

# A Framework for Multi-source Semantic Information Extraction & Fusion for Collaborative Threat Assessment (SIFT)

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**Abstract:** *This paper describes the motivations, methods, and automation architecture of a framework for multi-source Semantic Information extraction & Fusion for collaborative Threat assessment (SIFT). First, the technical and pragmatic challenges that motivate the research ideas are summarized. Next, a characterization of the activities for generating decision enabling information from multi-source data is provided. This characterization, called the 'SIFT Method,' specifies the SIFT automation support requirements. The SIFT architecture is described next. Finally, the paper summarizes the significance and benefits of the SIFT solution and outlines key areas that would benefit from additional research and development. The application of SIFT is expected to significantly reduce 'data-to-decision' time through the use of semantic and collaborative visual analytics techniques.*

**Keywords:**

## 1 Motivations

This section summarizes the technical challenges that motivate the ideas described in this paper.

### 1.1 Information overload challenges

Defense and security analysts are drowning in a flood of information. Modern sensors and reporting systems produce unprecedented amounts of data; modern processing capability is transforming, churning, and translating that data at an ever-increasing rate. Yesterday's analysts had to be experts at interpreting the sparse data they could obtain; tomorrow's analyst will need different expertise: finding, corroborating, and interpreting actionable information from the rising flood of data. Evolving and emerging information technology provides the opportunity to equip tomorrow's analyst for this challenge. Improvements in communications capabilities make collaboration in near real time and at continental distances a reality today. Semantic information processing provides the analyst with access to deeper understanding of data—bringing data closer to information even before the analyst

sees it. And modern visualization techniques allow for rapid assessment of large amounts of data and enhance the analyst's ability to communicate observations, hypotheses, and findings. A key challenge is to provide significant reductions in 'data-to-decision' time through the use of advanced methods and tools.

### 1.2 Asymmetric threat assessment challenges

Today our enemies can strike anywhere, anytime, and with a wide variety of weapons. As a consequence, a goal for homeland security should not be tied to a specific threat, but should rather address the underlying vulnerability of our society and the inherent unpredictability of hostile conspiracies. The Internet is a reflection of our social fabric, and we can leverage this open source information repository to measure indicators of threat around the globe. Most of this information is in unstructured textual form; consequently, automating the process of information extraction is particularly difficult. In spite of the significant advances made in the fields of machine learning, data/text mining, and information fusion, there are several technical voids that limit the utility of these techniques and tools for facilitating indications and warnings that support automated asymmetric threat detection.

An effective threat assessment scheme must support threat detection at the strategic, operational, and tactical levels of asymmetric warfare and must use information from a universe of data sources. These sources should enable the extraction of multiple measures supporting threat indications at the strategic, operational, and tactical levels. For example, threat dimensions should detect and track a potential adversary's wide variety of preparations such as an asymmetric attack, policy shifts, and/or advances in the capability or the acquisition of new technology. These requirements dictate the need for computational approaches to adapt to real time data feeds.

Emerging threats are fundamentally different in several ways. First, the threat is usually physically small (perhaps from a single operative) and is not easily observed, especially using existing reconnaissance systems. Second, the costs to carry out such asymmetric threats are very low.

For example, it no longer requires the resources of a nation state to develop a weapon of mass destruction. In today's world, analysts need to analyze vast amounts of information from multiple sensors and sources and piece together evidence necessary to understand, assess, and meaningfully interpret threat activities.

The next section describes the Multi-Source Semantic Information Extraction & Fusion for Collaborative Threat Assessment (SIFT) method.

## 2 SIFT method

This section describes the SIFT method: a characterization of the activities and their inter-relationships for generating decision enabling information from multi-source data. The SIFT method is comprised of four inter-related activities, shown in Figure 1.

As specified in Figure 1, SIFT provides four broad categories of functions: (i) Semantic Tagging; (ii) Information Fusion; (iii) Discover Knowledge for Sense Making; and (iv) Provide Collaborative Visual Analytics. These activities are summarized in the following paragraphs.

### 2.1 Perform semantic tagging

Semantic tagging refers to the activity of 'labeling' data with 'tags' that provide 'meaning' in the context of an application about the information contained in the data.

