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On-the-fly integration of soft and sensor data for enhanced situation assessment

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Abstract

Situation assessment is at the core of many critical tasks in the civilian and military domains: border monitoring, surveillance of areas and facilities, entity tracking and identification, all require accurate and up-to-day descriptions of the course of events. For all those applications, situations to be built are complex, dynamic and uncertain and their assessment is based on the integration of diverse sources, including sensors and their row values, images, observations, tactical information and knowledge expressed by domain experts or synthesized through discovery techniques. This paper presents a method to combine soft and sensor data to create enhanced situation assessment for a track-and-detect application. First we create a situation of entities and relationships by using only hard data provided by sensors and then we enrich this situation thanks to soft data, in the form of succinct or more complex observation reports. The system relies on semantic mediation to combine observations and sensor data by using ontologies as a common ground creating a bridge between two complementary yet incomplete representations of the world. The result is an augmented situation, having more precise, accurate or complete descriptions of entities and which is easier to analyze. This enhanced assessment allows for the situation to be understood and processed in a meaningful way by decision makers.

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Keywords: Situation assessment, heterogeneous fusion, soft data, sensor data, semantic mediation

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1. Introduction

Situation assessment in heterogeneous environments plays a major role in assisting end users and decision makers by providing them with accurate descriptions of events so that timely decisions can be made upon sound basis. In real life applications, where entities of interest can be not only mobile, but also geographically dispersed, versatile and unpredictable, sensing devices and networks come close to their limits of perception. Human sources and soft information become then a key feature to be considered, as they can provide input about entities and their descriptions, or reveal undisclosed relations between them.

There are three primary differences between sensor data and soft data which make heterogeneous fusion a challenging task. First, sensors typically deliver data in streams: data is produced continuously, often at well-defined time intervals, without having been explicitly asked for. Those streams need to be processed in near real-time, as data arrives, because sensor streams can refer to real-world events, like traffic accidents, which need to be responded to. Besides, saving raw sensor streams to disk can be expensive. In contrast, soft data arrives sporadically, late after the event occurred.

Second, sensors are blind producers of data and thus they are unable to change data delivered. Soft data is the result of various modes of perception, affect, skills and knowledge which all fall under the umbrella of subjective assessment and include social and cultural formations that shape any individual. In addition, humans also have the ability to provide a personal view, attitude or appraisal, in the form of a judgment of belief when reporting facts and events. Finally, sensors are typically connected together in ad-hoc networks that cover a geographic area, such that receiving data from arbitrary nodes allows the user to take into account the network when performing the analysis. Unlike sensors, human sources can be part of hidden networks, whose undisclosed ties can lead to unreliable conclusions. For example, dependent information pieces can be analyzed under the false assumption of there being several independent sources, with impact on the result accuracy.

This paper presents an approach combining soft and sensor data to improve situation assessment for entity tracking and identification. A general architecture was developed, which creates a situation thanks to sensor data and then enrich this situation by adding soft data items. The method is supported by field semantics, and a domain ontology is used to augment descriptions of entities by riffing their attributes.

The paper is organized as follows: section 2 discusses related approaches. Section 3 presents the application context, an entity track-and-detect task. Approaches adopted to process soft and sensor data are discussed in section 4 while situation assessment is described in section 5. Conclusion and perspectives for future work end this paper.

2. Related work

Enhanced situation assessment is often tackled in relation to heterogeneous information fusion, the main mechanisms enabling to combine soft and sensor data in an effective way. Heterogeneous information fusion is an emerging topic within the information fusion community, addressing both theoretical and applied aspects relevant for higher levels of the JDL model[15].

Various research efforts have addressed the fusion or analysis of soft data, by providing solutions to structure free messages[2] or to classify reports[5]. Although based on natural language processing techniques[12], several approaches aim at integrating semantic analysis[10],[11] when processing soft data in order to overcome limitations of key-word spotting[9] and have ambitious goals, such as threat recognition[16]. However, the challenge of heterogeneous fusion is to combine both sensor and human based information items.

