A Bayesian Approach to the Detection of Hazardous Shipping Activity

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ABSTRACT

Tracking of ships by means of various heterogeneous sensors is well understood and regularly practiced. But in order to carry out surveillance for security purposes, the tracking of single units is only the fundamental step for the detection and classification of activities. The decision about potentially hazardous activities shall not only be based on single tracks but rather on the relation of tracks from multiple objects. Particularly along the coastal strip and in the vicinity of ports the mostly crowded ship movement poses a huge challenge to activity detection and classification. In this article we describe the information flow in an intelligent surveillance system and clarify the separation of the real world and the world model, which is used for the representation of the real world in the system. The focus of this article is on modeling situations of interest in surveillance applications and inferring them from sensor observations. For the representation in the system, concepts of objects, scenes, relations, and situations are introduced. Situations are modeled as nodes in a dynamic Bayesian network, in which the evidences are based on the content of the world model. Several methods for inferring situations of interest are suggested, which make use of the underlying network modeling. Due to this modeling, we get a probability of all the situations in the network in every time-step. By collecting more evidences over time, the probability of a specific situation is either increasing or decreasing. Finally, we give an example of a situation of interest in the maritime domain and show how the probability of the situation of interest evolves over time.

1.0 INTRODUCTION

During the operation of complex systems that include human decision making, the processes of 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 [1], whereas the process to achieve and maintain that state is referred to as situation assessment. In today's surveillance system, the situation assessment process is highly supported through various heterogeneous sensors and appropriate signal processing methods for extracting as much information as possible about the surveyed environment and its elements. Using these methods is, of course, an essential capability for every surveillance system in order to be able to observe a designated area and to detect and track objects inside this area. The approach of collecting as much sensor data as possible and extracting as much information as possible from it is termed bottom-up, or also known as data-driven processing.

However, this approach is not useful for the situation awareness of an operator, because his workload in interpreting all this information will be too high. The challenge of intelligent surveillance systems is therefore not only to collect as much sensor data as possible, but also to detect and assess complex situations that evolve over time as an automatic support to an operator's situation assessment process, and therefore enhancing his situation awareness. The approach of defining and presenting only relevant information about events and activities is termed top-down processing. However, there is a need for concepts and methods supporting higher level situation awareness, i.e., methods that are able to infer real situations from observed elements in the environment and to project their status into the near future.

The paper is structured as follows. In Section 2, an overview of related work is given. As this article follows the top-down approach, the information flow in an intelligent surveillance system is highlighted in Section 3. In Section 4, the methods of modeling situations of interest and inferring their existence are explained. In Section 5, an example in the maritime domain is given.

2.0 RELATED WORK

Working with a system that uses heterogeneous sensors, the theories of multi-sensor data fusion [2] 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 [3], and also in the development of real-time methods for tracking moving objects [4]. 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 [5] and is a data fusion architecture based on the JDL (Joint Directors of Laboratories) data fusion process model [6]. Detailed description of the architecture and an example of an indoor surveillance application has been published in [7]. The OOWM has also been applied for wide area maritime surveillance [8].

First ideas of modeling situations in surveillance applications have been presented in our previous work in [9] and [10]. For the situation assessment process, probabilistic methods like hidden Markov models can be used, see for example [11]. In [12], Markov random fields are used to model contextual relationships and maximum a posteriori labeling is used to infer intentions of observed elements. However, most of the methods used for situation assessment are based on machine learning algorithms and they result in models that humans are not able to understand. They are also strongly dependent on training data, which are not always available, especially not for critical situations. The contribution of this work is the modeling approach from a top-down perspective, which tries to model situations from a human perspective, i.e., which situations an operator wants to detect, and how to link them to methods for automatic interpretation.

3.0 INFORMATION FLOW IN 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 for intelligent surveillance systems is visualized in Figure 1, wherein information aggregates are represented by boxes and processes are represented by circles. The information flow is as follows.

First of all, all elements in the real world are termed entities. By the term entity, not only physical objects are meant, as entities can also be non-physical elements in the real world like relations or the name of a vessel. Thus, entities can represent observable or unobservable elements. Sensor systems for observing the real world can be of extremely heterogeneous types, e.g., video cameras, infrared cameras, radar equipment, or radio-frequency identification (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 transferred to the world model. Analyzing sensor data includes for example the detection and localization of moving vessels at sea from 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 vessels in video streams.