Two types of data are tagged (within the scope of this project): text and images. Text data tagging is done using an ontology-based natural language processing (NLP) capability. This includes the capability to generate Resource Description Format (RDF) semantic labels from multi-format raw text data. The SIFT image data tagging (a) leverages previously image-processed data and (b) exploits the information provided within the image 'metadata' tags. The image processing includes object detection, tracking, and background/foreground segmentation.

A unique aspect of our semantic tagging approach is to use an ontology to increase the semantic quality (depth of meaning represented) of the resulting text and image tags. To illustrate, the semantic tagging activity for an example sentence is shown pictorially in Figure 2.

The 'heavy lifting' that is necessary to convert the raw text into meaningful information is provided by the KBSI NLP 'pipeline,' shown in Figure 3.

The process shown in the figure uses a combination of NLP techniques and is capable of scaling to handle large text data collections in multiple formats. A unique innovation is the ability to use an ontology to increase the richness of the semantic tags. Each block in the pipeline is labeled according to the set of tags that are added to the input text after the input text has passed through the block.

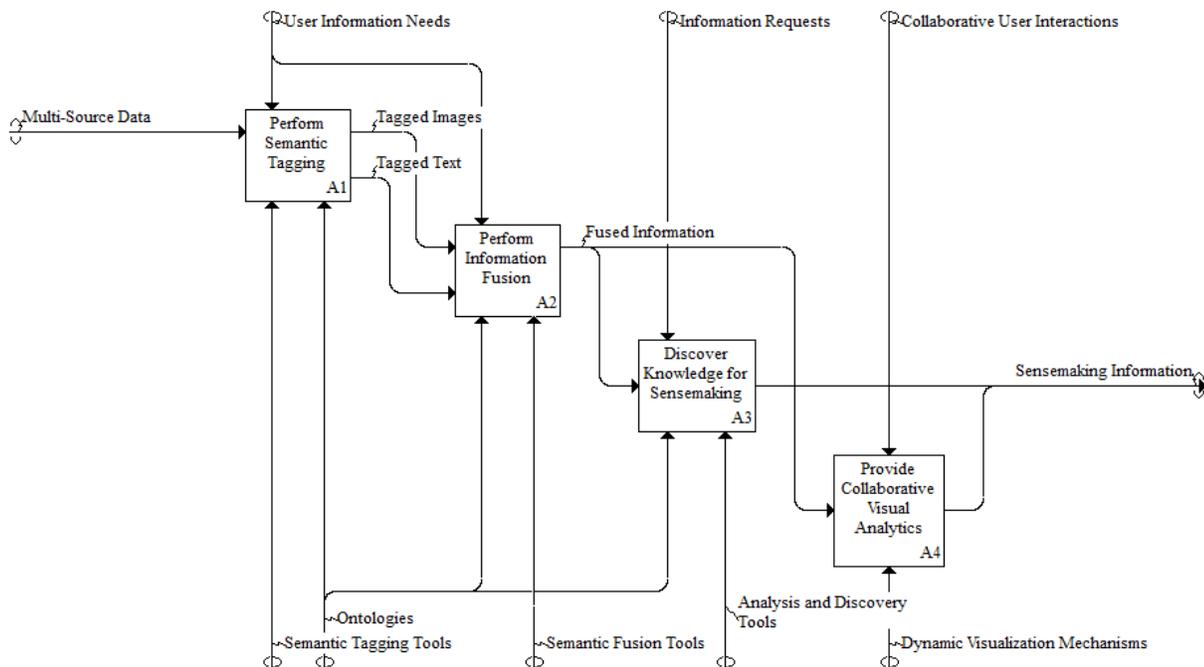


Figure 1. The SIFT Method

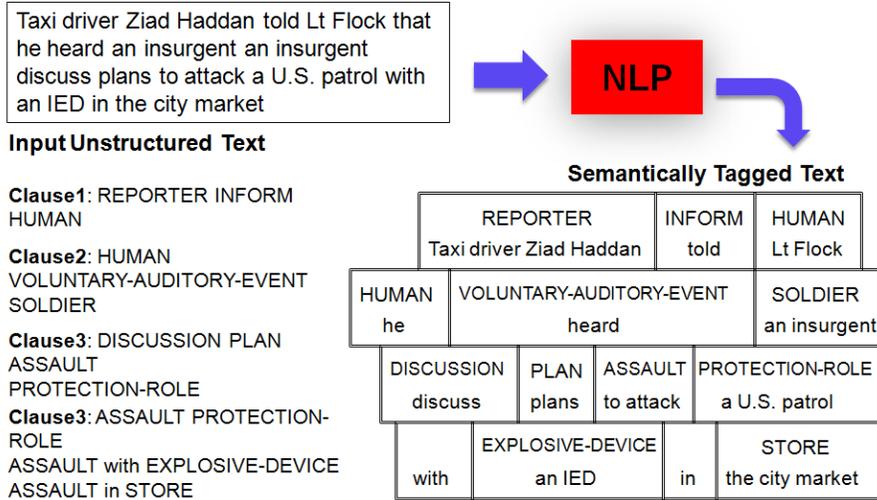
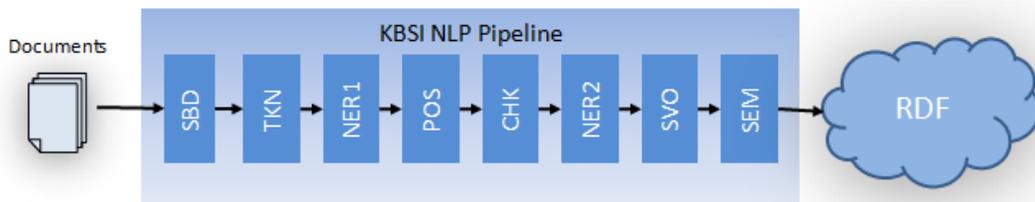


Figure 2. Semantic Tagging Induces ‘Semantic Labels’ to the Clauses in Every Sentence



- **Sentence Boundary Detection (SBD)**
- **Tokenization (TKN)**
- **Named Entity Recognition Level 1 (NER1)**
- **Part of Speech Tagging (POS)**
- **Phrase Chunking (CNK)**
- **Named Entity Recognition Level 2 (NER2)**
- **Subject-Verb-Object, Clause Identification (SVO)**
- **Semantic Analyzer (SEM)**

Figure 3. Dataflow Diagram of the KBSI NLP Pipeline

## 2.2 Perform information fusion

The semantic tagging activity produces an ‘integrated tagged data set’ that combines the semantic information contained in the tagged text, tagged images, and geospatial databases. The resulting integrated, semantically tagged dataset provides an expressively rich ‘knowledge base’ that will be useful for exploratory search and discovery and collaborative visualization and sense making. A key idea underlying our approach is the use of a ‘reference ontology’ to support the fusion of information derived from text and other types of intelligence-seeking sensors. The current implementation of SIFT focuses attention on fusing information from text and image data

