Acceptance of Automatic Situation Assessment in Surveillance Systems

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***Abstract*—In today's surveillance systems, there is a need for enhancing the situation awareness of an operator. Supporting the situation assessment process can be done by extending the system with a module for automatic interpretation of the observed environment. In this article we introduce a consistent terminology for the domain of intelligent surveillance systems. We clarify the separation of the real world and the world model, which is used for the internal representation in the system. For the definition of an automatic situation assessment module, we make use of an existing conceptual framework. We will further introduce a concept for an internal representation of situations of interest and show how the existence of such situations can be inferred from sensor observations. Based on these considerations, an automatic situation assessment module for a maritime surveillance system was developed. The module was evaluated with a small user group and the results show that such an automatic support reduces the workload of the user and is highly accepted.**

I. Introduction

During the operation of surveillance systems, acquiring and interpreting information from the environment forms the basis for the state of knowledge of a decision maker. This mental state is often referred to as situation awareness, whereas the process to achieve and maintain that state is referred to as situation assessment [1]. In today's surveillance systems, the process of situation assessment is highly supported through the various heterogeneous sensors and appropriate signal processing methods for extracting as much information as possible about the surveyed environment and its entities. The challenge of advanced surveillance systems is now to further support the decision maker in his situation assessment process by reducing his workload. This can be achieved by an automatic interpretation of the information. However, there is a need for concepts and methods that are able to infer situations from observed entities in the environment and to project their status in the near future.

In this paper, we present a method for automatic situation assessment in the maritime domain, which was developed based on a conceptual framework for supporting situation awareness in surveillance systems. The framework consists of four parts, namely situation characterization, situation abstraction, situation recognition and situation projection. The automatic situation assessment presented here, which is based on a Bayesian network approach, addresses three of the four parts, namely the situation characterization, abstraction and recognition of the framework. The situation itself is defined as a statement about the constellation of the entities in the environment and modeled as a binary random variable with values true or false. During the process of situation characterization, the focus was on developing a formal representation of a situation in the maritime domain, based on the description of some experts. The result is a Bayesian network in which the structure and the parameters, i.e. the probabilities, are defined by humans and not by training methods. This is due to the fact that there is not enough training data, especially not for critical situations.

In the situation abstraction process, it has to be defined, how the observations have to be mapped to predefined situations. As situations are defined as statements, they can't be measured directly. Moreover, they have to be inferred from quantitative observations, and these dependencies have to be modeled in advance. During the process of situation recognition, inference methods for Bayesian networks propagate the evidences collected by observations to the situations of interest, as defined in the abstraction process. As a result, a degree of belief is calculated, which can be interpreted as a probability for the existence of the predefined situation. Based on this value, it can be decided if the situation currently takes place or not.

The previously described automatic situation assessment was implemented and evaluated with a small user group. Complete ship traffic, i.e. every ship, their observed trajectories and attributes, was visualized in a dynamic situation map. The ship traffic was created by a simulation tool, as well as the sensor configuration. Running the simulation, the tool generates sensor observations from coastal radar and the automatic identification system (AIS), which are often used in real world maritime surveillance applications. The task for the test person was to detect vessels with a high probability to carry refugees on board. Before the test, the user was introduced into the characteristics of such kind of boats (size, speed, direction, etc.). The focus of the evaluation was on the user acceptance of the suggested support. However also an evaluation of the workload was done. The results show a first direction, that such an automatic situation assessment is really supporting the situation awareness of a decision maker and that he trusts the automatic support.

The paper is organized as follows. In Section II, an overview of related work is given. In Section III, we come up with a definition of a consistent terminology for the domain of intelligent surveillance systems. In Section IV, a concrete method for situation assessment is determined based on the conceptual framework from [2]. In Section V, the situation assessment is applied for a situation of interest in the maritime domain and in Section VI, the users workload and the acceptance of the automatic situation assessment is evaluated with a small user group.

II. Related Work

Working with heterogeneous sensors, the theories of multi-sensor data fusion [3] offer a powerful technique for supporting the situation assessment process. A lot of research has been done in combining object observations coming from different sensors [4], and also in the development of real-time methods for tracking moving objects [5].

