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Semantic Mediation for Dynamic Fusion of Human Observations and Sensor Data

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This paper addresses the problem of combining human observations and sensor data for entity tracking and identification in dynamic environments. The complexity of the track-and-detect task for realistic applications requires dynamic fusion of sensor data and observations, and a semantic mediation approach is adopted. Moving targets are detected and classified based on sensor data. Soft data in the form of short messages are automatically processed to identify relevant information, to be associated with entities detected by sensors. While sensor data provide rows of numerical features, observations convey finer descriptions of entities and contextual information that is intuitively included by human sources when reporting. A fusion system accommodates both sensor and soft input, and provides a unified framework for their effective integration. The system relies on semantic mediation to combine observations and sensor data and uses ontologies to create a bridge between two complementary representations of the same situation.

Introduction

In dynamic environments, where entities of interest can be not only mobile, but also geographically dispersed, versatile and unpredictable, sensing devices come close to their limits of perception. Human sources are then a key feature to be considered, since they can provide finer input about entities.

Traditionally, fusion systems handled sensor and soft data fusion as two distinct problem sets, based on the intuition that track-and-detect applications seemed to be well supported by fusion of sensor data, while human reports and open sources are more suitable to analyze asymmetric threats in urban areas. The following example shows that the sensor vs. soft data dichotomy is out of date, and makes the case for a unified approach. Let us consider a convoy of vehicles that illegally crosses the border between two countries. As with any illegal crossing, an alarm is triggered and the entity is tracked by a sensor-fusion system. While the convoy approaches a city, one of the vehicles enters the urban area and losing its track is highly possible, since urban terrain has a very dense traffic and affects visibility and line-of-sight communications. Once track loss occurs, any eyewitness sighting or testimonies from bystanders during their day-to-day activities can be of interest and the track-and-detect problem requires not only sensor based fusion, but rather a joint analysis of sensor and soft data. The task does not require qualified field analysts, but rather selecting people who are close to the incident and who may be opportunistic sources and provide meaningful input.

This paper presents a semantic approach to combine soft and sensor data for entity tracking and identification. A general architecture was developed for information fusion, which creates a situation using sensor data and enriches this situation by taking into account observations. The reminder of the paper is organized as follows: Section 2 presents related work on sensor semantics. Architecture of the system and fusion cycles are discussed in Section 3. Section 4 presents approaches developed to process soft and sensor data. Semantic mediation is discussed in Section 5, along with the ontology created to support the overall approach and a practical illustration for entity identification. The last section concludes with a summary and directions for future work.

Related work

The prevalence of heterogeneous systems and their use in applications ranging from health-care to urban traffic monitoring, or security and surveillance, are accompanied by an increase in the heterogeneity of devices connected and formats of data collected, processed and shared. For such systems, semantic technologies offer a way to manage heterogeneity, by providing a common interface to disparate sensors, combining their formats into a unified one and building a coherent view of data.

Several research efforts have been conducted to build ontologies modeling sensors and sensor data, in order to develop techniques augmenting their output and approaches combining heterogeneous sources, as discussed hereafter. Modeling sensor ontologies is a major direction investigated to represent sensor location and supply, along with accuracy, type and frequency of observations in a machine-readable form. SSN is an ontology created by the Semantic Sensor Networks Incubator Group[1] offering descriptions of four related perspectives: sensor, observations, system and property [5]. The model focuses on what and how can be sensed, systems of sensors and their deployment, and the description of observations made at entity level or for particular properties. Sensor Web Enablement (SWE) is a major initiative of the Open Geospatial Consortium (OGC)[2] aimed at improving the capacity to discover relevant sensor data on the Web, through standardized interfaces and specifications, and creating the Semantic Sensor Web, an infrastructure that enables the interoperable usage of sensors by providing services for discovery, accessing and identification based on sensor output augmented with spatial, temporal, and topic-specific semantic metadata [4]. A complement of the Semantic Sensor Web, Sensor Linked Data is a paradigm introduced by Janowicz and colleagues [13] to add interlink as a new challenge. The authors created a proxy delivering observations as Linked Data, connecting them with other data sources, and using ontologies and reasoners for observation alignment.