sources. The approach may be generalized to fuse information from multiple types of data sources.

The multi-source fusion is at a higher level (level 2 and above) in the context of the JDL multi-sensor fusion terminology described in [1] and [2]. There have been research studies to apply ontological semantic modeling for knowledge representation and fusion for image and video data [3]. These methods address some of the challenges in dealing with multi-sensor fusion and image data fusion. Our research focused on information fusion approaches incorporating semantic ontological information extracted from text data sources (human sources and open sources, such as social media) along with image data.

Combining the JDL characterization of multi-sensor fusion with widely used models of situational awareness (SA)

(e.g., [4]), information fusion may be summarized as follows:

- Object Level (Level 1 Fusion). The first level of information fusion relates to SA on the objects that participate within the environment (the status, attributes, and dynamics of relevant elements in the environment). Within the context of threat assessment applications, this refers to fusion that enables generating a good SA of the actors, their attributes and roles, spatio-temporal location within the physical and cyber-world, etc.
- Situation Level (Level 2): The second level of information fusion relates to SA on the intents and motives and the relationships between the objects that participate in the environment. Relative to a threat assessment application context, this would refer to fusion that allows for generating a good SA of the current situation: the state of the world in terms of the structural relationships between the actors, the intent and motives of individuals and the group, the level of achievements towards the intents and motives, etc.
- Impact or Future State Level (Level 3): The third level of information fusion relates to SA on anticipated future courses of action of the participating entities, or the future situation. Within the context of threat assessment applications, this would refer to fusion that allows for generating a good SA of future evolution – the state of the world that could be – in terms of the evolution of the structural relationships between the

actors, the evolution of intent and motives of individuals and the group, the projected level of achievement towards the intents and motives at a future point in time, etc.