Regarding data fusion in surveillance systems, the *object-oriented world model (OOWM)* is an approach to represent relevant information extracted from sensor signals, fused into a single comprehensive, dynamic model of the monitored area. It was developed in [6] and is a data fusion architecture based on the JDL (Joint Directors of Laboratories) data fusion process model [7]. Detailed description of the architecture and an example of an indoor surveillance application has been published in [8]. The OOWM has also been applied for wide area maritime surveillance [9].

In [2], a conceptual framework for automatic situation assessment, which is used here, was developed and first ideas of modeling situations in surveillance applications have been presented. We will present here a more detailed definition of a situation. For the situation assessment process, probabilistic methods like hidden Markov models can be used [10], but they are strongly dependent on training data. In [11], Markov random fields are used to model contextual relationships and maximum a posteriori labeling is used to infer intentions of observed elements.

III. Consistent Terminology for Intelligent Surveillance Systems

In surveillance applications, a spatio-temporal section of the real world, a so-called *world of interest*, is considered. The general information flow inside such a system is visualized in Fig. 1, wherein information aggregates are represented by boxes, and processes are represented by circles. The information flow for general intelligent surveillance systems will be described in the following.

First of all, we say that the real world consists of *entities*. By the term entity, we don't necessarily mean physical objects, as entities can also be non-physical elements in the real world like relations. Also, entities don't necessarily have to be directly observable by sensors. Entities can also be unobservable elements like the intention of a person.

The real world can be observed by sensors. Sensor systems can be of extremely heterogeneous types, e.g., video cameras,

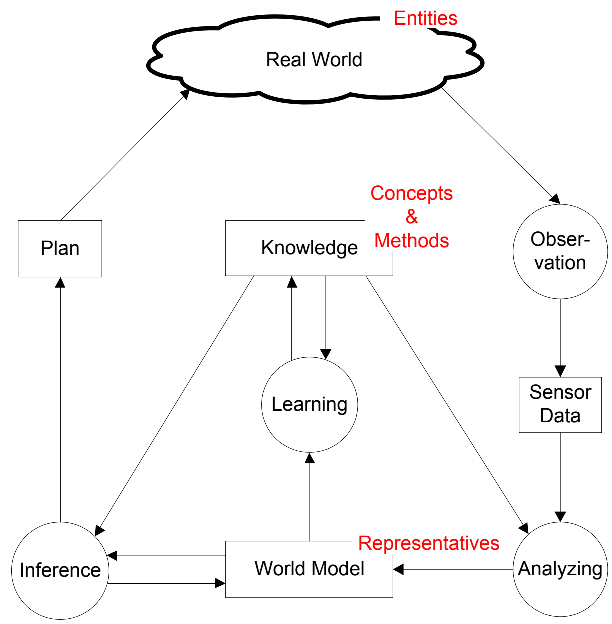

Fig. 1. Information flow and terminology in a surveillance system represented by information aggregates *(boxes)* and processes *(circles)*.

infrared cameras, radar equipment, or RFID-chips. Even human beings can act like a sensor by observing entities of the real world. Observing the world of interest with sensors results in sensor data, for example a radar image or a video stream. Sensor data is then analyzed by means of knowledge and the resulting information is passed to the world model. Analyzing sensor data includes for example the detection and localization of persons that are moving inside a building in a video stream. Knowledge contains all information that is necessary for analyzing sensor data, for example specific signal-processing methods and algorithms used for the detection, localization and tracking of people in video streams.

The world model is a representation of entities in the world of interest and therefore consists of *representatives*. Every representative has a corresponding entity in the real world. The mapping between entities in the world of interest and representatives in the world model is structure-preserving and can therefore be interpreted as a homomorphism. Specific mappings are defined by *concepts* and are part of the knowledge. Concepts are used for example in the analyzing process by defining how an observed person is represented in the world model. As the world of interest is highly dynamic and changes over time, the history of the representatives is also stored in the world model. However, as mentioned before, some entities can't be observed directly and therefore an inference process is reasoning about unobservable (and also unobserved) entities by means of knowledge. A simple inference is for example to calculate an object's velocity from the last and current position. A more complex inference is for example, to estimate if the intention of an observed person is benign or adversarial.

Doing this way, the world model is continuously updated and supplemented with new information by the inference process.