More related to the work presented in this paper, various research efforts consider the existing bridge between symbolic knowledge representations and raw data collected and measured by sensors. The concept of semantic perception is at the core of approaches developed to upgrade sensor output by attaching semantics to sensor data for enhanced interpretation [12]. The work of Jung [15] investigates the implementation of semantic annotation procedures for sensor streams. Roda and Musulin present in [24] an ontology-based framework to support intelligent data analysis of sensed data, while the construction of a complex situation using multi-layer ontologies is discussed in [22]. The BeAware framework [23] improves situation assessment by using ontologies and rules for spatial and temporal reasoning. Following the same line, graph inferences are used in [21] to combine information provided by heterogeneous sources for security applications. Ontology mapping is used in [14] to create a bridge between two representations of the world: the set of features, as sensed by sensors, and the set of objects, as viewed by humans.

Semantic mediation in sensor networks is addressed by Malewsky [17], who developed a semantic framework to improve matchmaking on sensor measurement and operating capabilities. A modularized Sensor Mediation ontology aligned to the SSN is at the core of the solution, and sensing entities and their attributes are modeled as instances of this ontology. Taking a step further, Bakillah and colleagues present in [2] a semantic mediation service that can support context-aware semantic mapping of sensor outputs and is adaptable to the dynamic of sensor metadata. The system integrates a set of empirical rules and rule-based reasoning mechanisms for semantic mediation.

From a different perspective, the rise of the Internet of Things (IoT) offers a wide application area for fusion methods able to discover potential knowledge from large amounts of perceptual information [9]. For this emergent application context, semantic-based solutions have been used to develop semantic-enhanced solutions for information retrieval [19], [20] to offer a shared understanding for event matching [11] or to support an integrated service platform in smart cities [18].

A more detailed discussion on pitfalls and challenges of heterogeneous fusion is presented in [7].

The research presented in this paper is in line with approaches developed for semantic mediation. While a generic ontology is used to provide uniform descriptions of both data extracted from observations and sensor output, reasoning mechanisms combine those augmented results into a finer description of entities.

A framework for heterogeneous fusion

Entity tracking and identification

Detection and classification of entities has a long tradition and extensive literature. Knowing exactly where the entity is, eventually who that entity might be, and monitoring its trajectory in real-time, has already attracted a lot of interest from both academia and industrial communities.

The main problem of track-and-detect in realistic applications is the combination of the sensor-level detection reports and human observations. Track-and-detect is performed under dynamic conditions: trajectories of entities can be out of reach for sensors, and human observations arrive on an irregular basis. Not surprisingly, results are impacted by the quality of the sensor algorithms for detection and identification, as well as by the ability to efficiently combine sensor output and human reports. In other words, the system should rely upon a mediation layer allowing for the sensor and human reports to share as precisely as possible the meaning of the information conveyed.

Definition of a situation and situation assessment

To avoid terminological confusion, in this work the term entity refers to vehicles, persons, or convoys in the real world. The outcome of the fusion is a situation assessment, to be provided to men in the field involved in operations or to commanders in tactical and operational headquarters.

Each entity is described as a vector of features, which, according to the sensor data used in the fusion process, provides the position and kinematics of the entity, its type and also relations to contextual information, such as geographical features (roads, airways) or to other entities in the situation. An entity is described as a set of

1 https://www.w3.org/2005/Incubator/ssn/
2 http://www.opengeospatial.org/

states, representing the knowledge of this entity at any moment in time during the surveillance task. Entity state gathers the estimated features and additional information related to traceability and information assessment, such as state likelihood, for instance.