The world model is a representation of entities in the world of interest and consists therefore 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 for example used in the analyzing process by defining how an observed vessel 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 cannot be observed directly. Therefore an inference process is reasoning about unobservable (and also unobserved) entities by means of knowledge. A simple inference process is for example the calculation of an object's velocity from the previous and current position. A more complex inference process would be to estimate if the intention of an observed vessel is benign or adversarial. Following this approach, the world model is always being updated and supplemented with new information by predefined inference processes.

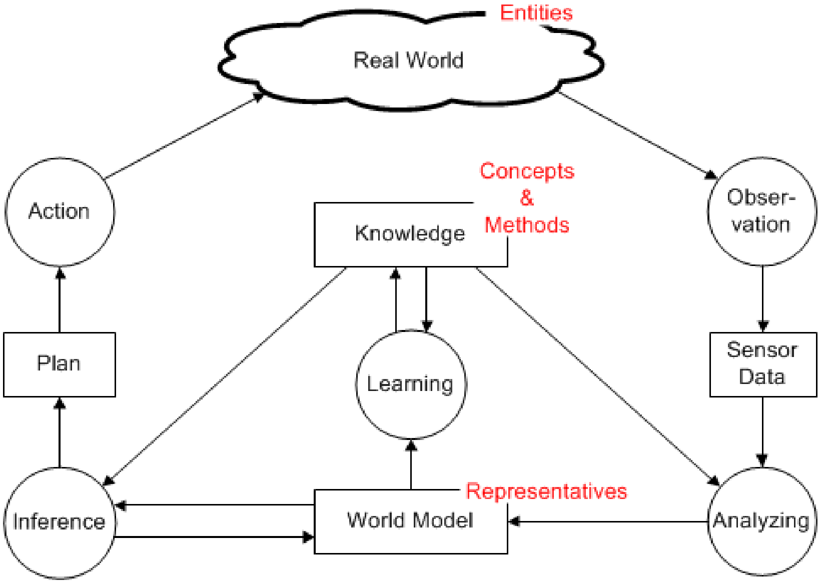

Figure 1: Information Flow in a Surveillance System represented by information aggregates (boxes) and processes (circles)

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 can 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 coast guard, or a sensor management plan, for example a request for more detailed information from a specific sensor.

4.0 MODELING AND INFERRING SITUATIONS OF INTEREST

In this Section we will describe how situations are defined and how they can be modeled by a situational network. The situational network can be interpreted as a dynamic Bayesian network (DBN), in which well-known inference calculations can be applied.

4.1 Situation Modeling

Moving objects and their relations to each other are always in the focus of surveillance systems. By an object, we mean a physical entity of the real world with a spatial position at each point in time. An object has several attributes, which can be divided into properties and states. Properties are time-invariant attributes, e.g., the name of a vessel. State values can change over time and are therefore time-variant, e.g., the position or the velocity of a vessel. As the representation in the world model, the aforementioned

OOWM, also has a memory, which means that the past states of an object are stored, the complete history of the observed object is always available. Furthermore, the representation of an object in the world model does not only include observed attributes, but also inferred ones. For example, based on observed positions of a vessel, its velocity can be inferred. Furthermore, attribute values can be quantitative or non-quantitative. For example, the absolute position and velocity of a vessel are quantitative attributes, and the name of a vessel is a non-quantitative one.

The configuration space Ω is defined by all possibly occurring attributes for each object. This configuration space is quite high dimensional and its dimension is growing with the number of objects occurring. But by defining Ω, we can define a situation as a statement about a subset $\widetilde{\Omega}$ of the configuration space, which is either true or false. Mathematically, a situation at a time t can be modeled as a binary random variable S_t, such that

$$S_t = \begin{cases} 1, & \text{if statement is true,} \\ 0, & \text{if statement is false.} \end{cases}$$

Then we are interested in the probability that $S_t = 1$, namely that the statement is true, and thus that the situation S_t exists at time t. We will write $P(S_t)$ shortly for $P(S_t = 1)$. This existence probability is dependent on the attribute values of the sub-configuration space $\widetilde{\Omega}$ and we define

$$P(S_t) \coloneqq P(S_t | \omega_1, \omega_2, \dots),$$

with $\omega_1, \omega_2, \dots \in \widetilde{\Omega}$. We will infer the existence of a situation, if its existence probability is larger than a certain threshold.