The concept of an *object* is defined as a physical entity of the real world. Regarding its spatial position, an object can be mobile, e.g., a person, or stationary, e.g., a room. An object has several attributes, which can be divided into properties and states. Properties are time-invariant attributes, e.g., the height or the name of a person. State values can change over time and are therefore time-variant, e.g., the position or the velocity of a person. As the representation in the world model also has a memory, which means the past states of an object are stored, the complete history of the observed object is always available. Additionaly, the representation of an object in the world model includes not only observed attributes, but also inferred ones. For example, based on observed positions of a person, the velocity can be inferred. Furthermore, attribute values can be quantitative or qualitative. For example, the absolute position and velocity of a person are quantitative attributes, and the attribute value that a person is smiling is a qualitative one.

We will now define how objects, scenes and situations can be represented in the world model. However, the world model can easily be extended by defining new concepts, e.g., for relations, activities or events.

By the concept of a *scene*, we define all observed and inferred object information at a point in time. A scene can therefore be interpreted as a time-slice, consisting of all objects and their attributes. To include the time aspect, we also speak of a sequence of scenes, when the scenes are considered at several discrete points in time. However, a scene does not include any type of relations in an explicit way. This means, that it is for example not explicitly modeled that two persons are close to each other. But implicitly, of course, this relation can be inferred by the positions of the two persons.

We say that the *configuration space* of the real world is defined by all possible types of objects, their maximum number of occurrence, and their attributes. Then we can say that a scene, which is represented in the world model, is exactly one point in the configuration space of the real world. A sequence of scenes can be interpreted as a trajectory through the configuration space defined by a series of points in time.

The concept of a *situation* is defined as a statement about a subset of the configuration space, which is either true or false. We also say that a specific situation of interest exists, if its statement was inferred to be true. Situations are therefore characterized by qualitative attribute values and their truth is inferred based on information provided by the world model. This means that they have a higher level of abstraction and the level of detail included in the quantitative attribute values of objects and relations is getting lost. The simplest situation is a statement about a qualitative attribute value of an object, e.g., that a person is smiling. There are also situations that can only be inferred by observing the real world over a period of time, e.g., that a person is dancing or that two persons have a conversation.

But although situations are characterized by information collected over a time-period, the only exist at a special point in time. Their existence at the next time-point has to be verified again. However, there are a lot of dependencies between different situations. First of all, situations can be inferred from other situations, e.g., if some persons are dancing and some persons are drinking beer, the inferred situation could be that there is a party going on. Furthermore, situations can exist in parallel or the existence of one situation can exclude the existence of another situation.

Summing up, knowledge contains all information for analyzing sensor data, updating the world model and supplementing it with new information. Concepts are used for the representation of real-world entities in the world model. Characteristics of the knowledge are of course extremely dependent on the application domain. Additionally, knowledge is not static. The content of the world model can be used for acquiring new knowledge by a learning process, for example structure or parameter learning in graphical models.

To close the loop of the information flow, the result of an inference process could also include a plan, of how to act further in the real world. This could be an action plan for an agent, for example to call the police, or a sensor management plan, for example a request for more detailed information from a special sensor.

IV. Framework for Automatic Situation Assessment

The conceptual framework for automatic situation assessment is depicted in Figure 2. As we do not cover here the temporal evolution of a situation, this is a reduced version of the framework where we left out the situation projection. The reduced framework consists of three major process parts (situation characterization, situation abstraction, and situation recognition) and the associated results of the processes. The three process parts and their connection is explained briefly in the following.

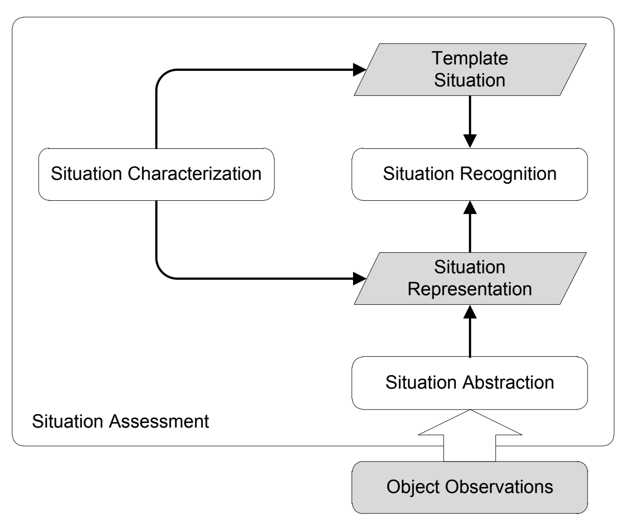

Fig. 2. Reduced version of the conceptual framework developed in [2].