Let E_i be an entity, having a set of states ES_k, with $ES_k = (t_k, K_k, Tr_k, A_k)$, a time stamped vector of features, composed of the knowledge K_k including kinematics, nature and additional properties, the traceability Tr_k to observations used to produce K_k and the assessment A_k of K_k, represented as a probability, a likelihood or even as a simple confidence score. Entity states can be built upon sensor-based data and soft observation reports: this only depends on the ability of the algorithms to associate these observations with a given entity. A situation of n entities is defined as the union of the set $E_{p,p\in\{1,\ldots,n\}}$ and the set of $p+q$ collected observations $\left\{O^{sensor}_{i,i\in\{1,\ldots,p\}}, O^{soft}_{j,j\in\{1,\ldots,q\}}\right\}$, some of which could be false alarms, or inaccurate or misleading reports.

Situation assessment combines information from multiples sources to reason about several entities over a range of time horizons. Often the situation is described by a collection of tracks, where a track is a temporal sequence of entity states and it is generally developed for individual or group entities, such as persons or vehicle convoys.

General architecture and cycles of dynamic fusion

The framework developed for heterogeneous fusion was designed to support field practitioners with the ability to select among various technological blocks or to implement new ones in a dynamic environment that demands innovative solutions for increasingly complex challenges. Figure 1 shows the general architecture of the framework.

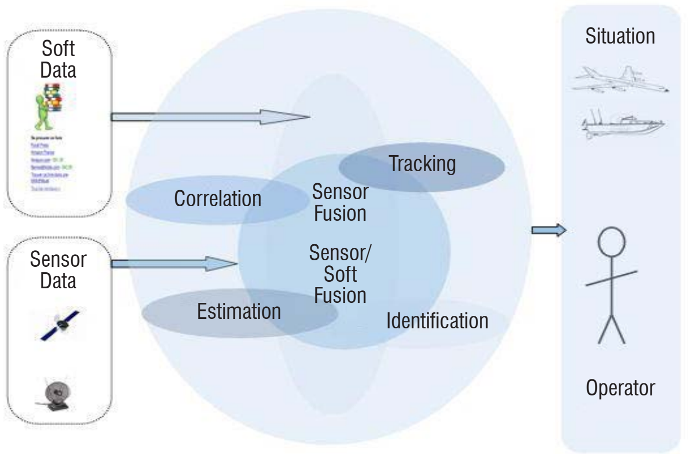


Figure 1 – General architecture for information fusion

For this work, the types of sources available include ground moving target indicator (GMTI), infrared and visible light imaging (IMINT), and signal intelligence (SIGINT) sensors. All of these sensing modalities generate elements that can be described by mathematical and numerical or symbolic representations (e.g., using a universe of discourse), and serve as inputs to automated processing procedures. Sensor measurements result in observations of objects, for which they provide information about properties like location, speed or signal characterization when these objects are electromagnetic emitters. Soft information derived from human or open source is fundamentally different in that its content is often more qualitative and requires additional context elements for complete human interpretation. As shown in Figure 1, heterogeneous fusion is carried out by means of two information fusion cycles. The core is a sensor-based kernel that provides several processes for entity correlation and tracking, along with estimation of their states.

The kernel implements a short-time classical tracking algorithm, since data are provided by sensors on a regular frequency. The outcome is a situation, whose entities are described by their spatio-temporal coordinates and their kinematics. At this stage, the type of entities is also estimated but only using sensor-based data.

The second layer of this architecture enriches the situation by integrating soft-data elements on a stream and irregular basis, as they become available. The enrichment is aimed at refining the states of entities by adding supplementary attributes, such as allegiance and military or civilian nature. Heterogeneous fusion can be considered as a long-time fusion cycle, triggering specific processes as soft-data observations arrive. Those processes first provide matching mechanisms to assign soft-data observations to entities of the situation and then perform fusion strategies in order to combine elements of entity states with items extracted from soft data. The approach is implemented by using a generic development and execution framework [16] providing a collection of basic algorithmic building-blocks for information fusion.

