity. That is, how can we obtain observations or reports with associated probabilities, confidence factors or other measures of uncertainty? Given the capability for an ad hoc community of observers to provide inputs about an observed event or activity, how should this information be solicited? Specific issues include:

- How to develop an effective human computer interface for handheld devices – how to obtain information in a rapid way in potentially stressful and complex environments (e.g., use of templates, prompts, menus, etc.)
- What methods should be used to prompt for or assess observer confidence (and second order uncertainty)
- What information should be collected to characterize the individual observer and their state (e.g. experience as an observer, demographic information, level of stress, mood, etc.)
- What methods (if any) should be used to provide effective feedback and direction to the observer

Human in the loop experiments will be conducted using the living laboratory approach and the extreme events laboratory infrastructure. We will access Penn State students as a pool of experimental subjects. In addition, we have established an agreement with the Penn State ROTC leadership to allow definition and conduct of experiments as part of their training maneuvers.

8. Tasking soft sensors

A related challenge in utilization of human reports involves the issue of sensor "tasking". Mullen and her colleagues have developed new approaches to dynamic tasking of traditional sensors and resources in a network centric environment using market based methods (see [26], [27], [28] and [29]). They have investigated the potential of market-based resource allocation algorithms to improve the performance of multi-sensor network systems in complex observing environments. The research formulated the sensor management problem as a competitive market, in which a sensor manager holds a combinatorial auction to "sell" the various items produced by the sensors and the communication channels. Because standard auction mechanisms are not directly applicable to this particular problem, it was necessary to develop specialized auction protocols. This approach has the capability to successfully deal with the strict real time considerations of the sensor network domain. Market based approaches require the explicit consideration of user-utility for the various resource allocations. Utility-based methods require that the relevance and importance of mission goals be explicitly defined. To study the effect of utility-based user modeling on sensor management, they conducted an initial comparative study of utility theory and information theoretic approaches to sensor management. The information theoretic approach models the sensor management problem as an optimization problem that involves sensor allocation to maximize information content about the environment. Direct information theoretic measures concentrate on maximization of quantity of information, neglecting the relevance of the information to the mission goals. The results of these simulations vindicate the rationale of a utility-based formulation.

While conventional sensor networks are composed solely of physical devices such as radar or infrared detectors, new technologies mean that networked data collection must consider novel "sensors" such as humans sending pictures via cell phone or intelligent software agents combing the web for information (see [27], [30]) Correspondingly, sensor management architectures must broaden their abilities to both express complex information gathering tradeoffs to users/decision makers, as well as effectively tasking fundamentally different types of sensing entities. The architectural challenge is to intelligently task humans, software agents, and sensor networks so as to best achieve various high-level goals and directives given limited resources. Using web services with service level agreements as a common Rosetta stone, adaptive sensor management middleware would compose and decompose task assignments into actionable sub-tasks. The system must be able to weigh task assignment tradeoffs such as cost, power consumption, and safety, either independently or by presenting meaningful visualizations to users/decision-makers for feedback. Such a system must be able to merge feedback from end users, from sensor performance measures, and from temporal pattern discovery so as to learn and to adapt its behavior over time.

9. Information visualization

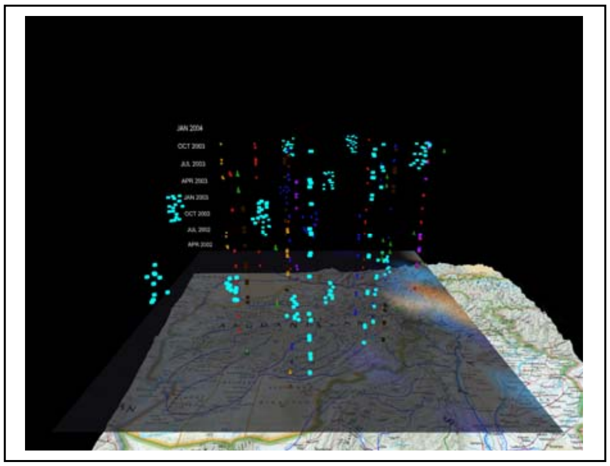

Figure 3: Sample 3-D Situation Display

Related to the overall problem of utilization of humans as soft sensors is the issue of visualization of their reports to improve situational awareness. Given an evolving situation with reports arriving for incorporation with traditional sensor data, how should such data (and associated uncertainties and SOUs) be visualized? Our on-going research has focused on development of advanced displays for situation awareness and decision making. The concept is to combine 3-D and 2 ½-D visualizations of evolving situations alternative hypotheses, consequence of selected decisions and associated uncertainties. Here, the term 2 ½ D visualization refers to the use of rotation and movement on a 2-D screen to provide an illusion of a 3-D display. We have created a basic concept, designed sample human-computer interactions, implemented a prototype software shell, and demonstrated sample displays. Both 3-D and 2 ½-D concepts have been implemented using Macromedia Flex implementation on PC platforms (for the 2-D and 2-½ D displays) and our 3-D full immersion display laboratory [31].

Figure 3 shows a tactical situation display in which multiple types of data are overlaid on a political and terrain map. In this 3-D environment, height above the terrain map is used to represent time (e.g., time of day or time of year). Different types of geometrical shapes are used to refer to different types of data. In this representation, a plane parallel to the terrain map would represent observations occurring at the same time, while a cylinder perpendicular to the map would represent a region of interest. In this view a sphere or ellipsoid would encapsulate observations within the same geo-spatial-temporal volume of interest. We can construct data base queries and resulting visualizations that focus of events, activities or targets of interest within a geo-spatial-temporal region of interest. We have implemented this capability in both our SEEL laboratory as well as in our synthetic environment application (SEA) laboratory hosted by the Penn State Applied Research Laboratory
(see www.arl.psu.edu/facilities/sealab_facilities.html).

10. Summary

We believe there will be an ever increasing generation of data by humans acting as a global community of observers. Moreover, this information via pictures, videos, text, Podcasts, and other media provide a unique opportunity for the data fusion community. Potential applications include crisis management, understanding and addressing natural disasters, and other situation assessments. Challenges for effective use of this information require learning how to treat humans and search engines as sensors with the ability to characterize their performance and potentially task or cue them, especially in crisis situations. This research area provides rich opportunities for both theoretical development and practical demonstrations of these new resources.

Acknowledgements

This research was supported in part by a grant from the U. S. Army Research Office to the Pennsylvania State University via grant # W91NF-07-1-0168.

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