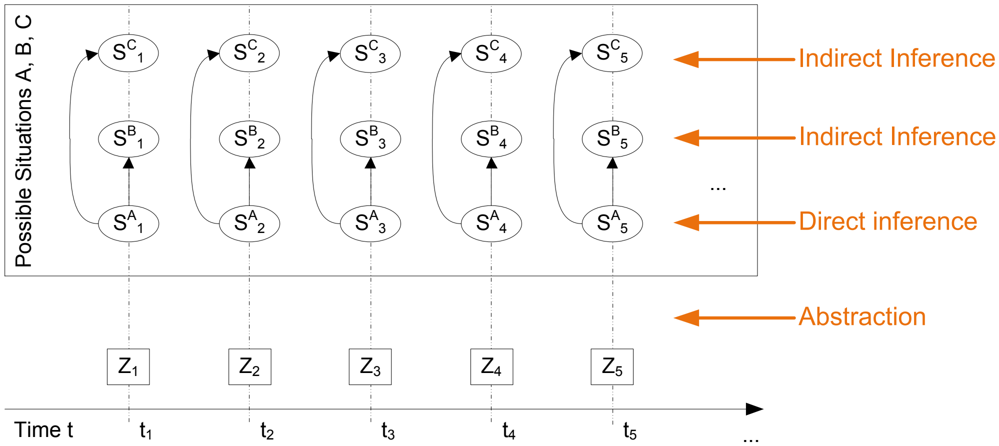

Fig. 3. Networks of situations, divided into directly and indirectly inferred situations.

A. Situation Characterization and Template Situations

The first process part of the situation assessment framework is the characterization of relevant situations. As learning-based methods for situation recognition are often not realizable due to the lack of training data, this process has to be performed by human experts. The experts provide descriptions of relevant situations, including their salient features. Such situations of interest determined by the experts are then tried to assess during surveillance operation. However, the description has to be transformed into a formalized representation, namely the template situation.

Due to the definition of a situation above, we can model a situation at a time t as a binary random variable S_t, such that

$$S_t(\omega) = \begin{cases} 1 & \text{if } \omega \text{ is true,} \\ 0 & \text{if } \omega \text{ is false,} \end{cases} \tag{1}$$

and ω is the statement of the situation of interest. We are interested in the probability that ω is true, and thus that the situation S_t exists at time t. We write this existence probability as $P(S_t = 1)$, or $P(S_t)$ in short.

For calculating this probability, the aforementioned dependencies between other situations have to be modeled. We can distinguish the following two cases:

- Direct inference: the existence probability $P(S_t)$ can be inferred directly from the information content of a scene (or from other concepts like relations or groups);
- Indirect inference: the existence probability $P(S_t)$ depends on the existence probability of other situations.

This concept of a network of situations in every point in time is visualized in Fig. 3. Please consider that we do not cover temporal evolutions of situations here and therefore we don't have any crossing arcs between any points in time. However, this concept can easily be extended to networks including temporal dependencies.

Due to this modeling, the network of situations can be interpreted as a probabilistic graphical model, namely a Bayesian network (BN). In a Bayesian network, the basic idea is to decompose the joint probability of various random variables into a factorized form. A BN is defined as a directed acyclic graph, where random variables are depicted as nodes and conditional probabilities as directed edges. The joint probability can then be factorized as

$$P(X_1, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | Pa(X_i)), \tag{2}$$

where $Pa(X_i)$ is the set of parents of the node X_i.

As we want to make use of the network in every time step, we assume that the structure of the BN doesn't change over time. For the modeling of the situational network, we divide the set of situations into the set of directly inferable situations E and the set of indirectly observable situations S, and interpret them as evidence variables and state variables, respectively. Then, a prior distribution $P(S)$ over all state variables S and the observation model have to be defined in advance. In the observation model, the dependencies $P(E|S)$ between the directly and indirectly inferable situations are determined. This can be done by specifying a conditional probability table (CPT). The joint probability can then be calculated in every time step by

$$P(S, E) = P(E|S)P(S). \tag{3}$$

In the process of situation characterization, the structure of the network (nodes and arcs) and the CPT have to be defined. The template situation has the form of the resulting Bayesian network.

