Semantic Information Fusion to Enhance Situational Awareness in Surveillance Scenarios

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***Abstract*— In recent years, the usage of unmanned aircraft systems (UAS) for security-related purposes has increased, ranging from military applications to different areas of civil protection. The deployment of UAS can support security forces in achieving an enhanced situational awareness. However, in order to provide useful input to a situational picture, sensor data provided by UAS has to be integrated with information about the area and objects of interest from other sources. The aim of this study is to design a high-level data fusion component combining probabilistic information processing with logical and probabilistic reasoning, to support human operators in their situational awareness and improving their capabilities for making efficient and effective decisions. To this end, a fusion component based on the ISR (Intelligence, Surveillance and Reconnaissance) Analytics Architecture (ISR-AA) [1] is presented, incorporating an object-oriented world model (OOWM) for information integration, an expressive knowledge model and a reasoning component for detection of critical events. Approaches for translating the information contained in the OOWM into either an ontology for logical reasoning or a Markov logic network for probabilistic reasoning are presented.**

I. Introduction

In the last decades, the development and usage of unmanned aircraft systems (*UAS*) has increased quickly, mainly for military purposes [2]. In recent years, this technology has also become available to the public, now being of interest, among others, in different areas of civil protection, such as police duties, rescue mission support, or fire fighting [3]. The deployment of UAS in distributed surveillance systems supports security forces in achieving enhanced *situational awareness*. However, in order to provide useful input to a situational picture, sensor data acquired by UAS has to be integrated with information about the area of operation and objects of interest provided by other sources.

In [4], a distributed airborne surveillance system based on UAS was proposed. The study was focused on cooperation of UAV swarms. Still, initial thoughts on the topic of information fusion were presented. The study at hands continues this direction and presents details on supporting operators through the *combination of information* from an airborne surveillance system with additional information extracted from intelligence databases. Such an *automated assistance* enables human operators to improve their capabilities for making efficient and effective decisions due to decreased workload and increased situational awareness. The presented approach to information fusion is based on the ISR-AA presented in [1] and entails the creation of an expressive knowledge model for the considered domain in combination with reasoning techniques for information integration.

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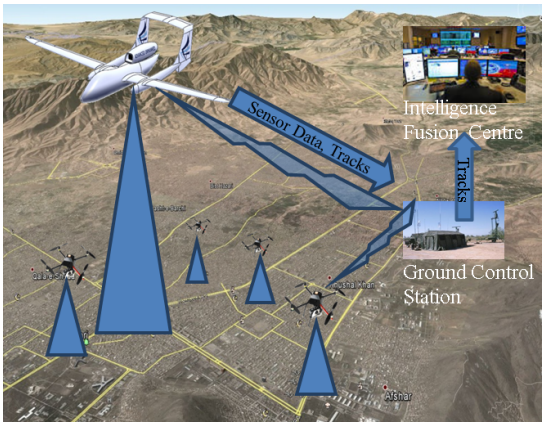

Fig. 1. System overview of a distributed surveillance system.

Section II gives an overview of our approach to information fusion as well as to the embedding surveillance system. In Sec. III, the architecture of the realized Information Fusion Component is presented, and Secs. IV, V, and VI detail the different modules for information management, integration and reasoning. Section VII concludes this study.

II. Approach

Starting point for our study is a *distributed surveillance system* (cf. [4]) composed of different UAS with e.g. sensors for video and radar data. Some of the UAS have processing capabilities as well, e.g., for producing tracks out of radar returns. A ground control station is in charge of controlling the missions of the UAS and collecting their sensor data.

The collected sensor data is processed, e.g., tracks of vehicles in the area are computed, and forwarded to an intelligence fusion center. The intelligence fusion center is responsible for aggregating UAS sensor data as well as correlating and integrating it with information from intelligence databases and background knowledge, using methods of high-level data fusion with the aim of supporting a commander's situational awareness. Fig. 1 gives a coarse overview of the structure of the surveillance system.

High-level data fusion is the process of integrating information about observed real-world objects into a consistent representation and of studying their relations [5]. According to the well-known JDL data fusion model [6], the integration

of object-related information on JDL level 1, such as their locations and further attributes, is the basis for situation assessment on JDL level 2, where the existence of relations between objects is inferred. All this information then allows performing impact assessment on JDL level 3.