Due to this modeling, situations are characterized by non-quantitative statements and their existence is inferred based on information in the world model, i.e., the attribute values in the sub-configuration space. This means that situations have a higher level of abstraction and the level of detail included in the quantitative attribute values of the observed objects is getting lost. The simplest situation is a statement about an attribute value of an object, e.g., that a vessel has a certain name. But there are also situations, which can only be inferred by observing the real world over a period of time, e.g., the situation that a vessel is heading in a certain direction.

Although situations are characterized by information collected over a time-period, they only exist at a special point in time. Their existence in the next time-point has to be verified again. Due to the semantics of situations, there are a lot of dependencies between them. First of all, situations can be inferred from other situations, e.g., if a vessel is close to another vessel and has just appeared, the inferred situation could be that the vessel could be a lifeboat. Furthermore, several situations can exist in parallel or the existence of one situation can exclude the existence of another situation.

For calculating the existence probability of all kinds of situations, the aforementioned dependencies between them have to be modeled. We can mainly distinguish between the following two cases:

- Level 1 situations: the existence probability $P(S_t)$ can be inferred directly from the attribute values of the configuration space,
- Higher level situations: the existence probability $P(S_t)$ depends on the existence probability of other situations.

This also includes temporal dependencies, e.g., that the existence probability of an inferred situation in future can be supported by the earlier existence of the situation itself. The complete modeling of the dependencies results in a network of situations.

An example network of situations is visualized in Figure 2. In this simplified example we have four situations of interest, namely *A*, *B*, *C* and *D*, where *A* and *B* are Level 1 Situations. They can be inferred directly by the values of the configuration space, which is 3-dimensional in this example with the three attributes ω_1, ω_2, and ω_3. The situations *C* and *D* are higher level situations and their existence is dependent on the existence of lower level situations. Note that the arrows can be interpreted as "is dependent on". Furthermore, we visualized three time steps in our example and we indicated the temporal dependencies by dashed lines.

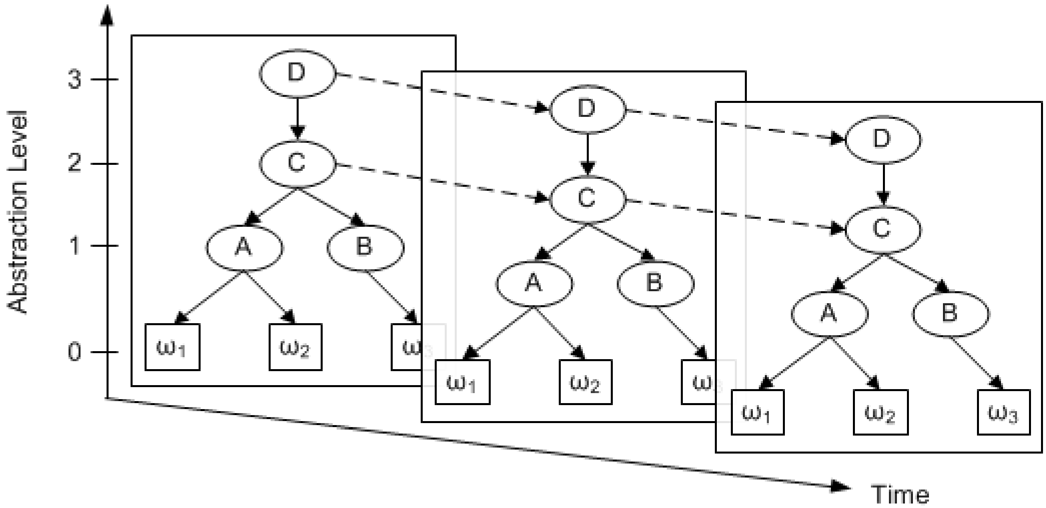

Figure 2: An example network of four situations, spread over three time steps and over three abstraction levels, where level 0 indicates the configuration space.

4.2 Inferring Situations of Interest

Due to this modeling, the network of situations can be interpreted as a DBN. In a simple Bayesian network, the basic idea is to decompose the joint probability of various random variables into a factorized form. Random variables are depicted as nodes and conditional probabilities as directed edges. The joint probability can then be factorized as

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

where $Pa(X_i)$ is the set of parents of the node X_i for any $i = 1, \dots, n$. If $Pa(X_i)$ is an empty set, then X_i is a root node and $P\big(X_i \big| Pa(X_i)\big) = P(X_i)$ denotes its prior probability.

