Multisource information fusion for critical infrastructure situation awareness

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Abstract

Protection of critical infrastructures requires understanding the state or situation of physical infrastructure components as well as monitoring the cyber domain and the human landscape. Achieving this situation awareness involves fusion of heterogeneous information from physical sensors as well as information from human observers. Historically, the information fusion problem evolved from traditional areas such as military situation assessment. These applications involved processing sensor data using a variety of techniques, ranging from signal and image processing to pattern recognition, state estimation and automated reasoning. Recently, four new trends have emerged: (1) rapid spread of cell phones and associated global communications that enable humans to act as *ad hoc* observers, (2) interest in observing and characterizing the human landscape as well as the physical landscape, (3) advances in human–computer interactions which facilitate human participation in the fusion and reasoning process and (4) collaborative tools which support distributed team decision-making and analysis. This chapter introduces the concept of information fusion, describes recent trends and discusses its application to critical infrastructure security.

Keywords: Multi-sensor Data Fusion, Participatory Sensing, Situation awareness

1 Introduction

Rapid developments in communications and the evolving Internet infrastructure including web-based information sensors have provided the ability to link data from multiple sources to enhance individuals' understanding of their environment, better predict events and improve the allocation of resources. Participatory sensing [1], the integration of a real-time human sensor network with static sensors, is based on the increased use of mobile hand-held devices by the general public to create awareness of the human surroundings. It allows the mapping and

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studying of the environmental impact on humans, connects seemingly unrelated events and improves the discernment of wide impact phenomena.

Multi-sensor data fusion uses humans' innate ability to sense and understand their surroundings in combination with data generated by more traditional sensors. This new 'soft sensing' increases the understanding of the human terrain (i.e., the complex interactions and trends among a specific human population) while using humans' capabilities to understand their surroundings to offer a more complete picture of an environment or a target's interaction with its local surroundings. This was quite evident in the human 'public reports' sharing information about the Iranian regime's crackdown on the opposition demonstrators after the June 2009 elections. Other examples of participatory sensing include Ushahidi's website [2] for worldwide reporting of information about environmental crises, political upheavals and other events. While 'soft sensing' has inherent problems, including everything from the uncertainty of human behaviour and personal biases to issues of privacy and second-order effects such as rumour generation, there remains a viable data set for functional modelling.

2 Joint Directors of Laboratories (JDL) data fusion process model

Before proceeding to discuss the new trends in information fusion, it is helpful to provide a brief review of the history and state of the art of data fusion. We distinguish between *data fusion*, focused on fusion of data from physical sensors such as radar, Light Detection and Ranging (LIDAR), acoustic arrays and so on, and *information fusion*, which includes information from human reports and from the web. An enormous amount of research in data fusion has been conducted in support of military applications such as target tracking, target identification, situation assessment and threat assessment [3–5]. This research has led to the development of engineering guidelines for system development [6], development of techniques focused on database issues in fusion systems [7], surveys of commercial off-the-shelf (COTS) software for implementing fusion systems [8] and multiple-process models [9].

The most well-known process model for understanding data fusion is the JDL process model. The original model was created in 1991 by the JDL Data Fusion Working Group led by Frank White [10] and subsequently revised by Steinberg, Bowman and White [11]. Details of the model are described in [3] and [5]. A top-level view of the model is shown in Figure 1.

At the top level the model prescribes six basis 'levels' of fusion. These include the following:

Level 0 fusion (data or source pre-processing) – It involves processing data from sensors (e.g., signals, images, hyper-spectral images, vector quantities or scalar data) to prepare the data for subsequent fusion.

Level 1 fusion (object refinement) – It seeks to combine data from multiple sensors or sources to obtain the most reliable estimate of the object's location,

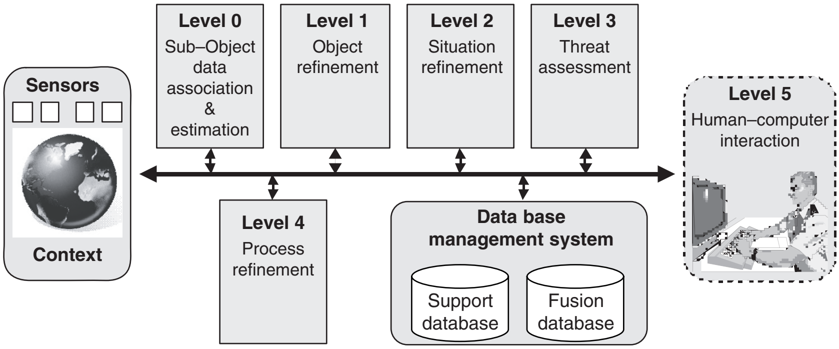

Figure 1: Top level of the JDL data fusion process model [3].

characteristics and identity. We speak here of an object (such as observing a physical object such as an airplane), but we could also fuse data to determine the location and identity of activities, events or other geographically constrained entities of interest.