The SIFT information fusion approach uses an application domain ontology to intelligently guide the focused contextualization of the fusion activity. The key idea here is that the ontology acts as a ‘bridge’ that helps determine the mapping between the information items in the different tagged data forms (text, images, and geospatial data). The fusion technique involves performing the following process tasks: (i) the ontology, (ii) the tagged image data, (iii) the tagged text data, and (iv) the tagged geospatial data. The results of (i) through (iv) are then used to compute the ‘semantic distance’ between the concepts in the ontology and the concepts in (i) the tagged data, (ii) the tagged text data, and (iii) the tagged geospatial data.

The next step is to use a set of heuristics (e.g., find the intersection of ‘low semantic distance’ mapped ontology concepts for the various mappings) in order to determine the relative strengths of the semantic connections between the concepts of the three different tagged sets (images, text, and geospatial). The semantic connections determined through the application of this ‘bridging’ heuristic will be used to create fused tags that combine the three tagged data sets.

The example shown in Figure 4 illustrates the above ideas of using an ontology for fusing text and image data.

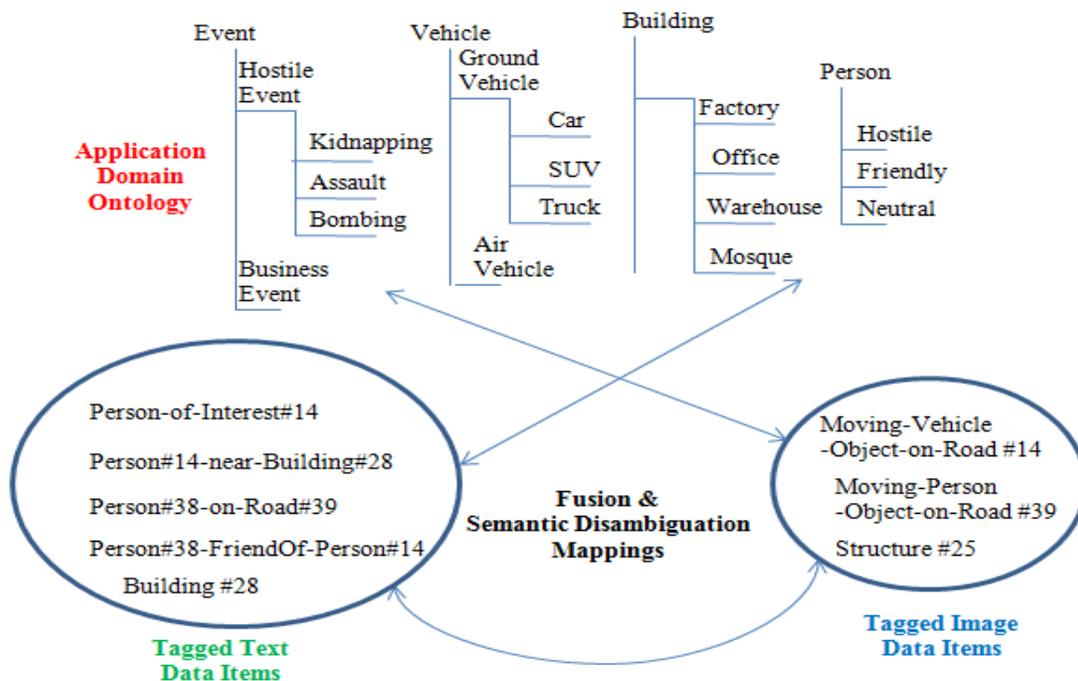


Figure 4. Example that Illustrates the Ontology-Driven Text and Image Fusion Solution Approach

In the above example, suppose that the instances of Moving-Vehicle-Object-on-Road, Moving-Person-Object-on-Road and the Structure (from the tagged image data) were determined to be ‘semantically close’ to the ontology concepts Vehicle, Person, and Building. In a similar manner, suppose that Person#28-on\_Road#39 and Person#14-near-Building#28 (from the tagged text data) were determined to be ‘semantically close’ to the ontology concepts Hostile Person (subclass of Person). Further, it is apparent that Building#28 is an instance of the Building ontology concept. Assuming that the tagged data had time stamps that were nearly identical, the above semantic distance determinations will be used to induce a ‘fusion mapping’ between Structure#25 and Building#28, and also between Moving-Person-on-Road#39 and Person#38-on-Road#39. The latter mapping might help make the determination that Moving-Person-on-Road#39 was in fact Person#39 (or increased the probability of the belief in this assertion). The above example, though simple, illustrates the power and utility of an application domain ontology in the multi-source fusion and semantic disambiguation process.