A DBN is defined as a pair $(B_0, 2TBN)$, see for example [13] or [4], where

- B_0 defines the prior distribution $P(\boldsymbol{X_0})$ over the set $\boldsymbol{X_0}$ of random variables, and
- $2TBN$ (2-timeslice Bayesian network) defines a conditional Bayesian network over two time slices with

$$P(\boldsymbol{X_t} | \boldsymbol{X_{t-1}}) = \prod_{i=1}^{n} P(X_t^i | Pa(X_t^i)),$$

where X_t^i is a node at time slice t and $Pa(X_t^i)$ is the set of parent nodes, which can be in the time slice t or in the time slice $t - 1$.

Based on the definition of the pair $(B_0, 2TBN)$, we can define an unrolled DBN as the probability distribution over $\boldsymbol{X_{0:T}}$ for every time span $T > 0$. The DBN is unrolled in that sense that we use B_0 for the definition of structure and conditional probability distribution of $\boldsymbol{X_0}$ and that we use $2TBN$ for the definition of the structure and the conditional probability distribution of $\boldsymbol{X_t}$ for any $t > 0$. The joint probability distribution of an unrolled DBN can then be calculated by

$$P(\boldsymbol{X_{0:T}}) = P(\boldsymbol{X_0}) \cdot \prod_{t=1}^{T} \prod_{i=1}^{n} P(X_t^i | Pa(X_t^i))$$

As we want to model a network of situations by a DBN, the structure of the situational network has to fulfill the following assumptions:

- Stationarity: the dependencies within a time slice t and the dependencies between the time slices $t-1$ and t do not depend on t.
- First order Markov assumption: the parents of a node are in the same time slice or in the previous time slice.
- Temporal evolution: dependencies between two time slices are only allowed forward in time, i.e., from past to future.
- Time slice structure: The structure of one time slice is a simple Bayesian network, i.e., without cycles.

For modeling the situational network, the set of situations is divided into the set of level 1 situations $\boldsymbol{E}$ and the set of higher level situations $\boldsymbol{S}$, as described above, and interpret them as observation variables and state variables, respectively. The state transition between two time slices satisfies the Markov assumption

$$P(\boldsymbol{S_t} | \boldsymbol{S_{0:t-1}}) = P(\boldsymbol{S_t} | \boldsymbol{S_{t-1}})$$

and the dependencies between level 1 and higher level situations are defined by

$$P(\boldsymbol{E_t} | \boldsymbol{S_{0:t}}, \boldsymbol{E_{0:t-1}}) = P(\boldsymbol{E_t} | \boldsymbol{S_t})$$

Due to this dependency, it is assumed that the values of the observation variables are only dependent on the values of the state variables. The joint probability of an unrolled DBN can then be calculated recursively by

$$P(\boldsymbol{S_{0:T}}, \boldsymbol{E_{1:T}}) = P(\boldsymbol{S_0}) \cdot \prod_{t=1}^{T} P(\boldsymbol{S_t} | \boldsymbol{S_{t-1}})\, P(\boldsymbol{E_t} | \boldsymbol{S_t})$$

By modeling the network of situations in this way, the following inference calculations are possible:

- Filtering: $P(\boldsymbol{S_t} | \boldsymbol{E_{1:t}})$ gives a solution to the existence probability of a set of situations $\boldsymbol{S}$ at the current time,
- Prediction: $P(\boldsymbol{S_{t+k}} | \boldsymbol{E_{1:t}})$ (with $k > 0$) gives a solution to the existence probability of a set of situations $\boldsymbol{S}$ in the (near) future,
- Smoothing: $P(\boldsymbol{S_{t-k}} | \boldsymbol{E_{1:t}})$ (with $0 < k < t$) gives a solution to the existence probability of a set of situations $\boldsymbol{S}$ in the past,
- Most likely explanation: $argmax_{S_{1:t}} P(\boldsymbol{S_{1:t}} | \boldsymbol{E_{1:t}})$ gives a solution to the most likely sequence of situations $\boldsymbol{S_{1:t}}$.

Due to this modeling, the existence probability of a set of higher level situations can be calculated in a recursive way at each point in time. A situation is then inferred to be true and represented in the world model, if the corresponding existence probability is larger than an instantiation-threshold. If the existence probability in the next time step is below a deletion-threshold, it is assumed that the situation doesn't exist any longer and its representation is removed from the world model. See for example [3] for the usage of such thresholds. This way, it is tried to keep an up-to-date representation of the existing situations of the real world.