Level 2 fusion (situation refinement) – Level 2 processing uses the results of Level 1 processing and seeks to develop a contextual interpretation of their meaning. This often entails understanding how entities are related to their environment, the relationship among different entities and how they interrelate.

Level 3 fusion (threat refinement/impact assessment) – Level 3 processing concerns projecting the current situation into the future to determine the potential impact of threats associated with the current situation. Level 3 processing seeks to draw inferences about possible threats, courses of action (in response to those perceived threats) and how the situation changes based on our changing perceptions. Techniques for Level 3 fusion are similar to those used in Level 2 processing, but they also include simulation, prediction and modelling.

Level 4 fusion (process refinement/resource management) – Level 4 processing is a meta-process (viz. a process that addresses a process). In particular, Level 4 processing 'observes' the ongoing data fusion process (the other levels of processing) and seeks to make the fusion process better (more accurate, more timely and more specific) by redirecting the sensors or information sources, changing the control parameters on other fusion algorithms or selecting which algorithm or technique is most appropriate to the current situation and available data.

Level 5 processing (human–computer interaction/cognitive refinement) – The Level 5 process seeks to optimize how the data fusion system interacts with one or more human users. The Level 5 process seeks to understand the needs of the human user and respond to those needs by appropriately focusing the fusion system attention on things that are important to the user.

It must be made clear that these 'levels' of fusion are defined simply for communications purposes. In actual data fusion systems, these processes are interleaved and overlap. The intent of the model is to assist in communications about data fusion functions and processing. References [3–5] provide details on these data fusion levels and associated algorithms and techniques for automated processing.

3 Comments on the state of the art

A general discussion of the state of the art of information fusion is provided by Hall and Jordan [12]. A brief summary of that review is provided below.

Level 0: Source refinement – Level 0 processing is commonly performed using advanced signal and image processing techniques. A wide variety of commercial tools are available to support this function. Emerging research is being conducted in automated semantic labelling of signal and image data [13], non-orthogonal signal processing and initial investigations of the characterization of human observers. A continuing challenge is absolute registration of image data (high accuracy mapping of image plane coordinates to geo-spatial referents). New 3-D sensors such as flash LIDAR create both challenges and opportunities.

Level 1: Object refinement – Level 1 processing involves applications such as target tracking and identification. This is a very old problem dating back to the creation of the method of least squares by Gauss to support orbit determination of asteroids. Current practices tend to explicitly separate the correlation from the estimation problem and use a wide variety of estimation techniques, ranging from Kalman filters to particle filters [14], multiple hypothesis tracking [15,16] and emerging methods such as random set theoretic methods [17]. Challenges in target tracking involve situations in which a target is erratically manoeuvring, in a dense tracking environment (with multiple targets), in a poor observing environment with low signal-to-noise or related challenges. Level 1 processing also involves automatic target recognition and characterization. Common techniques include machine learning, pattern recognition and automated reasoning [18]. Some efforts are underway to use methods such as intelligent agents and fuzzy logic methods [19]. Current challenges include situations in which there is limited or no training data (to train the pattern recognition methods), lack of context-based information and limited or weak link between observed characteristics of a target or event and the inherent *identity* of the target or event.

Level 2: Situation refinement – This is a challenging problem in which we seek to understand an evolving situation perhaps involving multiple targets, events or activities in the context of their environment. Current methods have sought to use automated reasoning methods (e.g., knowledge-based rule systems, neural networks, case-based reasoning, intelligent agents or other methods) [20–22]. To date there has been limited progress in developing effective cognitive models and translating those models into effective automated reasoning schemes.

The most recent methods for situation refinement involve representation of data and inter-relationships using graph theory, including so-called dirty graphs, in which relationships can exhibit uncertainty or imprecision [23].

Level 3: Threat refinement – This is analogous to Level 2 processing but is focused on the future, seeking to predict future threats or situations and understanding their potential impact. This is very domain specific. Except for physically modelled systems such as target motion, very limited predictive models exist. There are some efforts to use hybrid reasoning techniques in which information from historical data is mined and used in combination with contextual reasoning by human analysts and model predictions.

Level 4: Process refinement – This process is a meta-process which seeks to monitor the ongoing fusion effort and make refinements to improve the resulting inferences. For systems involving controllable sensors and communications links, robust optimization methods based on operations research perform well. Challenges occur when there is limited control over the information sources, a weak link between the observables and desired fusion results, and if there are confounding issues such as deception, adaptive adversaries and limited resources such as communications. There are particular challenges when humans are used as information sources. Not only is it difficult to task *ad hoc* observers, but the very act of requesting information can bias the observer's results. Recent research has used concepts from electronic market systems [24] and intelligent agents as proxies for bidding for resources.