Processing and fusion of sensor data and observations

Extraction of features from sensor data

The features that can be extracted from sensor data, although limited, are heterogeneous due to the different types of deployed sensors.

GMTI sensors are radars with specific signal processing leveraging the Doppler effect which can provide information about moving targets, mainly related to their kinematic state (location and speed in the direction of the sensor) and sometimes some classification information from signal analysis, limited to rough classes of identification, such as rotating objects (e.g., helicopter blades), tracked vehicles such as Tanks, or wheeled vehicles. The location is provided in range and azimuth and possibly in elevation for a 3-D radar, with associated imprecision in each of these dimensions, which can be quite large for azimuth information. The speed is also partially retrieved due to the fact that only one-dimensional information can be acquired, related to the line of sight between the radar and the detected object.

IMINT information is related to imagery or video acquired in diverse wavelengths (visible, or infrared), which may be further exploited through an automated extraction and tracking device and annotated by an operational user. Some sensors are also able to perform tracking on a given object, thus providing track information about the object with location and speed attributes. The operator can then complement this information with precise classification information.

SIGINT information is related to either the detection and localization of specific emitters (e.g., radars) or the interception of communication information between several actors. Through the use of several receivers or a maneuvering receiver, the location of emitters and specific technical information can be extracted.

From the set of items sent by these various types of sensors, a correlation scheme can be set up based mainly upon kinematic information to perform the right association between these detections, so there are a limited number of duplicated tracks related to the same real entity. From this association, a combined estimation of attributes is performed, which leads to a more precise kinematic information and, if available, a rough estimate of the type and hostility of the entity. Different methods, using mainly Bayesian, evidence theory or heuristic techniques, are involved to combine classification results from these detections.

Identification of properties from soft data

Processing of soft data identifies properties of entities within natural language messages. Messages also have a heterogeneous content, and can provide insight on different aspects, such as entity location, and evolution. The methods developed extract binary association attribute-value from messages, which can be easily modeled as properties of entities and integrated into entity states. Attributes specify the type (vehicle, bus, person, etc.), allegiance (foe, friend, neutral) or nature (civilian, military, insurgent, etc.) of entities.

Attributes are identified from soft data by using a text-mining approach based on collocation identification. Collocations are associations of words that co-occur frequently within the same sentence, whether because the meanings of words are related to each other (e.g., vehicle- road, car-driver) or because the two words make up a compound noun (car stop, subway station). The extraction algorithms focus on collocations composed of two words, also called bi-grams. The method developed to extract collocation is shown in Figure 2.

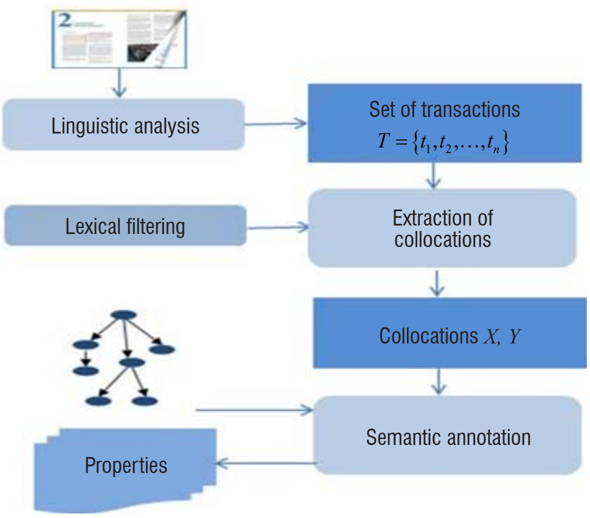


Figure 2 – Processing of soft data

Linguistic analysis reprocesses documents to split texts and filter stop words, and perform lexical normalization. Lexical normalization identifies and removes lexical heterogeneities, which appear as the same type of information provided by different lexical forms, and concern namely: date/ time expression (11 November 2011 vs. 11/11/2011); currency; geographical coordinates; metric units (m vs. inch); expression of quantifiers (two vs. 2 vehicles) and abbreviations (poss. vs. possible). Linguistic analysis also concerns the identification of sentence boundaries and performs tokenizing, while filtering a list of stop words. The output of this phase is a set of transactions, where each transaction is a sentence whose items are words. The set of transactions is the input for the next step. Collocations are generated by using a window placed over a sentence, such that two words are analyzed at a time by moving the window from the first to the last word of the sentence, see Figure 3.