### 2.3 Discover knowledge for enhanced situational awareness

The results of the semantic tagging and the information fusion activities produce a rich repository of information that may be exploited to support enhanced SA, sense making, and improved decision making. SIFT provides multiple mechanisms for collaboratively ‘discovering’ action-enabling knowledge from this information, including the following: (a) semantic search, (b) social network extraction and analysis, and (c) event extraction and analysis. The SIFT semantic search capabilities employ an ontology-driven approach that produce results with higher precision and recall; the social network extraction and event extraction are accomplished using ontology-directed semantic querying over the semantically tagged information. Lastly, the ‘search collaboration support’ in SIFT provides the following distinguishing features: (i) automatic detection of similar tasks between different users with notifications, (ii) the ability to browse the results of a different user who is working on a similar task, and (iii) the ability to modify one’s own query builder with the user feedback provided by a different user.

### 2.4 Perform collaborative visual analytics

This activity provides dynamic visualization mechanisms to enable collaborating end users to better understand information contained within multi-source data leading to sense-making and enhanced SA [5]. This activity uses a semantic tag-based approach that maintains and traces through hierarchies of different scales of space and time granularity for asynchronous collaborative visual analytics. The semantic tags, carrying scaled spatio-temporal information, helps users navigate between text visualization, space visualization, temporal visualization, and spatio-temporal visualization.

## 3 SIFT architecture

An automation support toolkit has been developed and tested for the SIFT method described in the last section. The SIFT conceptual architecture is shown in Figure 5.

As shown in Figure 5, data streaming from multiple and distributed sources is first pre-processed and then semantically tagged using information extraction and ontology-based NLP methods. The semantically tagged information from multiple text and imagery sources is then fused using information fusion methods to collaboratively derive useful information for decision making. Collaborative and interactive visualization mechanisms are used to facilitate enhanced understanding and SA based on the information contained in the multi-source data. The results of the tagging, analytic processing, and collaborative visualization provide directed insight and enhanced SA to collaborating end users. The SIFT architecture solution provides the capacity to answer questions such as what are the objects or who are the persons of interest in the emerging situation, who are the key leaders and what are their social networks, where are the events taking place, how are the events being carried out, why are the operations of interest, etc.? Answering these questions involves augmenting human subject matter expertise with fused threat assessments derived from multiple sources and sensors while taking into consideration subject matter expert knowledge.

*Text Processing Tools:* This set of tools enables automated extraction of semantically tagged information from multi-source text data. The text data includes human observation-based data and social media data. Ontology-based NLP methods are used to perform the semantic information extraction and semantic tagging as described earlier. The text processing activities produce semantically tagged text data that is persistently stored and managed.