Generic mathematical frameworks for heterogeneous fusion can be approached from either a parametric or a nonparametric modeling perspective. The first ones specify parametric models of the state space based on domain knowledge, whereas in the non-parametric approach these models are empirically determined from data. A common parametric approach to tackle heterogeneous fusion uses probabilistic graphical models to build a unified representation of data, such as Hidden Markov Models or richer Bayesian Networks[6]. In practice, such models may be difficult to construct due to limited domain knowledge. Random Finite Set theory (RFS) is another theory suitable for the fusion of disparate information[13]. RFS uses the random finite set as a common representation and data in the form of qualitative statements or quantitative values are translated into this representation. RFS can also encode the disparate forms of uncertainty inherent in the data.

In[17] the foundation of an emerging framework for hard-soft information fusion based on Dempster-Shafer (DS) theory is described. The solution takes into account inherent data and source uncertainties such as reliability and credibility, and uses the conditional approach, an extension of DS frame to handle soft data.

A graph-based representation is proposed in[8] to process uncertainties of soft data for the purpose of situation assessment. An attributed data graph is created to represent intelligence information, where nodes represent entities and the arcs correspond to relationships. A template-graph is used to specify a situation of interest, and uncertainties correspond to an inexact matching of those structures.

From a different perspective, various approaches propose solutions for hard-soft data fusion by using Controlled Natural Languages in the form of subsets of natural languages, obtained by restricting the grammar and vocabulary in order to reduce or eliminate ambiguity and complexity. In the military field, BML (Battle Management Language)[3] was developed and it provides a standardized representation to communicate orders, request and reports, and it is sufficiently expressive to formulate both military and non-military data exchanges for a variety of tasks.

An analytical review of recent developments for multi-sensor information fusion is presented by Khaleghi and colleagues in[14] while trends and pitfalls of soft data integration are discussed in[7].

3. Application context

3.1. Definition of situation for entity track and detect

Detection and classification of entities, the need to know exactly where the entity is, eventually who that entity might be has already attracted a lot of interests from both academia and industrial communities, due to the large number of applications it enables for urban surveillance or home security. These sensors send rows of data acquired locally, which are then fused with human reports before sending the result to human operators. Users of this information are either men in the field, vehicles involved in ongoing operations or a commander in a tactical or operational headquarters.

The main problem of this approach is the combination of the sensor-level detection or identification reports and human observations. Practical requirements include the fact that the users of this system wish to maximize the number of true positives detections for this identification task which 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, this requirement relates not only to the quality of the sensor algorithms for detection and identification, but also to the ability of this surveillance system to efficiently combine sensor output and human reports. Data provided by various sensors along with human reports or brief messages are fused to identify and track several entities in order to monitor and protect a zone of interest. 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, 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 navigable waterways) or to other entities in the situation. More precisely, an entity is described as a set of states, representing the knowledge of this entity at any moment in time during the surveillance task.

An entity state gathers all the estimated features mentioned earlier as well as more technical 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 to a given entity. The data model used in the framework to represent the situation or picture of it at a given moment is relational, and so, implemented in XML but also designed to embed more generic knowledge representations such as generic properties in the form of hierarchical Key/Value pairs or ontologies in XML compatible syntax.

A situation of n entities can be defined as the union of the set : $\left\{E_{p,p\in\{1,\ldots,n\}}\right\}$, 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, inaccurate or even 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 can be viewed as a temporal sequence of entity states and it is generally developed for individual or group entities, such as persons or vehicle convoys.

3.2. General architecture for situation assessment

As the fig. 1 illustrates, situation assessment is carried out thanks to two information fusion cycles, designed to take into account characteristics of sensor and human sources. The core of the framework is a sensor-based kernel fusion that provides several processes for entity correlation and tracking along with estimation of their states. The kernel implements a short-time classical tracking algorithm, as data are provided by sensors on a regular frequency. The outcome of this process 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 thanks to sensor-based data.