Figure 3 – Extraction of collocations

Because simply taking the entire list of collocations captures an excess of extraneous and incoherent information, additional processing is needed to filter relevant word associations thanks to semantic annotation.

Semantic annotation is performed automatically, using procedures based on lexical similarities, which associate a real number with a pair of words. Lexical similarity offers a measure of the degree to which two words are similar and are used to label a collocation by ontological concepts. The hierarchy of concepts allows the *attribute* part of the association to be retrieved. Thus, given a concept C considered as *value*, the associated *attribute* is identified as the least specific concept subsuming *Property* and generalizing C, as shown in Figure 4.

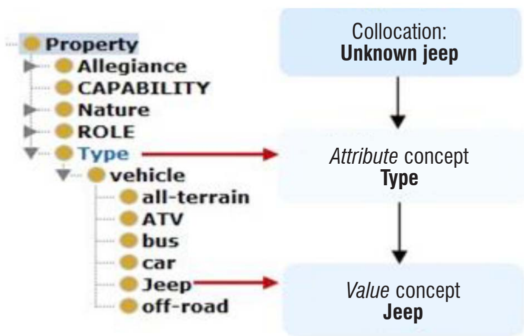


Figure 4 – Semantic annotation

For instance, the collocation *unknown bus* will be matched to the set (*Bus*, *Bus*, *Type*), since *unknown* is not assigned to a concept, while the *insurgent vehicle* is annotated by (*Vehicle*, *Vehicle*, *Type*) and (*Insurgent*, *Insurgent*, *Allegiance*), since both *Vehicle* and *Insurgent* are concepts of the ontology.

At the end of this phase, annotations of collocations are generated in the form of tuples:
$A_i=(W_i,C_i,T_i)$ where A_i is the annotation of item i, W_i is a word, part of a collocation, C_i, is a concept assigned to W_i by lexical similarities, and T_i is the category of C_i, as identified by inferences.

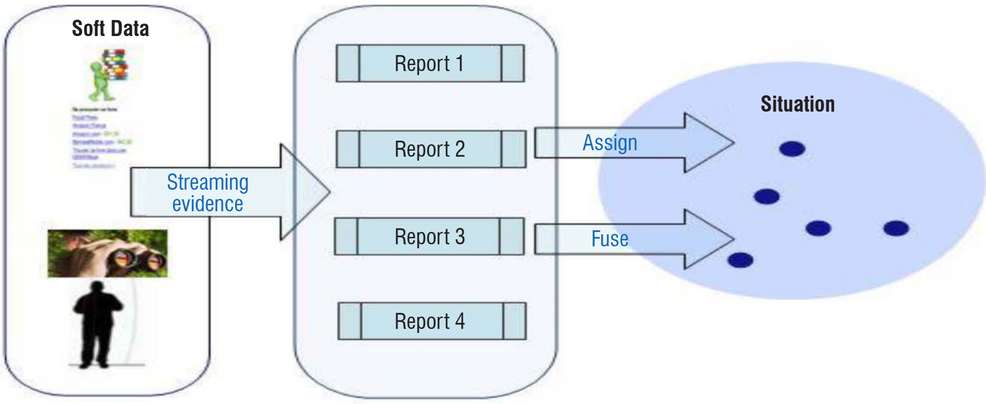


Figure 5 – Combining soft and sensor data

Integration of sensor data and observations

The overall solution for human observations and sensor data integration is summarized in Figure 5 and consists of the assignment of observations sent by humans to entities created by sensor data processing. Soft data used are brief human reports, conveying information about entities in the field. Among those entities, some could be of interest, already detected and eventually tracked by sensors. Information extracted from incoming soft reports will not be considered for tracking purposes; instead, it will help human-operators to have a better description of the situation.