5.0 APPLICATION SCENARIO IN THE MARITIME DOMAIN

For a representation of the world model, the OOWM system as described in [8] was adapted to the maritime domain. The graphical user interface of the OOWM is depicted in Figure 3. It shows observed vessels near the Port of Tripoli in Libya. 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 Figure 3, an observed vessel is selected and it's observed attributes can be seen on the left side of the user interface. These are exactly the attributes that are stored in the world model and are used for inferring situations of interest. One can also see that the positional information of the selected ship is fused from observations coming from two sensors, namely a coastal radar and an AIS-receiver, both located in Tripolis.

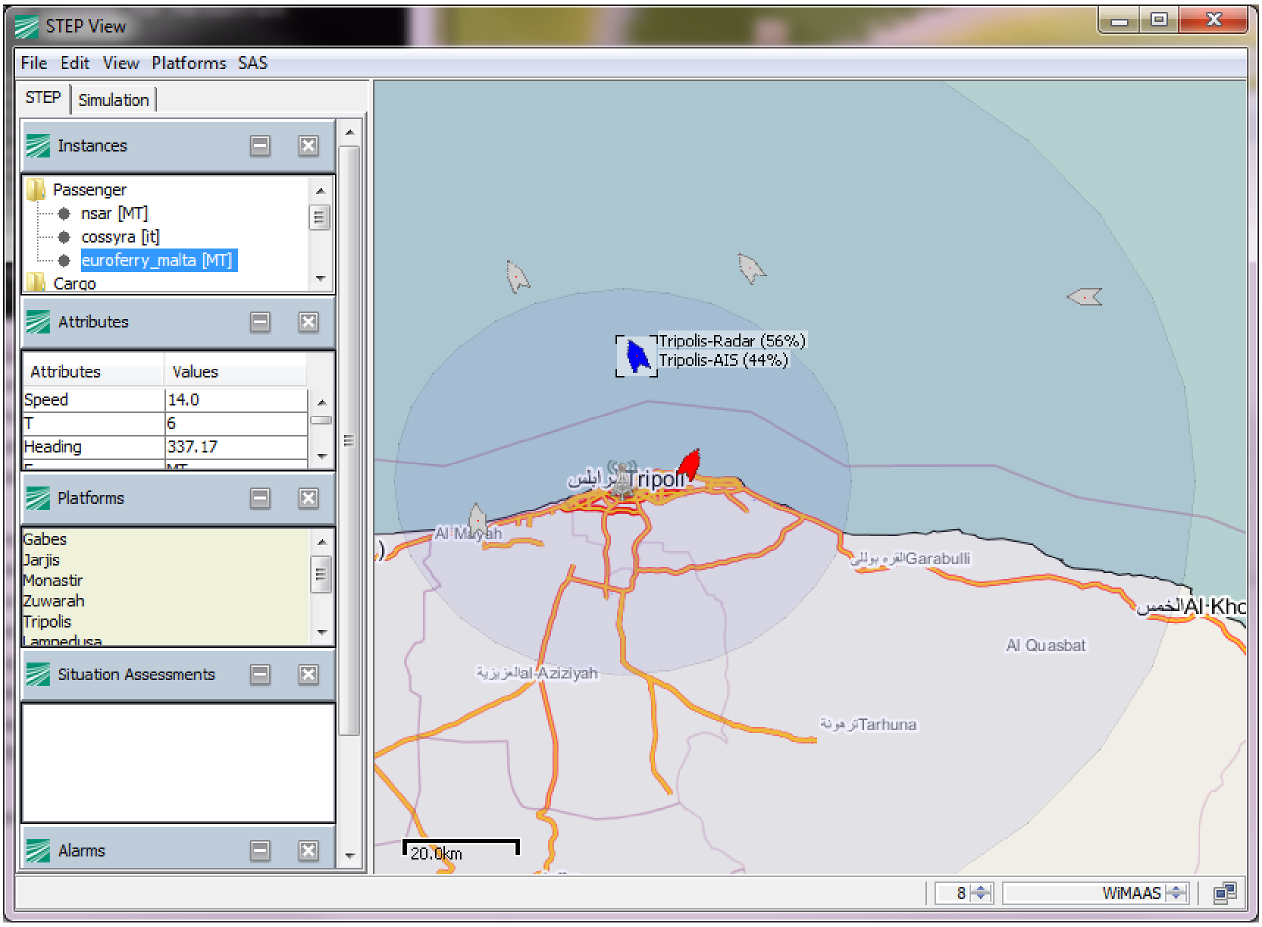

Figure 3: The OOWM system applied to the maritime domain.