In this study, the term information fusion is used for high-level data fusion. When developing the methodology for fusing information delivered by heterogeneous information sources (semi-)automatically, a top-down approach was applied. The approach is top-down in the sense that the requirements on information elements serving as input for information fusion tools (such as threat detection modules) are at its basis. These requirements are e.g. in terms of semantic scope or quantification of uncertainties. The scenario used in this study implies the detection of possible threats, such as an assault on a critical infrastructure. The *Information Fusion Component* (*IFC)* to be realized has to support operators in the information fusion center by integrating information from different sources with general knowledge and performing high-level reasoning on the integrated information. At the heart of the IFC thus is an *expressive knowledge model*, which represents the general and domain-specific knowledge needed for scenarios such as threat detection, in a formalized way suited for reasoning, and allows expressing rules that enable integrating and correlating current sensor data and exploitation information with this prior knowledge.

The contents of such a knowledge model have to be carefully designed. For the considered threat detection scenario, conclusion drawing requires knowledge about general facts (such as, what means are required to perform an assault), background information related to these facts about the considered area of operation, its infrastructure and people (such as, factories located in the area, roads and their conditions, typical travel routes, known insurgents, their abilities and facilities), current information (e.g., observing suspicious activities) and sensor data (e.g., track data for a vehicle possibly loaded with explosives).

All this information has to be encoded into or processed by the IFC. General facts and background information constitute a-priori knowledge and can be encoded into the IFC prior to its operation. Current information and sensor data must be integrated during operations. General facts (e.g., how to build an explosive) can be encoded as rule templates. Such rule templates are used in reasoning when respective evidence, allowing to instantiate a rule, becomes available. Relevant background information (infrastructure, facilities, known insurgents etc.) can either be encoded manually, or semi-automatically by extraction from sources such as geographic information systems or intelligence databases. For integrating current information (scenario-specific, contained e.g. in sensor data exploitation reports or open source documents), interfaces and extraction mechanisms for respective databases are needed. The same applies to sensor data. Prior knowledge (rules, facts) and current information (evidences) have to be represented in the IFC in a consist way, allowing to instantiate reasoning mechanisms for information integration and conclusion drawing.

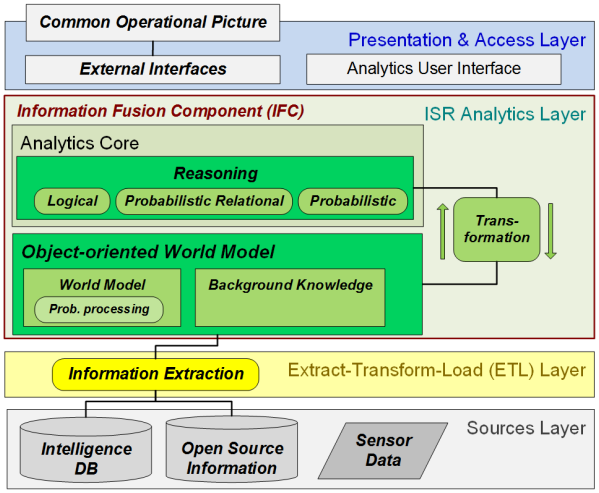

Fig. 2. Architecture of an Information Fusion Component (*IFC*), based on the ISR Analytics Architecture [1] and its layers.

III. Architecture of the Information Fusion Component

In order to realize an IFC with the previously described capabilities, an architecture based on the ISR-AA [1] was chosen, depicted in Fig. 2. The designed IFC consists of two main sub-components: an *Object-Oriented World Model* (*OOWM*) and a *reasoning component*. The OOWM ([7], [8], [9], [10]) is a component for world modeling, applied e.g. in video surveillance or autonomous systems, developed by Fraunhofer IOSB. It serves as the main facility for integrating and representing current information about the considered environment in a so-called *World Model* part, as well as for storing respective background information and general facts in the *Background Knowledge* part. The reasoning component provides methods for performing different kinds of reasoning, including logical reasoning, probabilistic reasoning (e.g., Bayesian inference) and probabilistic relational reasoning (e.g., using Markov logic networks). Based on the prior knowledge contained in the Background Knowledge, the reasoning methods are pre-configured with respective rule templates, into which the current information, stored in the World Model, can be inserted as evidence. The results of reasoning are passed back to the OOWM and integrated into the World Model. A *transformation component* is responsible for mediating between the OOWM and reasoning, by translating the information and knowledge stored in the OOWM into the representations required by reasoning methods. The IFC provides an external interface, e.g., for components displaying a *common operational picture* (*COP*). In this way, threat indications, e.g., for a possible assault, or threat levels of observed objects can be supplied for visualization to operators. This output aims at supporting a commander in identifying critical events more easily and enhancing his or her situational awareness while relaying only relevant information, preventing information overflow.