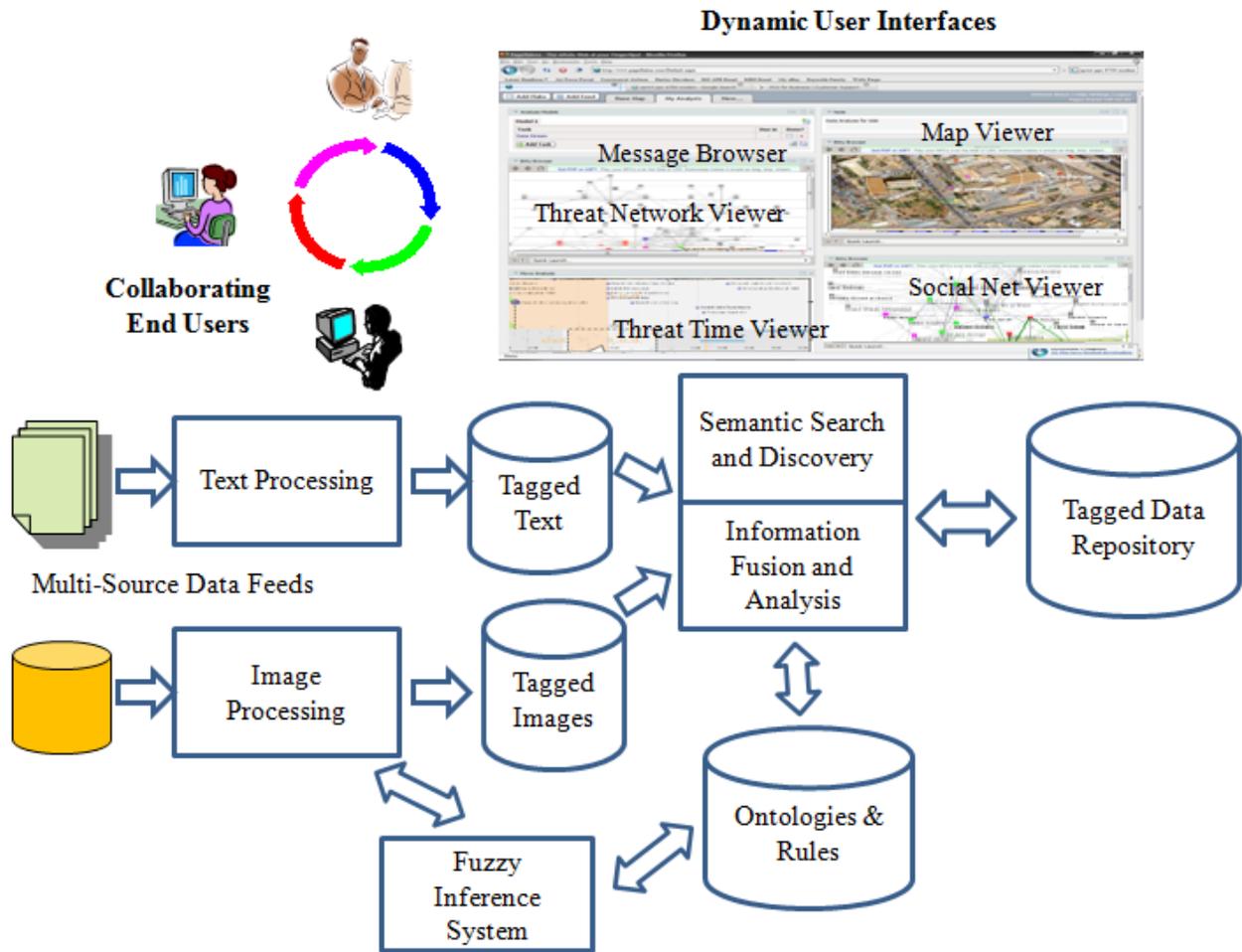


Figure 5. Automated Semantic Tagging, Information Fusion, Discovery, and Collaborative Analytics

**Image Processing Tools:** This set of tools enables automated processing of surveillance imagery data. The image/video processing algorithms perform lower and mid-level processing tasks such as moving target detection, tracking, object detection, background-foreground detection, learning classification model parameters, image segmentation and registration, etc. Human-in-the-loop ‘anomaly detection’ is performed using fuzzy inferencing techniques based on an analysts’ assessment of imagery data. The image processing steps produce semantically tagged imagery data that is persistently stored and managed.

**Fuzzy Inference System:** This set of tools enables the capture of surveillance imagery analyst inputs and generates a characterization of ‘anomalous objects’ in the imagery based on the intuition of the human analysts. The intuition input classification for anomaly detection uses a fuzzy logic-based approach.

**Semantic Search and Discovery Tools:** This set of tools provides for intelligent search and collaborative discovery of information that will support threat assessment and decision making. Ontology-directed semantic querying

methods are used to support intuitive discovery and information sharing between collaborating end users.

**Information Fusion and Analysis Tools:** This set of tools enables fusion of information generated from multi-source and multi-modal data. As described earlier, the types of data include surveillance imagery, human observation-based data and reports, and social media-based text and image data. The fusion-enabled collaborative analysis is a semi-automated process with a human-in-the-loop aiding the analysis and incorporating the reasoning results as part of new analysis hypotheses and explorations. There are tasks that humans can perform better such as *connecting the dots* and *intuition* to generate potential hypotheses about an event or persons of interest. A computer is better at validating or refuting these hypotheses by processing, retrieving, and rank ordering various sources of information and facts in the presence of various levels of uncertainty. By combining the strengths of human analysts with that of the computers, SIFT supports faster and more accurate threat analysis.