B. Situation Abstraction and Situation Representation

The second process part is the situational abstraction of the observed objects. The aim of this process is to determine the dependencies between object observations and situations, namely the evidence variables. However, there is no general approach for the definition of the situation abstraction as it depends strongly on the semantics of the evidence situations. In some cases, the abstraction process is straightforward. E.g., if the statement of the evidence situation is "two objects are close to each other", the abstraction process could simply be defined by applying a threshold to their distance. A more complex abstraction process is necessary if the statement "a person is aggressive" has to be verified. This could be done by a machine learning algorithm, being applied to various input features.

During operation, the methods defined for the abstraction process are applied and they result in the values of evidence situations, namely the situation representation, in every time step. We will give a more concrete example of the abstraction process and its resulting representation in Section V-B.

C. Situation Recognition

The third process part of the framework is the situation recognition, which deals with matching the situation representation to the situation template. As the situation recognition has to deal with challenges like incomplete information, the result of the situation recognition should not be a binary decision whether the situation is recognized or not. The result should be a degree of belief for each template situation, indicating the existence of the underlying and ongoing situation.

By modeling the situations of interest as nodes in a Bayesian network, we can use inference methods based on Bayes' rule (see for example [12]). We can thus calculate the probability of situations S, given some evidence situations E as

$$P(S|E) = \frac{P(E|S)P(S)}{P(E)}, \tag{4}$$

for each point in time.

A situation is represented in the world model, if the corresponding existence probability is larger than an instantiation-threshold. If the existence probability of the same situation at the next time step is below a deletion-threshold, it is assumed that the situation does not exist any longer and its representation is removed from the world model. This way, it is tried to keep an up-to-date representation of the existing situations of the real world.

V. Situation Assessment in the Maritime Domain

For a representation of the world model, the OOWM system as described in [9] was adapted to the maritime domain. The graphical user interface of the OOWM is depicted in Fig. 4. It shows observed vessels at the Mediterranean Sea between the African coast and the island of Lampedusa. Sensor observations are simulated in the system, but they are assumed to be generated by coastal radar systems or signals from the automatic identification system (AIS). In Fig. 4, an observed vessel is selected and it's observed attributes is shown on the left side. These are exactly the attributes that are stored in the world model, and which are used for inferring situations of interest.

A. Situation Characterization and Template Situation

In the maritime domain, one situation of interest is the detection of vessels that carry refugees on board. Based on various statements by maritime experts, these vessels have the following (observable) characteristics: They are heading

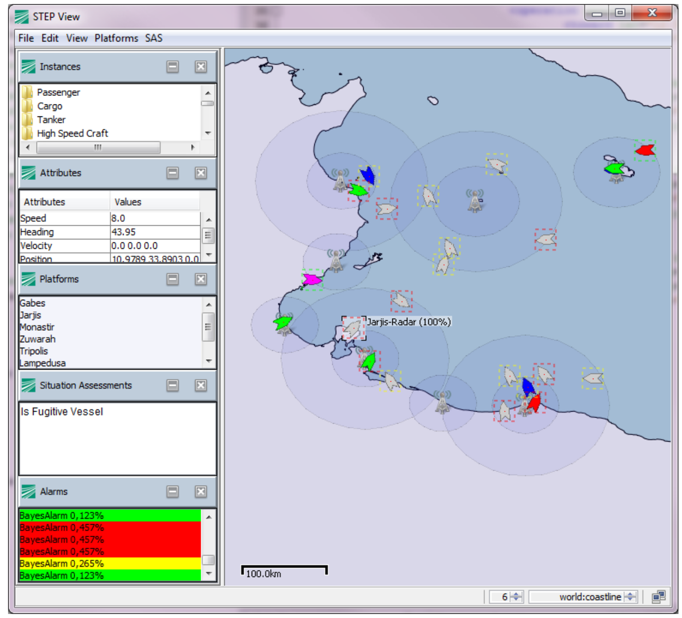

Fig. 4. The OOWM system applied to the maritime domain

towards Lampedusa, they take a direct course, they don't send any AIS-Signal for identification, and they are either wooden boats or motor-boats, where the wooden boats are slower and smaller than the motor-boats.