Level 5: Cognitive refinement – As fusion systems transition from a situation in which humans are considered to be passive users of the fusion results to hybrid systems in which humans are actively engaged in observation, pattern matching, context-based reasoning and collaboration, the Level 5 area becomes increasingly important. Rapid advances in human–computer interface (HCI) technologies have been demonstrated in areas such as 3-D immersive displays, haptic interfaces, 3-D sound and direct computer/brain interfaces. As a result, it is anticipated that new concepts for human/data interaction will emerge. Creative HCI research is needed to adapt fusion systems to the needs of individual users and to promote the mitigation of known human cognitive biases and illusions. There is limited work on 'crowd-sourcing' of analysis (e.g., using virtual world technologies) and on *ad hoc* analysis [12].

4 Human-centric information fusion

Hall and Jordan [12] describe the concept of human-centred information fusion (illustrated in Figure 2) and identify four new trends in information fusion.

The key trends include the following.

The domain of interest is changing – Traditional data and information fusion systems have focused on observing and characterizing the physical domain or landscape. For critical infrastructures this might translate into monitoring the machinery or equipment in a factory or power plant or monitoring the condition

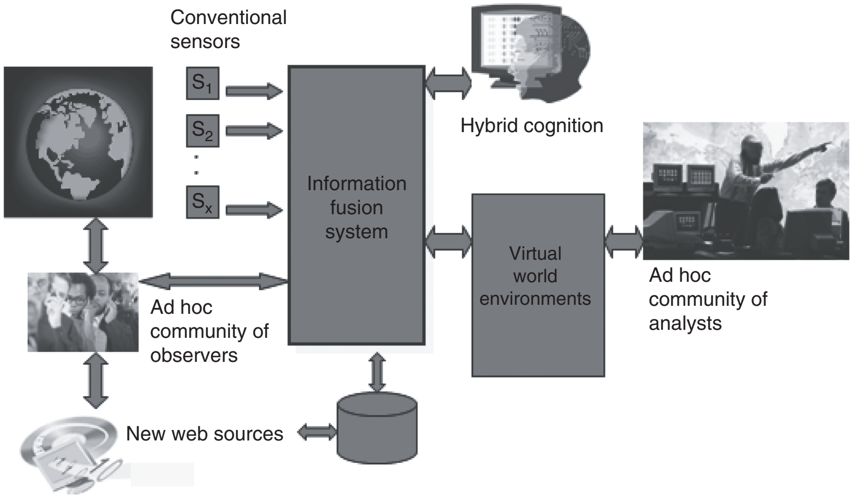

Figure 2: Concept of human-centred information fusion (adapted from [12]).

of a road or communications network. The focus has been to observe the physical situation via physical sensors. Increasingly, however, there is recognition and interest in monitoring the human landscape. In an extreme event such as environmental disaster, it is just as important to understand the make-up, mood, cultural factors, health and other factors that affect how humans would be affected by the disaster as well as how they would react. Similarly, in order to protect the critical infrastructures against criminal or terrorist threats, it is necessary to understand both the potential adversaries as well as the people affected by any adversarial action or threat.

The new human observer – The rapid growth of cell phone dissemination and continually improving cellular communications bandwidth provide the opportunity to create a dynamic observation resource allowing humans to act as 'soft' sensors. Information obtained by humans (via direct reports and information from open source information on the Internet) can be valuable and significantly augment data obtained from traditional sensors, such as unattended ground sensors, radar and sensors on-board airborne vehicles. While extensive techniques exist to combine data from traditional sensors, only limited 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. However, humans can provide valuable inferences and observations not available from standard sensors, such as inferring identity, intent and interactions with other people. Llinas, Nagi, Hall and Lavery [25] describe a new research programme focused on the fusion of hard and soft information. Hall and Jordan cite a number of challenges in processing human source information, including (1) tasking, how to effectively task *ad hoc* observers; (2) knowledge elicitation, how to solicit information from observers without unduly biasing them; (3) how to translate human language observations (e.g., 'I see a man near the car') into quantitative values; (4) how to determine the reliability of the human observer; and (5) how to address the truthfulness of an observation and many others.

The human as hybrid analyst – A second new role of humans in information fusion involves humans acting in a cooperative way with automated computing processes. This may entail human visual and aural pattern recognition and semantic reasoning to augment the automated processing performed by a computer. We imagine a human/computer team working together to understand an evolving situation or threat. Pinker [26] notes that humans have the ability to recognize and reason with language, and the ability to recognize patterns and reason using a kind of visual physics. It is easy, for example, for a human to identify containers or objects in a room that could hold a liquid – despite the fact that these may include glasses, cups, pots, pans, a sink or a bottle. This would be challenging to automate. The variety of possible containers and the concept of 'hold liquid' would be difficult to encode into a pattern recognition algorithm. Similarly, we can express contextual knowledge via sentences, descriptions or stories about an event, activity, groups of humans or collection of entities. Despite advances in automated reasoning via rules, frames, scripts, logical templates, Bayesian Belief Nets or other methods [27,28], it is challenging for a computer to match the semantic abilities of almost any human.