Particularly along the coastal strip and in the vicinity of ports, a situation of interest is, if the observed vessel is likely to be a smuggling vessel. These vessels have several characteristics and their dependencies can be defined in a situational network. First of all it is assumed that a smuggling vessel fulfills one or more of the following critical criteria. If one knows in which harbor the vessel previously was, it could be either declared as a critical harbor or not, for example if the last harbor is in a critical country. It is also an indicator for a smuggling vessel, if it had a rendezvous at sea with another vessel, for example for changing some goods, or if it passed a suspicious smuggling area. Furthermore it is assumed that a smuggling vessel is likely to send no AIS signal, because it doesn't want to be identified (we will skip the case here when AIS signal is faked). Other indicators for suspicious vessels in general are an abnormal rate of turns or abnormal behavior with respect to the ship type. The last two criteria can be established by comparing the track of a vessel by a learned normal model, for example a hidden Markov model.

An example of a dynamic Bayesian network that covers the structural dependencies between the abovementioned criteria is shown in Figure 4. The three criteria that indicate some events happening in the past are combined in one higher level situation, namely the fulfills-critical-criteria-node. By modeling the dependencies this way, it is much easier to set the probabilities, because it is enough if one of the criterion is fulfilled. The temporal arrow (arrow number 1) is indicated by the red color and shows the temporal dependency of the situation that an observed vessel is a smuggling vessel to itself. This is due to the fact that if the vessel is likely to be a smuggling vessel in the previous time step, it is likely to be a smuggling vessel in the current time step.

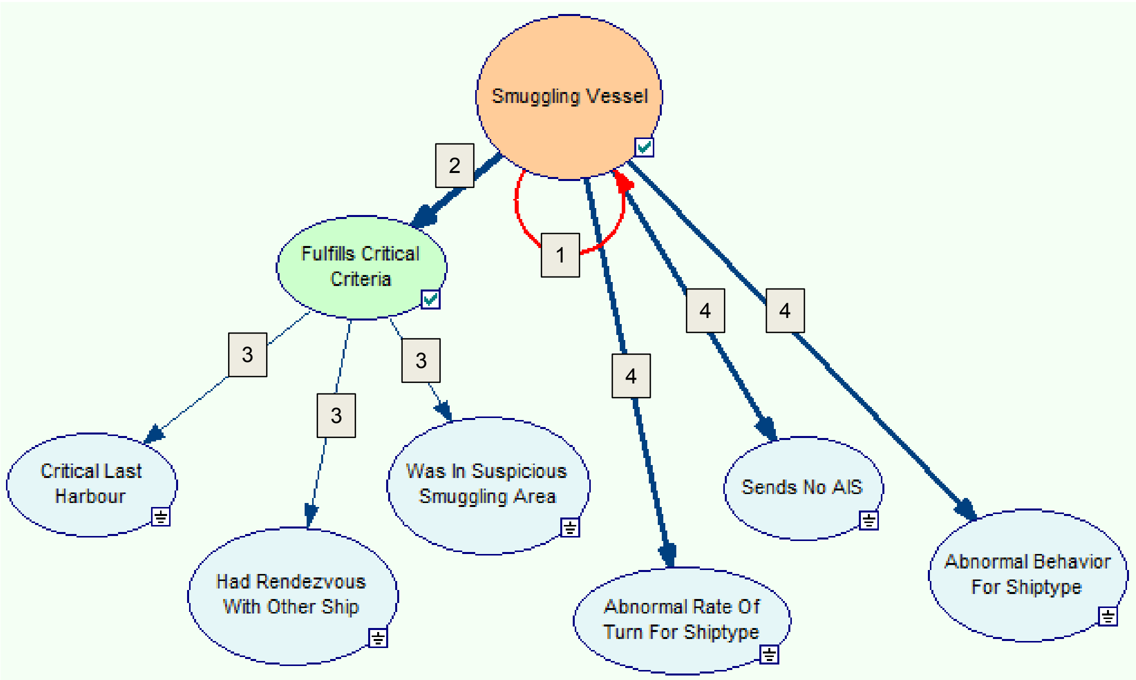

Figure 4: Dynamic Bayesian Network structure for defining a smuggling situation (colored in orange). Temporal arrows over one time slice are colored in red.