Based on these descriptions, the structure of the Bayesian network can be defined. As the arcs in a Bayesian network model the causality, arcs are drawn from cause to effect. The resulting structure of the network is shown in Fig. 5. The evidence situations are colored in blue and the situation of interest is colored in red.

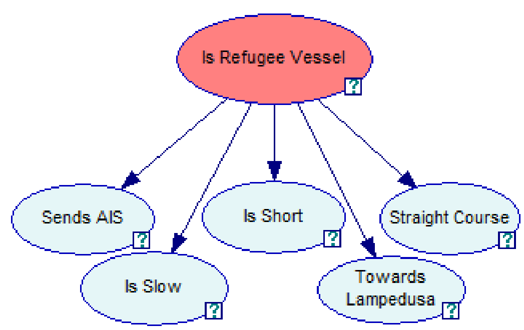

Fig. 5. Bayesian Network the situation of interest colored in red.

The prior probability of the situation of interest has been set to $P(\text{is refugee vessel}) = 0.3$. In the next step, the CPT of the network has to be defined. It has been tried to set the conditional probabilities in a realistic way. The complete CPT is shown in Table I.

So far we have fully defined the template situation, namely the Bayesian network with its CPT. The challenges of modeling the situational network during the situation characterization are firstly to model the structure of the network. Secondly,

TABLE I
CPT FOR BAYESIAN NETWORK IN FIG. 5.

		Is Refugee Vessel True	False
Sends AIS	True	0.1	0.4
	False	0.9	0.6
Is Slow	True	0.7	0.5
	False	0.3	0.5
Is Short	True	0.6	0.4
	False	0.4	0.6
Straight Course	True	0.7	0.5
	False	0.3	0.5
Towards Lampedusa	True	0.9	0.5
	False	0.1	0.5

the parameters of the network, namely the conditional probabilities have to be determined.

B. Situation Abstraction and Situation Representation

During the abstraction process, methods have to be defined and established of how to get information for the evidence nodes. In our previously determined network, we identified five evidence nodes, namely

- $S^A =$ “sends AIS”,
- $S^B =$ “is slow”,
- $S^C =$ “is short”,
- $S^D =$ “is heading towards Lampedusa”,
- $S^E =$ “is taking a straight course”,

and one situation of interest, namely S^F, which is the situation that the observed vessel is carrying refugees on board. In our example, the abstraction processes have been defined in the following way:

- $S^A = 1$, if the vessel's Maritime Mobile Identity (MMI)-Number is available. This number is only available if the vessel is sending its data actively by AIS.
- $S^B = 1$, if the vessel is slower than 10kn.
- $S^C = 1$, if the vessel is shorter than 20m
- $S^D = 1$, if the distance to Lampedusa is decreasing with respect to the previous and the current point in time.
- $S^E = 1$, if the vessels heading didn't vary more than 5 degrees over the last 10 time steps.

These methods are the result of the pre-operational abstraction process. During operation, the methods are executed for each observed vessel seperately. Note that this is due to the semantic of the situation of interest, as the situation of interest demands for a probability for each vessel to carry refugees on board. However, this approach can easily be extended to situations that involve several objects. Thus, the result of the abstraction process is a situation representation in the time point t, which has the following form:

$$R_t = (S^A = s_a, S^B = s_b, S^C = s_c, S^D = s_d, S^E = s_e)_t,$$

with $s_{a,b,c,d,e} \in \{0, 1, \emptyset\}$. The empty set is very important here, because it could happen that we don't have information about every feature of the vessel in every time step. However, this doesn't mean that we cannot execute the situation recognition process, as we will see in the next section.

C. Situation Recognition

During the situation recognition process, we want to establish the degree of belief of the situation of interest $P(S^F)$. This is done by inserting the values of the evidence variables, namely the vector R_t, into the Bayesian network. This is repeated in every time step. By several well-established inference methods for Bayesian networks (see e.g. [12]), the probability of the situation of interest can be calculated.