As input to the IFC, different sources of data and information can be used. For one, information from intelligence

analysis or exploitation of reconnaissance data can be added to the IFC by integrating respective reports contained in reconnaissance or intelligence databases. Input to the OOWM must be given as object-oriented observations [7], [9]. In order to use reports as inputs for the OOWM, relevant information contained in a report must be extracted and adjusted to the knowledge model used in the OOWM (e.g., with respect to the terms employed to name entities, events etc.). For this purpose, an *information extraction component* can be employed to extract relevant facts from reconnaissance and intelligence reports. Extracted facts can act as both, background knowledge or evidence, depending on their nature with respect to the scenario and desired outputs. In addition, the IFC shall be able to consider information from open sources (such as newspaper, the Internet etc.) as possible input. The information extraction component thus shall additionally be able to at least support an operator in extracting and preparing relevant information from open sources for being integrated into the IFC (e.g., as evidence).

As a second kind of input, sensor data acquired by UAS can be integrated into the IFC. Special focus in the study at hand is given to track data provided by UAS performing area surveillance. Although such track data can originate from different sensor types (e.g., video or ground moving target indicator (*GMTI*)), it has in common that a sensor discovers a certain plot or target at a point of time having certain characteristics. The track data contains surveillance information about time and location of a target, as well as static features such as its color or extents (in case of video tracking). The track data provided by UAS adds detailed information about certain, possibly suspicious objects (like observed vehicles) to the IFC. Based on such detailed information, the (re-)identification of previously observed objects (e.g., in still images) can be performed. In addition, such surveillance information allows inferring suspicious or abnormal behavior for a tracked object in the light of threat detection.

IV. Information Integration and Management

The IFC is responsible for consistently integrating and managing the information acquired via sensor observations, reports, open sources etc. and relating this information to background domain knowledge as well as historic information. In addition, reasoning is performed based on this integrated information, allowing to explicitly uncover additional facts. The two sub-components responsible for these tasks, as described above, are the OOWM and the reasoning component. In this section, the OOWM will be described. Reasoning will be detailed in subsequent sections.

The OOWM [10] consists of a World Model part, responsible for representing the current state of an observed domain, and the Background Knowledge part, providing a semantic domain model as well as further domain-specific knowledge such as rules. In the World Model, each observed real-world object is represented by a data structure called a *representative*. This data structure subsumes all the information acquired from sensor data, reports and other sources about the represented object. Each relevant object feature is represented by an attribute in a representative.

In Background Knowledge, the object types relevant for the considered domain are described by an expressive semantic domain model. Each object type is represented by a so-called *concept class* [10], modeling relevant features of the object type (again, as attributes) as well as relations to other object types. Concept classes are structured by a taxonomy of concepts, with the higher level of the taxonomy describing the more abstract concepts (e.g., categories such as building, vehicle, event). In addition, relation types relevant to the domain are modeled, describing the relationships in which objects (or categories of objects) are assumed to participate.

In this study, furthermore, rules specified for the application domain can be stored directly in Background Knowledge. Modeling causal relationships between relevant domain objects, such rules must refer to the concept classes and relation types defined in Background Knowledge.

The domain model in Background Knowledge is an engineering artifact created prior to operations by domain experts. Different alternatives exists for representing such a knowledge model. One viable choice is the use of a formal ontology, more specifically, an ontology based on the description logic fragment of first order logic. In this study, the description logic (*DL*) profile of the Web Ontology Language OWL is used for knowledge representation (further details will be given in Sec. V).

The OOWM is responsible for information integration and management. In general, probabilistic information processing [8], [9] is employed for the tasks related to information integration. These tasks comprise data association (assigning newly observed information to representatives in the World Model) and information fusion (updating representative attributes with newly observed values, temporal evolution of values). Information management concerns the creation of new representatives and the deletion of obsolete ones, as well as tasks such as access to and retrieval of information from the World Model and notification services.

Probabilistic information processing is aimed at handling uncertainties in observation data resulting from measurement processes. Yet, not of all the information provided to the IFC is quantified by uncertainties (e.g., information extracted from exploitation or intelligence reports). For such information, adequate processing methods are required which are able to take into account unquantified uncertainties inherent to input information (e.g., object descriptions in reports) during processing. This is e.g. relevant when associating the description of an object extracted from a report with sensor data about the same object provided by UAS. The OOWM, thus, must be able to handle deterministically provided values (with no quantified uncertainty) as well as probabilistically described values. Therefore, the OOWM used in this study is able to operate in different modes: a mode for handling deterministic values, a mode for probabilistic values, and a mixed mode (as assumed in this study).