The thickness of the arrows in Figure 4 shows the strength of influence of the conditional probabilities. The prior probability of a vessel being a smuggling vessel is set to 0.5. The conditional probabilities associated with the temporal arrow (arrow number 1) are set to

$$P(\text{Smuggling}_t | \text{Smuggling}_{t-1}) = 0.9 \quad \text{and} \quad P(\text{Smuggling}_t | \neg\text{Smuggling}_{t-1}) = 0.1.$$

The conditional probabilities of fulfilling a critical criterion when the vessel is a smuggling vessel or not (arrow number 2) are set to

$$P(\text{Criteria}|\text{Smuggling}) = 0.9 \qquad \text{and} \qquad P(\text{Criteria}|\neg\text{Smuggling}) = 0.5.$$

The conditional probabilities of a selected critical criterion (harbor, rendezvous or area) when the vessel is fulfilling a critical criterion or not (arrow numbers 3) are all set to the same values. One example of them is the critical harbor, where the probabilities are set to

$$P(\text{Harbor}|\text{Criteria}) = 0.7 \qquad \text{and} \qquad P(\text{Harbor}|\neg\text{Criteria}) = 0.5.$$

The conditional probabilities of the three remaining situations when the vessel is a smuggling vessel or not (arrow numbers 4) are set to the following values, for example for the abnormal behavior

$$P(\text{abnBehavior}|\text{Smuggling}) = 0.7 \qquad \text{and} \qquad P(\text{abnBehavior}|\neg\text{Smuggling}) = 0.7.$$

We will now show some results of probabilities (calculated by filtering) of a vessel being a smuggling vessel with respect to different observed evidences. Note that the DBN is defined for exact one vessel, so for every observed vessel we get a different probability. For the observable situations, namely the level 1 situations (harbor, rendezvous, area, no AIS, abnormal turns, abnormal behavior), we only admit hard decisions of zero and one, i.e. the situations either exist or not. We will show the results over 10 time steps and we assume that the time between two time steps is 30min.

The first results are visualized in Figure 5. In this case we assume that the three critical criteria (harbor, rendezvous, area) haven't been fulfilled, i.e., are set to zero. In the first five time steps we have an AIS-signal from the vessel, but then it is assumed to be turned off. At some time steps we detect abnormal turn rates (time steps 4,5,6,9,10) and abnormal behavior (time steps 3,4,7,8,9,10). We can clearly see that the probability of the vessel being a smuggling vessel is almost zero at the beginning. Because the influence of AIS and abnormal behavior and abnormal turn rate is quite high, the smuggling probability is increasing, even if no critical criterion has been observed.

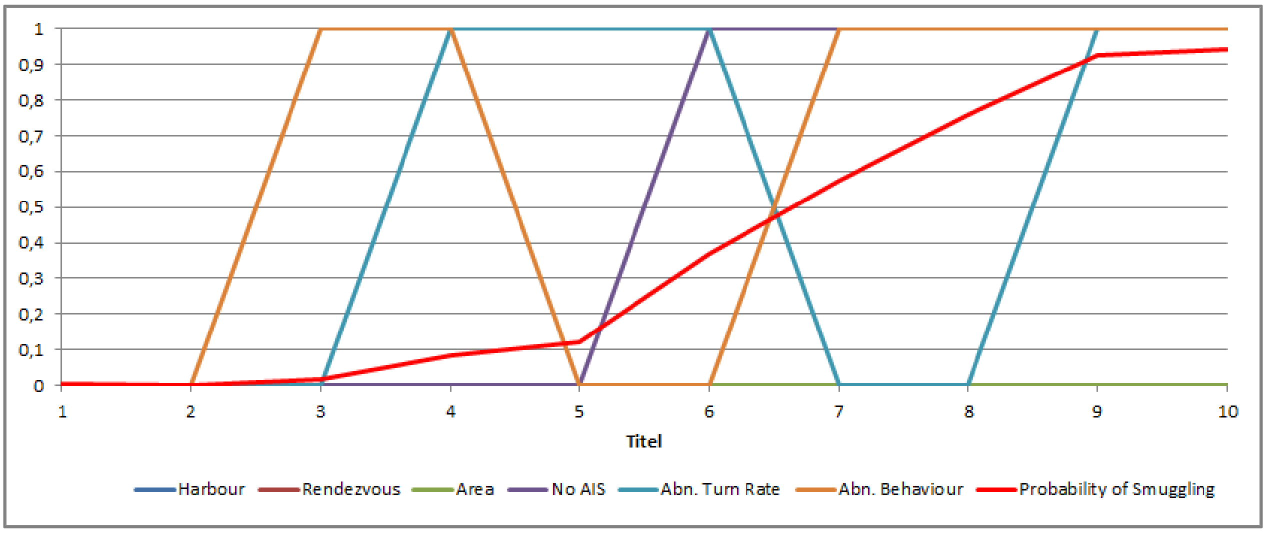

Figure 5: Resulting probabilities of smuggling vessel over time.