The most challenging part of the situation recognition process is the interpretation of the resulting probabilities. This can be seen by having a look at some results listed in Table II. In the first row, all evidences values should lead to a high probability, because all features described by the experts are fulfilled. However, the resulting probability is about 77%. This is due to the fact that although all evidence is supporting the existence of the situation of interest, it is still possible that it can be a boat without refugees on board with a probability of 23%. The second row shows that omitting the information about the length of the boat reduces the probability to 69%. In row three, the vessel is sending the AIS-signal and the probability is 36%. A probability of 20% is reached if the vessel sends AIS and it is too long (row four). The same probability is calculated, if the vessel does not send any AIS-signal, but is not heading towards Lampedusa. In the sixth row, all feature values argue against the situation of interest, and the resulting probability is only about 1%. This is due to the fact that there is still a possibility that the vessel is carrying refugees on board.

TABLE II
RESULTING PROBABILITIES FOR THE SITUATION OF INTEREST

Row	S^A	S^B	S^C	S^D	S^E	$P(S^F)$
1	0	1	1	1	1	0.77
2	0	1	$\emptyset$	1	1	0.69
3	1	1	1	1	1	0.36
4	1	1	0	1	1	0.20
5	0	1	$\emptyset$	0	1	0.20
6	1	0	0	0	0	0.01

Therefore, all possible values of $P(S^F)$ range from 1% to 77%, and not as one would intuitively think from 0% to 100%. The interpretation of all the resulting probabilities is often not straightforward and strongly dependent on the values of in the CPT. Changing the conditional probabilities in the CPT can lead to very different ranges for $P(S^F)$. The interpretation of the resulting probabilities can be used for the specification of the instantiation- and the deletion-threshold as mentioned in IV-C.

VI. Evaluation of Acceptance

In this section we describe how the situation assessment has been evaluated to determine the workload and acceptance and present the results.

The user interface used for the evaluation is shown in Fig. 4. The task was explained in the following way:

"Assume you are a decision maker in a maritime control station, where the current vessel traffic is displayed in a dynamic map. You have to make a decision based on the information about the observed vessels. Based on observed attribute values, you have to identify three vessels that are most likely to carry refugees on board. Which ones would you choose?"

The test persons have been introduced in the characteristics of such kind of boats before the evaluation. They were able to select vessels in the displayed dynamic map and to have a look at their attributes (velocity, AIS-information, etc.). If the ship symbol is colored (and not grey), then there is AIS-information available and the ship is assigned to a specific type (passenger, cargo, tanker, etc.). The test persons had as much time as they wanted to solve the task.

For the experiment, the eight test persons have been divided into four groups. All of them had to execute the experiment twice, once without a situation assessment support, and once with support. Therefore, two scenarios have been defined. In both scenarios, three vessels with the aforementioned features have to be detected. Mixing up the two scenarios in order and enabling/disabling the support respectively is resulting in four different evaluation groups.

When working with the situation assessment support, the test persons had additional information about a vessel. This was indicated by a blinking box around a vessel, where the color coding is as follows:

- Red box: Probability of the situation of interest is between 40% and 100%.
- Yellow box: Probability of the situation of interest is between 20% and 40%.
- Green box: Probability of the situation of interest is between 10% and 20%.
- There is no box: Probability of the situation of interest is below 10%.

The exact probability was written in the lower-left info-box of the user interface.

For the evaluation of the workload, a modification of the NASA Task Load Index [13] has been chosen. Five questions have been asked, namely

- Mental Demand: How mentally demanding was the task?
- Temporal Demand: How temporally demanding was the task?
- Performance: How successful were you in accomplishing what you were asked to do?
- Effort: How hard did you have to work to accomplish your level of performance?
- Frustration: How insecure, discouraged, irritated, stressed, and annoyed were you?

The results of these questions are shown in Fig. 6, where the values have been scaled to the range of 0 to 100, and lower values can be interpreted as better results.

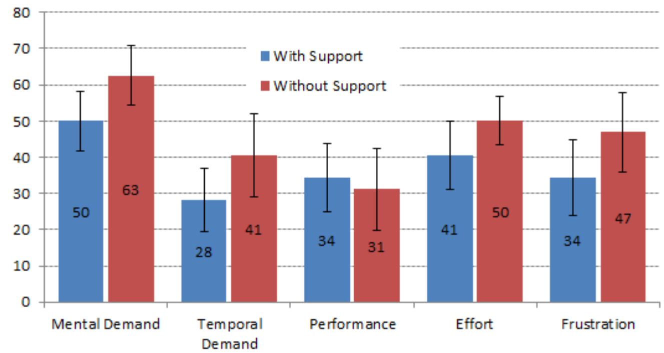

Fig. 6. NasaTLX results (lower values indicate better results).