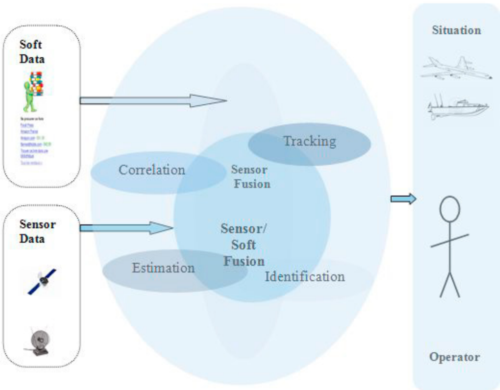

Fig. 1. General architecture for situation assessment

The second layer of this architecture enriches this previously created situation by integrating soft data elements on a stream and irregular basis, as they become available. The enrichment aims at refining the states of entities (more precise location, more accurate type description) or at adding supplementary attributes to entities (allegiance, military or civilian nature, etc.).

Situation assessment can be considered as a long-time heterogeneous 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.

4. Processing of soft and sensor data

4.1. Extraction of features from sensor data

The features which 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 object (such as helicopter´ blades), tracked vehicle such as Tanks, wheeled vehicle. 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. GMTI sensors can also provide already processed information in the form of tracks if the environment and number of detected objects is tractable.

IMINT information is related to imagery or video acquired in diverse wavelengths (visible, infrared) which may be further exploited through an automated extraction and tracking device and annotated by an operational user. For space and aerial imagery, operators can provide numerous information from a given acquisition, with very specific classifications and precise locations. In that case, however, no information on the speed of objects can be provided. 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. This latter capability is however limited to the tracking of few objects at the same time.

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. The content of the communication is often encrypted and cannot be easily exploited, apart as a soft data information. The communication technical information is however processed in order to identify relationships between entities when there is direct communications. 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, one can setup a correlation scheme based upon mainly 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 entity.

In addition, sensor data can also provide estimations of reliability and credibility, the set of classical measures proposed by NATO recommendations[1] and used in the military field to assess the quality of sources and the truthfulness of information items.

4.2. Identification of properties from soft data

Processing of soft data identifies properties of entities within natural language messages, whose size can range from a few phrases to more important size. Messages also have a heterogeneous content, and can provide insights on different aspects such as entity location, evolution, whereabouts, etc. . Given a collection of documents as input, the method developed for soft data processing has three main steps as shown in fig. 2.

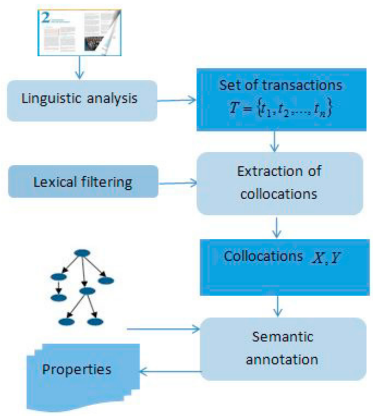

Fig. 2. Processing of soft data

Methods developed extract binary association *attribute-value* from messages, which can be easily modeled as properties of entities and integrated into entity states. Linguistic analysis reprocesses documents to split texts and filter stop words and perform lexical normalization. Lexical normalization identify and remove lexical heterogeneities, which appear as the same type of information id provided by different lexical forms, and concern namely: date/ time expression (ex. 11 November 2011 vs. 11/11/20011); currency; geographical coordinates; metric units (ex. M vs. inch); expression of quantifiers (ex. two vehicles vs. 2 vehicles) and abbreviations (ex. poss. vs possible). Those heterogeneities are removed by adopting a unique format to express date/time, currencies, geographical coordinates and quantifiers. Linguistic analysis also concerns the identification of sentences 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 of the next step, aiming at extracting binary collocations.

Attributes are identified from soft data by using a text mining approach based on collocation identification. Collocations are associations of words which co-occur frequently within the same sentence, whether because the meanings of words are related to each other (i. e. vehicle- road, car-driver) or because the two words make up a compound noun (car stop, subway station). The extraction algorithms focuses on collocations composed of two words, also named by-grams, as often entities of interest are named by short lexical units.