The results of the fusion are used by a group of analysts working together collaboratively with the help of the automatic and semi-automatic analysis software tools. The

collaboration support provided by the SIFT architecture includes ‘intra-group’ (e.g., within a single analysis center) and ‘inter-group.’ The iterative and incremental understanding of the overall picture of the situation emerges based on such a collaborative effort, with the help of multi-source fusion techniques. Collaboration plays a crucial role in the collective ability of threat assessment teams to effectively process and understand the various individual pieces of discovered “knowledge-bits,” each with its own level of inherent uncertainty, piecing them into context, and drawing conclusions. A key aspect of collaborative knowledge discovery is information integration and reasoning with uncertain information in order to derive the optimal collective SA.

In addition to fusion, the deep semantic content of the tagged data is exploited for automated social network extraction and analysis and automated event extraction and analysis. The example SIFT user interface displayed in Figure 6 illustrates how Bayesian fusion may be used to resolve uncertainties in a social network.

*Collaboration & Visualization Tools:* this toolset enables collaboration and dynamic visualization support using collaborative visual analytics techniques to support end user interpretation and enhanced decision making. Specifically, SIFT provides dynamic and interactive visualization aids to help collaborating end users visualize information to support sense-making as shown in Figure 7.

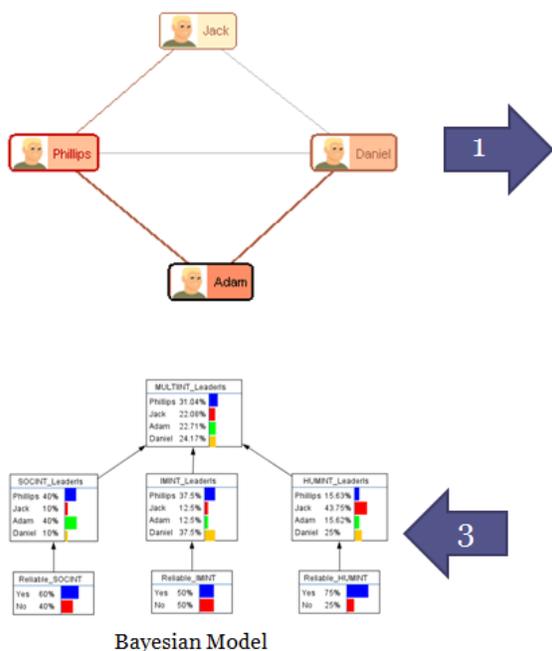
SIFT supports the technique of ‘brushing and linking,’ which enables a change in one view to automatically

propagate to all other views of related information [6]. The SIFT automation architecture provides brushing and linking for multiple user interface views including social networks, events (including a timeline view), and geospatial map-based visualizations as shown in the figure.

## 4 Benefits and opportunities for further research and development

### 4.1 Summary of SIFT benefits

This paper described the motivations, methods, and automation architecture of a framework for multi-source Semantic Information extraction & Fusion for collaborative Threat assessment (SIFT). The main benefits of the SIFT solution described in this paper are (i) significant reductions in ‘data-to-decision’ time through the use of semantic and collaborative visual analytics techniques; (ii) substantial gains in the quality of shared SA through fusion of information gained from multiple sources; (iii) significant increases in the ability to exploit information and knowledge embedded within data through the use of ontology-driven semantic methods; and (iv) superior abilities to leverage and better use increasingly scarce and time-constrained human cognitive and decision making skills through the use of collaborative sense-making techniques.



Degree grouped by Source Type:

Name	HUMINT	SOCINT	IMINT
Jack	2	0	0
Phillips	1	1	1
Adam	1	1	0
Daniel	2	0	1

2

Probabilities calculated from above table:

Name	HUMINT	SOCINT	IMINT
Jack	43.7%	10%	12.5%
Phillips	15.6%	40%	37.5%
Adam	15.6%	40%	12.5%
Daniel	25%	10%	37.5%

