Ontologies for Probabilistic Situation Assessment in the Maritime Domain

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Abstract—In the maritime domain, surveillance systems are used to track vessels in a certain area of interest. The resulting vessel tracks are then displayed in a dynamic map. However, the interpretation of the dynamic environment, i.e., the situation assessment (SA) process, is still done by human experts. Several methods exist that can be used for automatic SA, but often they are based on machine learning algorithms and do not include the knowledge of the decision maker. In this article, we describe how expert knowledge can be used to determine models for automatic SA. The knowledge about situations of interest is modeled as an ontology, which can be transformed into a dynamic Bayesian network (DBN). The main challenge of this transformation is the determination of the structure and the parameter settings of the DBN. The resulting DBN can be connected to real-time vessel tracks and is able to estimate the existence of the situation of interest in every time step.

I. INTRODUCTION

Today, situation awareness of decision makers in the maritime domain is supported by visualizing ship traffic in a certain area of interest. The vessel tracks are generated by a surveillance system that processes sensor observations from various kinds of sensors, e.g., from coastal radar or from the automatic identification system AIS. For the detection of specific situations of interest, e.g., a vessel deviates from a shipping lane, the decision maker has to interpret the ship traffic by himself, i.e., he has to assess the situation without any support.

Probabilistic graphical models are often used for realizing automatic situation assessment (SA). In such models, the choice of appropriate parameters is a crucial point for an optimal performance. A typical approach is to learn the parameters from training data representing normal ship traffic. By applying this model to sensor observations, deviations from the model can be detected and abnormal behaviors can be detected. The problem of the learning approach is that training data is required. Particularly, if there are several specific situations of interest, a model for every situation has to be learned, i.e., there has to be training data for each situation. This training data is of course not always available.

Thus, our approach is to include expert knowledge into a probabilistic graphical model, namely a dynamic Bayesian network (DBN), instead of using training data. As domain experts are in general not familiar with DBNs, the knowledge is modeled as a human-understandable ontology. In this ontology, dynamic objects (e.g., vessels), static structures (e.g., shipping lane), and situations of interest (e.g., vessel is moving on shipping lane) are modeled. The ontology has to be transformed into a DBN in order to perform the automatic SA. The main challenge of the transformation is to determine the structure and the parameters of the DBN. The aim is to generate a model that behaves like the user would expect it to behave.

In this article, we present some general rules for transforming the presented maritime ontology into a DBN and show an application example. As a result, we get an existence probability of the modeled situations of interest in every time step.

II. RELATED WORK

First ideas of modeling and recognizing situations in surveillance applications have been presented in our previous work [1]. Many approaches in SA are based on logic, but we support the use of a probabilistic method because of the possibility of modeling uncertainties. A very popular method for SA is the hidden Markov model (HMM), which is able to recognize specific sequences; the potential of these models is shown in [2] for maritime surveillance and in [3] for traffic scenarios. However, most of the probabilistic methods used for SA 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, particularly not for critical situations. In our previous work [4], a human-understandable probabilistic model, a Bayesian network, was applied to observed objects in the maritime domain and the user acceptance of such an automatic SA module was shown. Further work has been done in including temporal dependencies into the model, i.e., by defining a DBN for the detection of vessels that are most likely to carry refugees on board, see [5]. However, modeling a DBN is a difficult task for a maritime expert who is in general not familiar with probabilistic methods. For an expert, it is much easier to model relevant relationships in a ontology [6], as done in [7] for the maritime domain. The contribution of this work is a first approach for defining situations of interest in a maritime ontology and to extract the corresponding DBNs for performing an automatic SA.
III. AN ONTOLOGY FOR MARITIME SITUATIONS

Ontologies are often used for modeling the knowledge about a domain of interest. An ontology represents knowledge as a set of concepts and a set of properties, i.e., relationships among these concepts. A well-known standard of an ontology language is the web ontology language (OWL). We used the Protégé editor for modeling our ontology in OWL.