During this step, collocations are generated by using a window placed over a sentence, such that two words are analyzed at a time and moving the window from the first to the last word of the sentence, cf. fig. 3.

Fig. 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. Traditional methods for collocation extraction often evaluate a statistical score to estimate the relevance of word pairs. However, data used for this work are short messages whose volume is not appropriate for statistical validation. For this reason, we developed a complementary approach able to select relevant collocations thanks to semantic annotation.

Semantic annotation is performed automatically, by using procedures based on lexical similarities which associate a real number to a pair of words and offers a measure of the degree to which two words are similar. Lexical similarities are used to label collocation by ontological concepts. Thanks to lexical similarity, concepts of the ontology label the overall collocation or just one of its words individually, as shown in fig. 4 and they represent the *value* part of the *attribute-value* association.

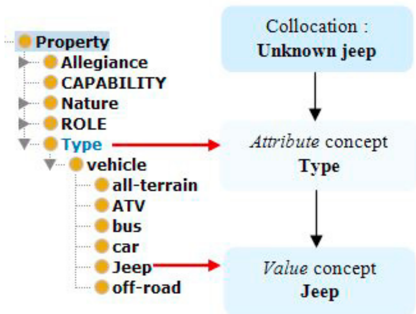

Fig. 4. Semantic annotation

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

Properties extracted for this work specify the type (*vehicle, bus, person*, etc.), allegiance (*foe, friend, neutral*) or nature (*civilian, military, insurgent,* etc.) of entities.

5. Enhanced situation assessment

Situation is enhanced by two mechanisms: first, complementary properties extracted from human reports are added to states of entities; then, 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.

5.1. Enrichment of entity states

The overall solution for human observations and sensor data integration is summarized in fig. 5 and consists on the assignment of observations sent by humans to entities created by sensor data processing.

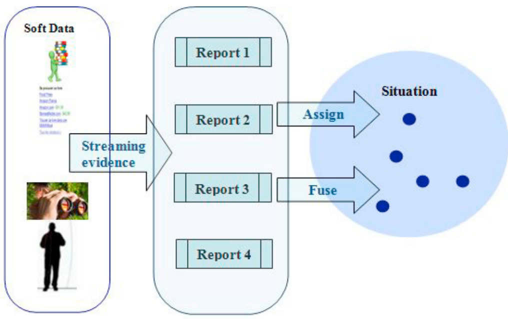

Fig. 5. Integration of soft and sensor data

Assignment of human observations to entities of the situation is carried out in the light of spatio-temporal correlation. As 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, as 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 to e_i. Thanks to heterogeneous fusion, the overall situation is enriched, as more observations are added to states of different entities with the incoming human reports.

5.2. Refining entity states

In order to update the type, reasoning mechanisms are used to combine attributes of entities. More specifically, as 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 fig. 6, where the final state of entity highlights the type *bus*, as a more specific concept than *vehicle*.

As the reliability of human reports is not guaranteed, observations can be noisy, incomplete and sometimes irrelevant and inference mechanism fails to identify the most specific concept of both type labels. In this case, the fusion is inconclusive. Inconclusive inference highlights contradictions between sensor reports and observations or accidental associations of human reports to entities of the situation.

When successful, the result of fusing soft and sensor data at entity level is a more accurate identification of the type of entities, and the enrichment of their state thanks to additional properties which cannot be inferred by sensor processing.

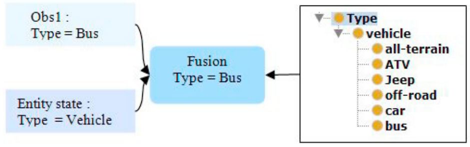

Fig. 6. Type refinement

5.3. *Practical validation and metrics for evaluation*

The work described in this paper tackles the developed on an approach for enhanced situation assessment adapted to surveillance-related queries made by operators within a heterogeneous environment composed of various types of sensors, communication relays as well as human observers providing information to monitor and protect zones of interest.