Assignment of human observations to entities of the situation is carried out in the light of spatio-temporal correlation. Given that observations are associated with a timestamp and have specific locations, this method first estimates a correlation coefficient to describe the probability of a human observation to be assigned to e_i , an entity of the situation. The current states of e_i along with its previous states are taken into account for this estimation, since soft observations are not necessarily synchronized with the current situation. Results of this estimation are then ranked and the observation maximizing the value is selected and added to the set of observations associated with e_i .

This combination of soft and sensor data is supported by the fusion architecture.

Semantic mediation

Semantic mediation relies on using a domain ontology to describe data semantics, and implementing semantic annotation procedures to associate sensor output and human observations with corresponding elements of the domain ontology along with reasoning mechanisms for data integration.

While spatio-temporal association enriches the overall situation by adding a set of human observations, semantic mediation is used at entity level to enable the fusion of sensor data and observations.

Semantic mediation is implemented as a process allowing data provided by different types of sources to be combined and a domain ontology is at core of this process, as shown in Figure 6.

The role of the mediation process is to integrate relevant observations to sensor inferred entities according to a shared semantics modeled by a domain ontology and to master the gap between low-level features and richer conceptual descriptions of each entity. Ontologies, as introduced by Gruber [10], are formal domain descriptions defined as: $O = (C, R, H^C, H^R)$ having: C a set of concepts, R a set of relations, H^C and H^R hierarchies defining a partial order over the set of concepts and relations, respectively. The ontology used for this work was created by using a top-down approach. The development began with a preliminary conceptualization, where a list of high-level

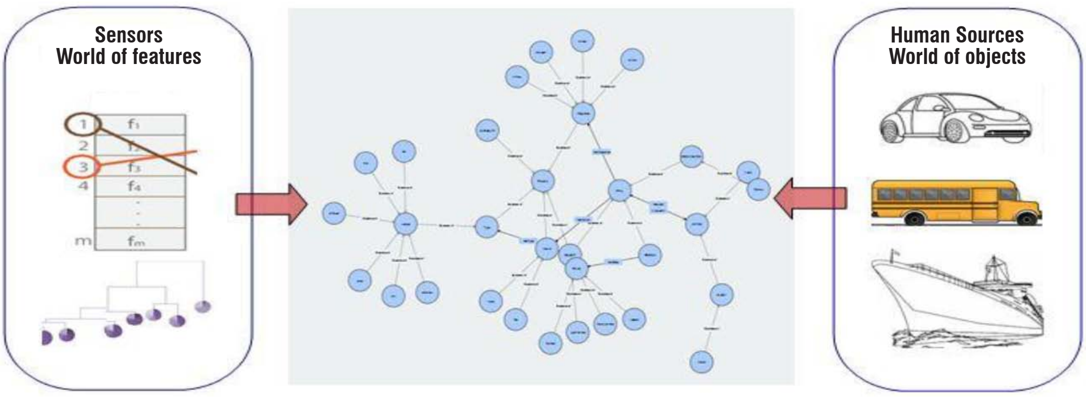


Figure 6 – Semantic mediation

concepts was identified by using the MIM Information Model (MIM)[3]. The hierarchy of concepts was iteratively enriched by adding new classes. The result is a domain ontology composed of 31 concepts, see Figure 7.