Figure 6. Multi-Source Bayesian Fusion to Support Enhanced Situational Awareness

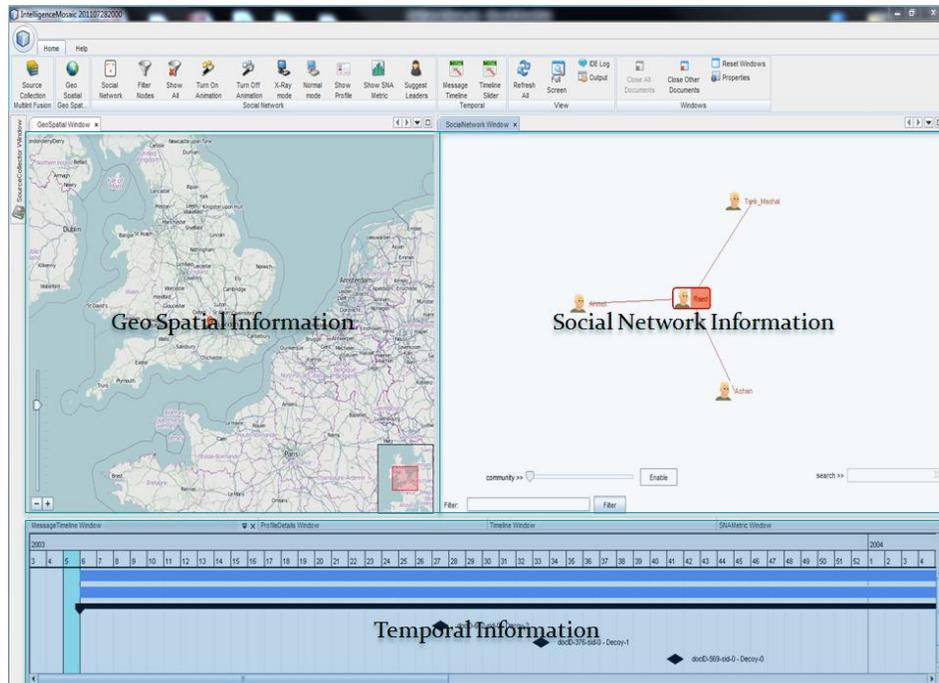


Figure 7. Dynamic, Multi-view, Intelligence Analysis SIFT User Interface Example

## 4.2 Opportunities for future research and development

Areas that would benefit from further research and development activity are summarized in the following subsections.

### 4.2.1 Ontology management capabilities

The SIFT method uses an ontology-based approach for semantic information extraction and semantic tagging. Needed are better tools for discovering, eliciting, and maintaining ontologies.

### 4.2.2 Addressing uncertainty and errors in data

The SIFT method processes raw data of multiple types and modalities and in different formats. Real world data sources contain data that is incomplete, corrupted, and include different types of errors and inconsistencies. There is a need for methods and tools to address and manage errors and uncertainties inherent in data.

### 4.2.3 Multi-source fusion

Much of the research in data fusion is focused on generating useful information from multiple types of (structured) sensor-based data. There is a need for research on fusion methods that focus on unstructured data types and fusing information derived from structured data with information derived from unstructured data (e.g., fusing information derived from a sensor with information derived from unstructured text).

### 4.2.4 Truth maintenance

The SIFT methods include the use of automated reasoning for inferring new information. The problem of maintaining and evolving a complex knowledge repository derived from the application of multi-source fusion and reasoning techniques has not been addressed in the current implementation of the SIFT solution. There is a need for better methods and tools that support truth maintenance in knowledge repositories.

### 4.2.5 Collaboration support

The SIFT solution provides collaboration support for synchronous collaboration among distributed end users. Better methods for collaboration are needed that support synchronous and asynchronous collaboration among users that are distributed in time and space.

## 5 References

- [1] A. Steinberg et al., "Revisions to JDL Datafusion models," Technical report ERIM International, Inc., 1999.
- [2] D.L. Hall and J. Llanas, "An Introduction to multisensory data fusion," Proc. of the IEEE, Vol. 85, No. 1, Jan 1997, pp-6-23.
- [3] Christopher Town, "Ontological inference for image and video analysis," J. of Machine Vision and Applications (2006) 17(2): 94–115, Springer-Verlag.

[4] Endsley, M. R. Theoretical Underpinnings of Situation Awareness: A Critical Review. In Endsley, M. R., and Garland D. J. (Editors). 2000. *Situation Awareness Analysis and Measurement*. Lawrence Erlbaum Associates.

[5] Heer, J., Viegas, F., Wattenberg, M., Voyagers and Voyeurs: Supporting Asynchronous Collaborative Information Visualization, ACM Human Factors in Computing Systems (CHI), 1029–1038, 2007.

[6] Heer, J and Shneiderman, B., Interactive Dynamics for Visual Analysis: a Taxonomy of Tools That Support the Fluent and Flexible Use of Visualizations. ACM Queue, Feb. 1, 2012.