The objects in our domain are either vessels or locations. Both types of objects are characterized by a set of attributes. As our main interest is to model situations, we skip details about modeling these objects in our ontology. Note that we model a situation as a binary random variable and we define the existence of a situation at a point in time and not on a time interval. For inferring the existence of a situation at time $t$, all the information collected up to the time $t$ can be used. Further information on situation modeling and the definition of abstraction levels can be found in [8]. We defined several situations of interest in our ontology using three abstraction levels. Situations in abstraction level 1 are depicted in Figure 1. They are further divided into three categories. Either a situation is semantically interpreted as a behavior, an information about a situation that happened in the past, or a statement about current relationships, e.g., spatial relationships. Of course, there can be defined more categories, but for our situations, these three were sufficient.

The existence of level 1 situations is either true or false and its value can be calculated directly from the attribute values of the observed vessels. We will give some representative examples here; the rest of the level 1 situations can be interpreted in a similar way.

- **AbnormalBehaviorRegardingType**: This can be implemented by a HMM. Therefore, states from regular vessel traffic are used as training data, e.g., the position, speed, course. For every vessel type, a model representing normal ship traffic is trained. This is done as, e.g., a tanker behaves completely different than a fishing vessel. During observation, an abnormal behavior can be detected when the deviation from the normal model is too large.

- **WasInSuspiciousZone**: This situation is true for every time step, if the situation was true for the same vessel in the past, i.e., if the position of the vessel was inside the polygonal area of the suspicious zone.

- **CourseTowardsIsland**: This situation is true if the course line of the vessel has an intersection with the island.

- **RendezvousAtIntersection**: This situation is true if the estimated time points for the arrival at the intersection point of two course lines of two vessels are close to each other.

Existences of higher level situations depend on the existences of the respective lower level situations. Some examples of level 2 and level 3 situations are depicted in Figure 2. They are further divided into three semantic categories, namely situations that try to estimate intentions, i.e., what is going to happen in future, situations that describe a state change in a level 1 situation, and situations that make statements about current or past relationships.

The dependencies between higher and lower level situations are modeled by situational relations in the ontology, namely hasCharacteristics, hasPastInformation, and resultsFromStateChange. Some representative examples of dependencies between higher level situations and lower level situations are listed in Table I. In Table I, all situations are level 2 situations except the last one, which is a level 3 situation.

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1W3C Web Ontology Language, see http://www.w3.org/2004/OWL
2Protégé Ontology Editor, see http://protege.stanford.edu/
TABLE I
DEPENDENCIES BETWEEN HIGHER AND LOWER LEVEL SITUATIONS.

<table>
<thead>
<tr>
<th>Higher Level Situation</th>
<th>Dependencies</th>
<th>Lower Level Situations</th>
</tr>
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</table>
| WillLeaveZone                  | hasCharacteristics                  | IsApproachingZoneBoundary
|                                |                                     | IsInZoneOfInterest                               |
| ChangeCourseTowardsIsland       | resultsFromStateChange              | CourseTowardsIsland                              |
| IsHeadingTowardsIsland          | hasCharacteristics                  | IsApproachingZoneBoundary
|                                |                                     | IsInZoneOfInterest                               |
| IsLeavingZone                   | hasCharacteristics                  | IsApproachingZoneBoundary
|                                |                                     | IsInZoneOfInterest                               |
| IsMovingOnShippingLane          | hasCharacteristics                  | CourseTowardsNextWaypoint
|                                |                                     | IsCloseToZoneBoundary                            |
|                                |                                     | IsInZoneOfInterest                               |
| IsPossibleSmugglingVessel       | hasCharacteristics                  | AbnormalSpeedRegardingType
|                                |                                     | IsNoTanker/Freighter/Passenger                   |
|                                |                                     | HadRendezvousWithOtherVessel                     |
|                                |                                     | WasInSuspiciousZone                              |
| DeviatesFromShippingLane        | resultsFromStateChange              | IsMovingOnShippingLane                           |

IV. GENERATING PROBABILISTIC MODELS

We will now generate probabilistic models for every situation, i.e., DBNs, by extracting the structure and the parameters from the concepts and types of relations in the ontology. A definition of a DBN can for example be found in [9]. First, we define two rules for generating the structure of the DBN. We represent the situations A and B as binary random variables and connect them with arrows. We defined three kinds of arrows between the random variables, namely temporal, observation and change arrows. The temporal arrow is meant to start in the time slice before, all other arrows start and end in the same time slice. We keep the different types of arrows because they result in different parameter settings. The rules are depicted in Figure 3 and will get clearer when we have a look at the resulting DBNs.