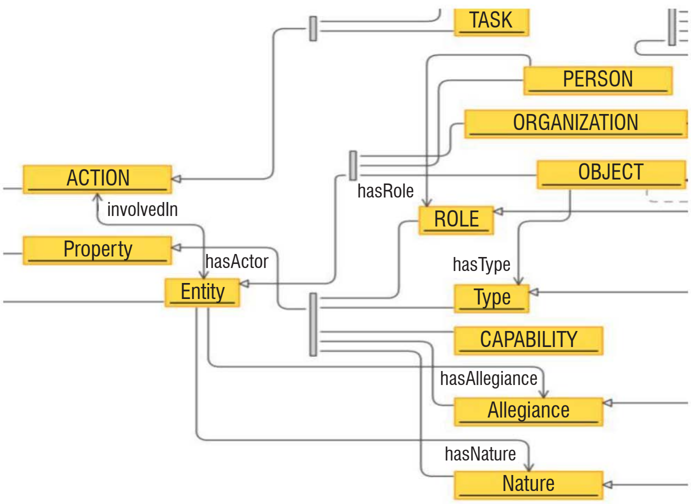


Figure 7 – Semantic mediation

Main classes are *Entity*, *Action* and *Property*. The ontology also has 6 object properties, to make explicit interactions between classes. Thus, hasActor (Event, Entity) models the association of an Entity with an Event and its reversed relation is involvedIn (Entity, Event). The four remaining relations associate entities and their properties: hasRole (Entity, Role), hasType (Entity, Type), hasNature (Entity, Nature) and hasCapability (Entity, Capability). All developments and testing were carried out using Protégé[4], and the ontology is represented in OWL DL, a description logic [1] sub-language of OWL [6].

Refinement of entity states

In the surveillance problem described in this paper, complementary and overlapping inputs exist. Sensor processing has the capacity to identify the type of entities, which is then added to the entity state in the form of a tuple attribute, value-of-attribute, for instance type, bus.

Sensors classify entities based on their measured features and by using some supervised methods for classification, which provide a limited number of categories. Besides having a limited number of categories, sensor processing also has its own detection limitations, and more subtle aspects such as the allegiance of entities are out of reach for their sensing capabilities.

Fusion of sensor and soft data is twofold: first, complementary properties extracted from human reports are added to states of entities; second, the type of entities is updated by taking into account the type of entities as stated by sensor processing and the type as extracted from soft data. In order to update the type, reasoning mechanisms are used to combine attributes of entities. More specifically, given that operators are interested in having a more precise description of entities, reasoning procedures identify the most specific concept of both type labels. This concept is then used to describe the entity, as illustrated in Figure 8, where the final state of the entity highlights the type bus, as a concept more specific than vehicle.

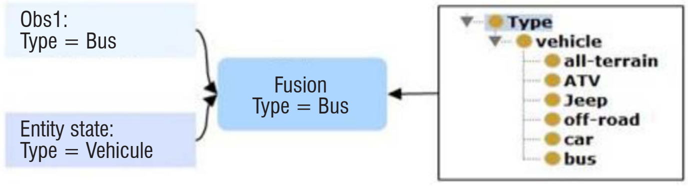


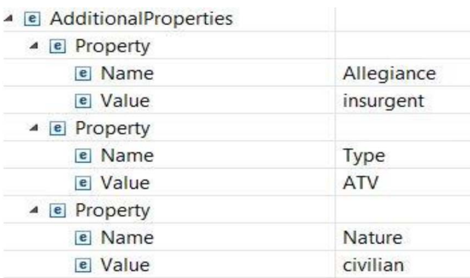
Figure 8 – Inference for type refining

Observations can be noisy, incomplete and sometimes irrelevant, and the inference mechanism fails to identify the most specific concept of both type labels. In this case, fusion provides inconclusive results. Inconclusive inference is due to contradictions between sensor reports and observations, or accidental associations of observations with entities. When successful, the result of fusing soft and sensor data at entity level is a more specific identification of the type of entities, and the enrichment of their state thanks to additional properties that cannot be inferred by sensor processing.

Practical validation and evaluation metrics

An experimental track-and-detect scenario was adopted to provide a valid proof-of-concept of the fusion system. The scenario involves a multi-sensor multi-tracking task with a network of sensors, several observers and a main information fusion functionality.