Information integration and management in the OOWM is performed with the aim of making integrated informa-

tion available to other components, such as the reasoning component or components for behavior analysis. Information exchange with such components is designed to be event-driven in the OOWM (e.g., events concerning specific representatives or spatial areas [9]). In this study, a change notification service is provided to external components. Each component desiring to process OOWM-managed information can register to the OOWM, specifying on with information changes it wished to be notified. Specifiable change events include the creation of new representatives of a given object type, changes on a given list of representatives, updates on attributes of a given type, as well as combinations of those.

More details about the OOWM be found in e.g. [10].

V. Logical Reasoning

The reasoning component of the IFC is responsible for conclusion drawing, allowing to uncover and explicitly state additional facts contained in the integrated OOWM information. For this purpose, different reasoning methods can be employed, including (and relevant to this study):

- logical reasoning,
- probabilistic reasoning, and
- probabilistic relational reasoning.

The classical approach to reasoning is based on logical inference. In logic, there are three components to inference: premises of an inference, conclusions of an inference, and rules relating the conclusions to their premises. Depending on the way these three components serve as input(s) and output(s) of a reasoning process, different types of logical reasoning can be differentiated: deductive, inductive and abductive reasoning. In deductive reasoning, rules and their premises serve as input, and the conclusions constitute the result of a reasoning process. In inductive and abductive reasoning, in the contrary, the conclusion is given, and rules are to be obtained. Deductive reasoning is the kind of reasoning needed in the IFC for uncovering additional information contained in a knowledge base. Based on rules (modeled a priori by domain experts) and evidences (acquired via sensor data and current information) satisfying the premises of a rule, logical reasoning allows to uncover additional information as conclusions from the knowledge base.

In logical reasoning, different *types of logics* can be employed to encode the rules and evidences, such as propositional logic, first order (predicate) logic (*FOL*) or modal logic. The choice of logic defines the *expressiveness* of the language that can be used to model facts and rules, as well as the kind of inferences that can be performed by reasoners. A *reasoner* is a software algorithm automatically checking which conclusions can be drawn given set of facts (acting as evidences) and a defined set of rules. Time complexity and termination of reasoning operations are factors depending on the type of logic chosen, with the general rule of a more expressive logic being more complex to reason in.

For the IFC, time of reasoning is an important constraint since the indication of possible threats has to be performed in near real-time to be of value. Additional constraints on the choice of a logic type for the IFC can be derived from the knowledge model representing the input information (evidences) to reasoning: the OOWM. Here, the object-oriented information representation in the OOWM can be mapped to a restricted version of FOL. More specifically, the DL fragment of FOL can be employed to represent the information about observed real-world objects, contained in the World Model, as well as the general information about object types and categories in Background Knowledge.

Current research in the area of semantic web technologies has produced mature tools for knowledge modeling and reasoning in DL. The Web Ontology Languages (*OWL*, e.g., [11], [12]), a standard of the World Wide Web Consortium (*W3C*), specifies several FOL fragments, including OWL DL. In OWL DL, entities, their attributes, as well as relations between entities and entity types can be modeled. In addition, several efficient reasoners are available, as well as tools for the initial creation of a domain model. Thus, OWL DL constitutes a suitable choice of logic, under the aforementioned constraints of near real-time performance and the use of the OOWM for supplying evidential facts.

Yet, only a specific subset of rules can be represented in OWL DL, not including general implications of the form

$$p_1 \wedge p_2 \wedge \cdots \wedge p_n \;\longrightarrow\; c_1 \vee c_2 \vee \cdots \vee c_m \;, \qquad (1)$$

with $p_i,\ i = 1, \ldots, n$ being premises and $c_j,\ j = 1, \ldots, m$ being conclusions ($n, m \in \mathbb{N}$). This deficit can be compensated by employing the semantic web rule language (*SWRL*) [13], a W3C standard proposal, which smoothly integrates with OWL DL and (some of) its reasoners. For this study, OWL DL, SWRL and reasoners such as Pellet [14] or HermiT [15] are the tools of choice for performing deductive logical reasoning in the IFC. A general drawback of purely logical inference is that it is only able to handle deterministic evidences. Thus, if the OOWM is operated in a mixed or probabilistic mode, facts contained in the OOWM first have to be converted to deterministic values, e.g., by thresholding (for binary variables) or as expectation values.