However, computers are excellent at numerical calculations such as computing physical motion of objects, fluid flow, statistical estimation and physics-based modelling. Computers can perform calculations and predictions that are not feasible for humans. Clearly, information fusion systems should combine the capabilities of humans and computers to create hybrid reasoning systems capable of performing better than either alone.

The human as collaborative analyst – Finally, we believe that humans can perform a major role in information fusion by dynamic, *ad hoc* collaboration among multiple people. Examples of worldwide distributed collaboration are described by Shirky [29] and Howe [30]. The term 'crowd-sourcing' has been used to describe the concept of using a group to provide information or address problems. Sawyer [31] describes the concept of collaboration over a period of time, concepts of 'group flow' such as group improvisation and customer innovations and concepts of group genius. As a faculty member teaching information science and technology, I observe that the 'digital native' students, who have grown up in the age of the Internet, cell phones and online social networks, commonly address assigned problems by contacting 'the hive mind' to see if others in their social network have addressed such a problem before or have pertinent information. Similarly, Palrey and Gasser [32] describe the generation of digital natives and the impact that has on commerce, education and social interaction. New information technologies such as groupware, visual world tools such as Second Life, social networking sites and others provide the opportunity for distributed collaboration for problem-solving. Such concepts can be used in addressing complex situation awareness problems.

5 Implications for infrastructure situation awareness

What are the implications for infrastructure situation awareness? On the one hand, there is a rapid explosion of sensors throughout the world. Hall and Jordan [12] provide an extensive table of information (see Chapter 8, Table 8.5 in reference [12]) about categories of data such as the physical terrain, geology and natural resources; hydrography; weather; natural vegetation; transportation; agriculture; energy; commerce; communications; population; economic conditions; and human landscape information. The table summarizes the data types and sources of data and provides references for collection resources. The proliferation of embedded sensors, web cameras, commercial satellite resources and local sensors are available to virtually any user. Scientific data-collection projects such as the NASA earth observatory [33] provide global coverage of the physical environment, while projects such as the Gallup World Poll collect information about the human landscape. In addition, it is relatively easy to establish surveillance systems of physical environments using web cameras. A recent iPhone application (the iCam App) allows anyone to easily set up cameras to monitor a home or area and send alerts and video information about potential intrusions.

On the other hand, the emergence of *ad hoc* human observers provides an opportunity to extend the monitoring of critical infrastructures to human reports. Numerous examples are available regarding the value of human observations of an emerging event or activity. Examples include the following:

- Twitter reports of crime and information from first responders are available via a special website [34].
- International reporting of events and activities is enabled by the Ushahidi crowd-source project [2].
- The United States Geological Survey (USGS) earthquake hazards programme [35] provides a source for reporting civilian observations of earthquake activity.
- The use of sanitation workers' reports on unusual activities or crime [36].
- Multiple projects involving the concept of a global neighbourhood watch encourage local citizens to report on crime, the environment, accidents and other problems.

The emerging theme is that enormous amounts of data from physical sensors and human observers are becoming available to monitor the components of critical infrastructures. A challenge will be to fuse the hard and soft data to support situation awareness and effective decision-making.

6 Summary

Information fusion techniques have made great progress, spurred in part by funding of research for military applications such as target tracking, target identification, situation awareness and threat assessment. Thus, numerous techniques exist to support functions such as signal and image processing, data association and correlation, pattern recognition, state estimation and, to a lesser extent, automated reasoning for situation awareness. Such techniques have focused primarily on the use of physical (hard) sensors to observe the physical environment. Recent trends in information fusion have made humans a more integrated part of fusion systems as observers (soft sensors), pattern recognizers and conduct of semantic-level reasoning, and finally as collaborative decision-makers. Moreover, the object of fusion processing has extended to the human landscape as well as the physical domain. This human-centric evolution of fusion systems has significant application for critical infrastructures situation awareness. The rapid development and dissemination of sensors such as video, cameras, acoustic sensors, LIDAR and other devices provide a means of monitoring physical components of critical infrastructures. In addition, rapid deployment of cell phones and worldwide communications provides the opportunity for a 'global neighbourhood watch' in which everyone becomes a potential observer to defeat threats to critical infrastructures. Thus, it will increasingly become useful and necessary to fuse information from both hard and soft sensors, providing enhanced awareness of the current state and situation of our critical infrastructures.

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