The second results are visualized in Figure 6. In this case we assume that, additionally to the first case, the vessel's last harbor was a critical one, the vessel has passed a suspicious smuggling area, and that it had a rendezvous at sea with another vessel at time point 4. We can clearly see that the probability of the vessel being a smuggling vessel starts with a value of almost zero, but is increasing quite fast. At time step 4 the probability is already larger than 0.5, the prior probability.

However, in both cases it can clearly be seen that due to the evidence that has been collected over time, the existence probability of the situation that the observed vessel is a smuggling vessel is increasing over time. The probability would be decreasing over time if the last harbor would change to a non-critical one, the time since rendezvous and the time since suspicious area passing is over a certain threshold, i.e., their value can be set to zero. Further decreasing of the probability would be supported if the vessel would turn its AIS on.

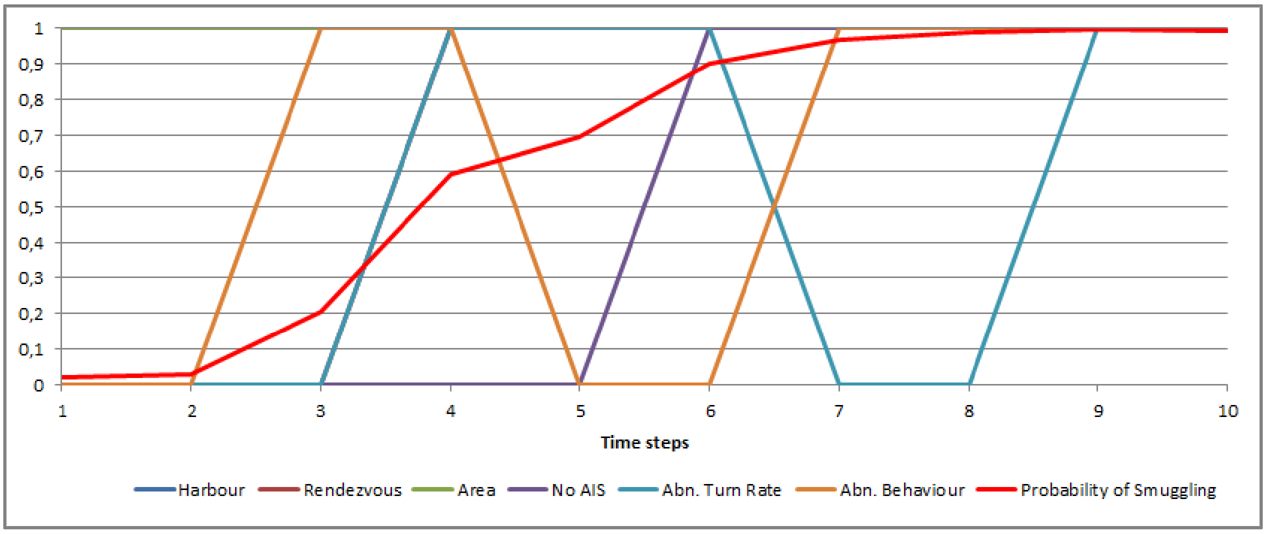

Figure 6: Resulting probabilities of smuggling vessel over time.

The challenges of designing the dynamic Bayesian network are to model the structure and to determine the parameters, i.e., the conditional probabilities. Finally, the resulting probabilities for different configurations have to be interpreted (e.g., for the specification of the instantiation- and the deletion-threshold), which is often not straightforward.

6.0 CONCLUSION AND FUTURE WORK

In this article the information flow in an intelligent surveillance system was highlighted and it was described how situations of interest in surveillance applications can be modeled. For modeling a network of situations, the framework of dynamic Bayesian networks is suggested, in which the values of the directly inferable nodes are based on the content of the world model. This modeling fulfills the requirements resulting from the definition of situations and allows the application of efficient inference methods. An example of a situation of interest in the maritime domain was given. By extending the surveillance system with such a module for automatic interpretation of the observed environment it is able to support the situation assessment process of an operator and thus enhances his situation awareness.

Future work includes an experimental evaluation of the proposed method and an investigation on supporting the human operator in designing a situational network without having a detailed knowledge of the underlying method. Also the real-time capability of the proposed method when using a large amount of data has to be investigated.

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