For performing logical reasoning in the IFC, the (current, observation-based) information in the OOWM World Model as well as the (a priori modeled) knowledge and rules in Background Knowledge have to be *transformed* into OWL DL and SWRL, respectively. As described previously, one alternative of representing a domain model in the OOWM is the use of an ontology - which can be encoded using OWL DL. In this case, the taxonomy of OOWM concepts, their defining concept classes (represented as OWL concepts with data property restrictions modeling the required and optional attributes), as well their formal relations (represented as object property restrictions) are readily available for logical reasoning. For all the representatives of real-world objects in the World Model, the transformation process has to create ontology individuals as instances of the respective concepts. For each attribute of a representative, a data property assertion with the respective (converted deterministic) value has to be created. For each relation of the representative, an object property assertion linking it to the individual representing the related representative has to instantiated. Finally, the rules

defined in OOWM Background Knowledge have to be expressed in terms of ontology concepts, object properties, data properties, and individuals, as well as normalized according to the form given in (1).

This transformation process basically allows the integration of deductive logical reasoning with (deterministically represented) OOWM information in the IFC. The results of such reasoning include the additional classification of individuals as belonging to (further) concepts (e.g., more specific ones) or their participation in additional relations to other individuals. Updated classifications and additional relations have to be propagated back and integrated into the OOWM after reasoning (using reverse transformations).

An aspect special care should be paid to is the fact that it is not possible to add new individuals to an ontology by reasoning. If a domain model allows specifying rules which can detect additional concept instances in the given data (e.g., instances of abstract concepts such as events, activities, alarms), it is thus not possible to express these rules in SWRL. To mitigate this fact, a workaround can be employed (to some degree). This workaround is based on splitting those ontology concepts for which instantiation by reasoning shall be possible into an abstract version of the concept and an actual version, being a sub-concept of the abstract version. Instances of the abstract version then constitute virtual instances and serve the sole purpose of being promoted (i.e., classified by reasoning) as instances of the actual concept, when indicated by sufficient evidence. This way, e.g., an assault event can be derived from observation data, by promoting an instance of an abstract assault concept, which was created prior to reasoning, to an instance of the actual assault concept. For such promoted instances, a new representative has to be created in the OOWM by the transformation component.

VI. Probabilistic Reasoning

In logical reasoning, each conclusion is necessary in the sense that when the premises of a rule are known to hold (e.g., given by observations), the conclusions follow with absolute certainty. This trait of logical reasoning can be desirable, e.g., as it facilitates the interpretation of concluded information, ensuring that the results hold with certainty. Yet, it also makes modeling inference rules a more complicated endeavor. For such rules, it has to be ensured that all the necessary prerequisites for an inference are explicitly stated in the premises of the rule. This, in turn, allows applying the rule only if and when all necessary premises are given as evidences (i.e., have been observed). In surveillance scenarios aimed at supporting situational awareness of operators, this, in its pure form, is rarely the case, since often e.g. only partial information can be acquired. In such cases, a purely logical inference is insufficient.

A related drawback of hard logical reasoning is that each of the premises of a rule either has to hold (i.e., be 100% true) or not (100% false). Thus, uncertainties in the facts constituting the premises of a rule can neither be considered nor be propagated to the conclusions of a rule by hard logical reasoning. In many scenarios, however, evidences as well as the causal relationships modeled by rules are considered to be true only with a certain probability.

In consequence, a reasoning approach accounting for and being able to handle incomplete and uncertain information and as well probabilistic rules is required for the IFC.

Many approaches to probabilistic reasoning exist for tackling these shortcomings of logical reasoning. Bayesian networks (*BN*) are one of the most prominent examples of the more general class of probabilistic graphical models devised to perform reasoning under explicit consideration of uncertainties. In BNs, evidences as well as conclusions are represented by random variables, and their interconnection is represented by the joint probability distribution of these random variables. Causal relationships between evidences are used to simplify the structure of the network via conditionally independent random variables. As degrees of freedom, the network structure as well as the conditional probabilities have to be provided when specifying a BN model. A drawback of BNs is that their design and maintenance can be rather tedious and costly for complex domain - at least when structure and probabilities of a BN cannot be learned due to lack of example data. A model-based approach relying on a formalized domain model is advantageous in such situations.