In the next step, we have to define the parameters of the DBNs. This means we have to determine the probabilistic relationships between the random variables, based in their type of arrows. In Figure 3, we named the higher level situation A and the corresponding lower level situation B. We will keep this notation for the following step and use the temporal indices only if necessary.

For the structure resulting from rule 1, we have to define the following probabilities. For the situation A, we set the prior probability at time 0 to $P(A_0) = 0.5$. Note that $P(\neg A_0) = 1 - P(A_0)$, so we only have to define one probability. This is because we cannot say if the situation is true or not and in this case we use the uninformative prior probability. For the temporal arrows, we set $P(A_t|A_{t-1}) = 0.8$ and $P(A_t|\neg A_{t-1}) = 0.2$. This value results in a noticeable filtering effect if situation A is either true or false. However, the values are chosen in a way that the values will converge to the prior probabilities of 0.5 if no further evidence is collected.

In the following, we will only define the probabilities necessary for defining the DBN. As before, we can calculate the remaining probabilities because the corresponding probabilities have to sum to one.

For the observational arrow, we set $P(B|A) = 0.9$ and $P(B|\neg A) = 0.5$. The first value is chosen because an observation that supports the existence of a higher level situation should have a big influence. The second value is due to the fact that if we know that A is false, we can observe B anyway. For the observational arrows, we also have to consider that there might be more than one higher level situation that is supported by the lower level situation, for example $P(B|A_1, A_2, \ldots, A^n)$. In this case, we have to set probabilities for all true/false combinations of the n higher level situations. We solve this problem by setting the probability to 0.9 if at least one higher level situation is true, i.e., only in the case of $P(B|\neg A_1, \neg A_2, \ldots, \neg A^n)$ the probability is set to 0.5. So if we know that at least one higher level situation is true, we observe the lower level situation with probability 0.9, otherwise we can make no statement about the observation and set it to 0.5.

In rule 2, we set $P(A_t|B_0) = P(A_0|\neg B_0) = 0$. This is because a state change can only be true if we have information about the previous time point, which we do not have at time point 0. The combination of the observational arrow with the temporal arrow means that we have to define the probability $P(A_t|B_{t-1}, B_{t-1})$. This makes sense, because the detection of a state change is dependent both on the current state and the previous state of the situation B. We will set all probabilities...
to 0, except in the case where the state change is true. i.e. if we are interested in a state change from true to false, only this combination will result in a probability set to 1.

V. APPLICATION EXAMPLE

In this section, we present an example of our approach, namely the combined DBN of the situations DeviatesFromShippingLane and IsMovingOnShippingLane. The result of the structure is visualized in Figure 4 and the corresponding conditional probability tables in Table II. Note that we did not list the prior probabilities.

![DBN-structure for situations DeviatesFromShippingLane and IsMovingOnShippingLane](image)

In Figure 5, we can see the resulting probabilities of the network for 10 time steps if we insert evidences for the first 6 time steps, i.e., the current time is time point 6. We assume the vessel has been always moving (evidence IsMoving: TTTTTT), but it was moving on the shipping lane only until time point 2 (evidence CourseTowardsNextWaypoint: TFFFFF). Then it is heading away from the lane, so after 4 time points it is not close to the shipping lane anymore (evidence IsCloseToShippingLane: TTTTFF).

The results show that the probability of IsMovingOnShippingLane starts to decrease after time point 3 and continues this trend up to time point 6. Then the probability is increasing again, as no evidence is available and the probability is converging again towards the prior probability. This is exactly the result an operator would expect when being interested in such situations and observing a vessel behaving like the one in our example.

VI. CONCLUSION AND OUTLOOK

In this article, we described, how expert knowledge about maritime situations can be modeled in an ontology. We showed how DBNs can be generated from this ontology in order to perform automatic SA. The DBNs have been configured in a way that the resulting existence probabilities behave as the operator would expect them to behave. By using this approach, the operator would be able to define situations of interest by himself and perform a probabilistic SA without the use of training data.

In a next step, more situations of interest will be modeled in the ontology, especially situations that involve more than one object. Furthermore, an evaluation with real data is planned.

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REFERENCES