A total of 20 observations sent by operators on the ground were used, in addition to 204 GMTI reports, 12 COMINT reports, 7 ELINT reports and 5 IMINT reports. At entity level, properties extracted from soft data describe allegiance (friend, foe, insurgent), type and nature (civilian, military), as shown in Figure 9.



AdditionalProperties	
Property	
Name	Allegiance
Value	insurgent
Property	
Name	Type
Value	ATV
Property	
Name	Nature
Value	civilian

Figure 9 – Processing observations: type, nature, allegiance

Sensor data is provided as formatted reports integrating position, time, type and potential subtype of an observed entity. Some additional features may also be present, such as vehicle color or even the vehicle identification number. Observations are in the form of structured reports, having a natural language paragraph to summarize information collected by human sources. After feature extraction from text and fusion of items, the type of entity is updated (*Tank*) and its hostility is identified (HO). Over time, 102 entities are detected and tracked in the situation. Although using an experimental scenario offers a basis to evaluate whether or not the system meets its objectives, a formal evaluation is needed to estimate the impact of using semantic mediation to support heterogeneous fusion. Since mediation affects both entity states and the overall situation, *information*

3 https://www.mimworld.org/portal/projects/welcome/wiki/Welcome
4 https://protege.stanford.edu/

gain and *quality of service* introduced in [3] to characterize situation assessment are metrics able to quantify this impact.

Information gain is a criterion intended to capture the value added to entity states after updating their descriptions by using semantic inferences. Information gain is the ability of the system to provide improvements, and its values can be assessed by taking into account the number of additional properties added to entities and the quality of their type.

Information gain is defined assuming that changing the state of entities by integrating observations improves the description of entities, as follows:

$$InfoGain = \frac{N_c}{N} \quad (1)$$

where N_C is the number of entities whose states are affected by observations, and N is the overall number of entities of the situation. Values of information gain are between 0, when observations are not related to entities of the situation, and 1, when ideally states of all entities are updated.

Quality of service is a criterion used to characterize the quality of situation assessment and encompasses aspects related to timeliness, uncertainty of the overall picture, and quality of individual descriptions at entity level. Nevertheless, uncertainty can also arise at the situation level, since soft and sensor data can provide contradictory information items.

Quality of service takes into account the number of failures due to inconclusive fusion:

$$QoS = \frac{U}{N_c} \quad (2)$$

where N_C is the number of entities whose states are affected by observations, and U is the number of valid inferences. QoS ranges between 0, when all inferences for type refinement are inconclusive, and 1, when they are valid.

The values of information gain and quality of service at the end of the scenario are 0.047 and 1, respectively. For this experimentation, all inferences for type refining are valid and low values of information gain are directly related to the small number of entities affected by incoming observations.

Conclusion and future work

This paper tackles challenges arising when combining sensor data and human observations in dynamic environments, and argues that semantics provide a basis to augment results provided by sensors, facilitating their fusion with items extracted from observations. More particularly, the authors describe how semantic annotation of both soft and sensor items allows the implementation of reasoning mechanisms and improves the overall situation to be presented to human operators. From a practical standpoint, a unified fusion framework allows the integration of sensor rows and human observations, and offers specific procedures to extract information in an unsupervised way from sets of numerical values and textual reports. Assuming that results are compliant with an ontological description, reasoning mechanisms are then applied for the automated mediation of information items extracted from heterogeneous data. While enriching description of entities, the approach provides a way to adapt to an evolving context, since ontology-based models can be consistently modified to keep peace with the latest evolutions in the field. The long-term vision underlying this research is to enable on-the-fly integration of human observations in various systems already capable of processing sensor data, and the expected result is a roadmap towards a semantically-enabled heterogeneous fusion. The main difficulty is the implementation of reasoning mechanisms flexible enough to match features extracted from human observations and sensor data. In the short term, the use of semantics to identify, not only entities, but also relationships, is currently under analysis [8]

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