Probabilistic relational domain modeling is an area of research suited for such situations by, at the same time, handling a complex domain with a relational structure as well as handling probabilistic reasoning with uncertain information. For this purpose, two components are combined: a logical description or model of the considered domain, e.g., given in FOL, and a probabilistic reasoning approach, for example, a probabilistic graphical model. Examples of respective approaches are multi-entity BNs (*MEBN*) [16], which enable the construction of complex BNs on the basis of a relational domain description, and Markov logic networks (*MLN*) [17], which combine a FOL domain model with probabilistic reasoning by specifying the importance of each FOL formula in reasoning in terms of weights.

MLNs have the advantage of basically employing a set of weighted formulas (including rules) as domain model, with the weights corresponding to a kind of (inverse) uncertainty specification. Information given in the form of an OWL ontology, such as a taxonomy of defined concepts as well as relations, can be easily converted into FOL formulas and integrated into an MLN model. Also, reasoners (e.g., Tuffy [18]) for MLNs are readily available. The integration of MEBNs with the OOWM is, however, more complex. For these reasons, this study follows the MLN approach for integrating probabilistic relational reasoning into the IFC.

In the IFC, relevant information including rules is stored in the OOWM. As described earlier, this information can be converted into an OWL DL ontology. For integrating MLN reasoning, two alternatives are possible: transforming OOWM information directly into a MLN, or using the DL ontology as an intermediate artifact. Since the transformation to DL was already available in this study, the second alternative was chosen. However, certain extensions of this ontology

are necessary towards MLN reasoning. As mentioned earlier, only deterministic values (for attribute values, concept membership, existence of relations etc.) can be specified in OWL DL. As uncertainties are essential for probabilistic reasoning, the uncertainty quantification originally given for each value in the OOWM has to be reflected in the intermediate representation. For this purpose, OWL annotations were used for adding uncertainties to OWL values (transparent to logical reasoning). Likewise, annotations for SWRL rules were added, specifying the weight for each rule.

For the transformation component, a toolchain was implemented, able to generate a MLN model based on the information given in the OOWM. The first step of this toolchain is as previously to generate the ontology model, but now including annotations for uncertain values. The next step is to transform this extended ontology model into a set of weighted FOL formulas as well as probabilistic evidences. In this step, ontology concepts and object properties (relations) are converted into unary and binary predicates, respectively, and taxonomy relationships are reformulated in terms of rules. This step was performed with the help of the Incerto [19] tool. In the final step, the transformed model has to be converted into an input form suitable for MLN reasoners, e.g., by separating evidences from formulas as well as representing formulas in conjunctive normal form.

MLNs address the drawbacks of logical reasoning (no incomplete, inconsistent or uncertain information, no probabilistic rules) by introducing weights for formulas and evidences. The weight of a formula roughly corresponds to the penalty incurred if a formula does not exactly hold during reasoning. The results of MLN reasoning crucially depend on these weights, which are usually learned from examples.

In this study, no learning data can be assumed for the considered scenarios. Thus, a heuristic approach based on expert domain knowledge had to be devised for specifying the weights of inference rules. The developed approach has two steps: first, each (SWRL) rule is assigned an a priori probability of being true in the real world by an expert. Then, this value is scaled with a pre-defined factor, determined heuristically during optimization. For hard facts such as taxonomic relations, weights are determined in the same way, assigning them a probability value of 1 in the first step.

Using the described approach, this study allowed to integrate MLNs into the IFC as a proof of concept. For considered example use cases, this approach allowed reasoning (e.g., threat detection) in the light of incomplete and uncertain information. In comparison the logical reasoning, yet, MLN are only able to answer pre-stated inquiries (e.g.: "given these evidences, how likely is the following fact?"), whereas logical reasoners derive all inferable conclusions for an evidence set. Furthermore, the generalization performance of MLN reasoning in the IFC is improvable, since a set of weights seems to enforce a very specific MLN behavior.

VII. Conclusion and Future Work

In this study, an architecture and details of an information fusion component for a distributed ISR system integrating sensor data and intelligence information has been presented. The component is aimed at enhancing the situational awareness of operators. Special focus was on integrating different reasoning methods linked to an object-oriented world model.

As future work, the integration of probabilistic reasoning based on relational models is intended (e.g., MEBNs, probabilistic relational models). First concepts for such an integration exist, similar to the integration of MLNs: The results of transforming object-oriented information and rules are used to define and ground a probabilistic reasoning model. Details of such a grounding as well as the specification of probabilities are subject to future work.

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