Interpreting the results, one can see that in four out of five questions, working with the situation assessment support yields better results than working without it. Only the estimate of the own performance is lower when using the support. However, when looking at the true results, all test persons performed better or equal when working with support. The overall rate of detection was about 71% without support, and 79% with support. However, the performance was not in the focus of this evaluation.

Now calculating the workload by building the average of the five question results leads to the values depicted in Fig. 7. Looking at the different values, we can conclude that working with the proposed situation assessment support for this specific application, the workload of a decision maker is lower than the workload of decision makers working without the support.

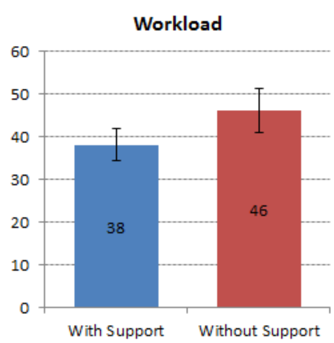

Fig. 7. Average Workload of test persons.

Regarding the acceptance of the automatic situation assessment, the following questions have been asked:

- How long was the familiarization time with the system?
- How easy was the system to use?
- How useful was the color coding regarding the situation of interest?
- How useful was the actual probability in the lower left info-box?

- How useful was the support function in general?

The results for this question are shown in Fig. 8, where the values range from 0 to 100, and higher values indicate better results. Except the usefulness of displaying the real probability, all questions got a quite high score, especially the color coding of the situation of interest. The reason for the low value of the probability display is due to the design of the user interface. Users have to guide their focus of attention to the lower left corner of the interface in order to read the probabilities. But often they didn't even look at these values and kept their focus of attention on the dynamic map.

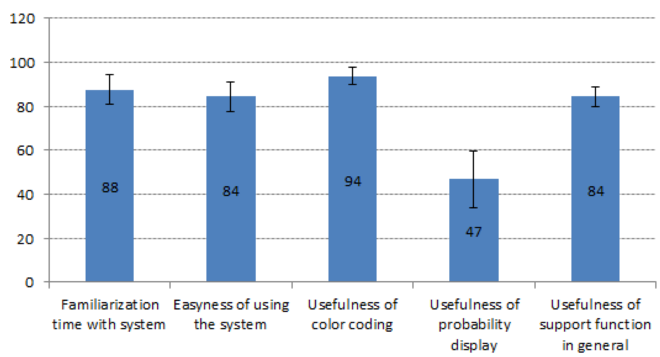

Fig. 8. Acceptance of automatic situation assessment (higher values indicate better results).

The test persons also have been asked if they would prefer the automatic situation support, and 100% of them answered the question with "yes". Thus, the proposed automatic situation assessment is well accepted by users, even though they don't know exactly how the probabilities are calculated.

VII. Conclusion and Future Work

In this article, we presented a definition of a consistent terminology for intelligent surveillance systems. We gave a description of an already existing framework for automatic situation assessment and extended it by defining concrete methods. We further introduced a concept for the definition an internal representation of situations of interest and showed how the existence of such situations can be inferred from sensor observations. Following this proposition, we developed an automatic situation assessment module for a maritime surveillance system. The module was evaluated with a small user group and the results show that such an automatic support reduces the workload of the user and is highly accepted.

As the results of the situation recognition are strongly dependent on the conditional probabilities of the network, further work will regard the sensitivity of the network with respect to the conditional probabilities and the interpretation of the resulting probabilities. The aim is that the expert does not necessarily have to be familiar with the underlying probabilistic method and that the probabilities of the Bayesian network can be set automatically.

Also, the focus of this evaluation was on the user acceptance of the module and not on the reliability of the probabilistic method. Therefore, the influence of the conditional probabilities on the results of the situation recognition has to be further investigated. Further work will also be done on exploring the capabilities of dynamic Bayesian networks. Using them, dependencies in time can be included and also the projection part of the framework, which was omitted here, can be covered.

For a general conclusion about the workload and the acceptance of the module, the method should be evaluated for different scenarios and with a lot more test persons. Also, an evaluation with experts in the domain of maritime surveillance could yield to different results. Additionally, the results strongly depend on the visualization of the user interface. Therefore, the module should also be evaluated by using different visualization techniques of the recognized situations.

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