An experimental track-and-detect scenario was adopted to provide a valid proof-of-concept of the overall approach. The scenario involves a multi-sensor multi-tracking task with a network of sensors, several observers and a main situation assessment functionality. The example also highlights capabilities for: integration of heterogeneous sources, entity creation from sensor data, type and hostility identification from numerical data along with type refinement and attributes enrichment from soft data.

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).

Sensor data is provided as formatted reports integrating position, time, type and potential subtype of an observed entity. Some additional features may be also present such as vehicle colour 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 features extraction from text and fusion of items, the type of entity is updated (*Tank*) and its hostility is identified (HO) see fig. 7.

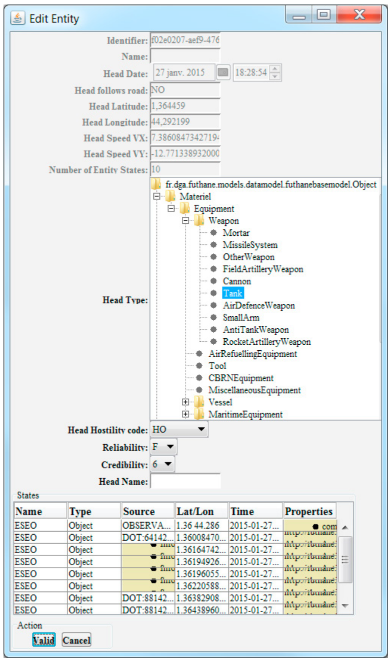

Fig. 7. Situation assessment: hostility identification and type refinement

Although using an experimental scenario offers a basis to evaluate whether the system meets its objectives, a formal evaluation is needed to estimate the impact of combining sensor and soft data. *Information gain* and *quality of service* as introduced by Blasch and colleagues in[4] 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. Ideally, information gain increases with the integration of textual reports, as potentially they provide more details about entities in the field. In a similar way, inferences should allow for a finer description of types, and thus can improve information gain.

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

$$InfoGain = \frac{N_c}{N} \tag{1}$$

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. If some aspects of this criterion potentially improve thanks to the integration of soft and sensor data, others can be impacted in a negative way. Thus, we can expect richer and better descriptions of entity states, but timeliness can decrease as heterogeneous fusion is a rather slow process. Uncertainty can also rise at situation level, as soft and sensor data can provide contradictory information items.

Quality of service is defined by taking into account the number of failures dues to inconclusive fusion.

$$QoS = 1 - \frac{U}{N_c} \tag{2}$$

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

Estimation of information gain and quality of service require adaptations of the fusion framework, allowing for the algorithms to provide additional output and intervention of experts for in depth analysis of outcomes. This process is currently ongoing and intermediate values of those criteria are not currently available. 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 being affected by incoming observations.

However, a more accurate definition of those metrics should take into consideration the volume of observations with respect to the overall amount of numerical data processed, as for the considered scenario numerical detections largely outnumber human reports and generate more than 100 entities among which only 5 are updated by observations.

6. Conclusion

This paper presents a method developed to combine soft and sensor data in order to improve situation assessment. This situation assessment approach is suitable for situation assessment in dynamic environments, when sensors are deployed and humans in the field send brief observations and there is a need to constantly update entity states.

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. Starting with an abstract view on the process of situation assessment we describe how domain semantics can serve as a basis for reasoning-based combination and hence improve the overall picture to be presented to human operators.

Directions for future work are threefold. First, we can improve the overall approach, by allowing a better integration of soft data observations and creating entities in the situation based on soft observations. The second direction should allow us to analyze uncertainties arising when combining items, in order to avoid the processing of irrelevant data or the propagation of unreliable results. The last direction for future work is intended to set up en evaluation protocol, assessing values of information gain and quality of service for several use cases in an effort to quantify how the integration of sensor data and soft items is of interest to end users.

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