Application of Bayesian Techniques to Behavior Analysis in Maritime Environments

Francesco Castaldo[1], Francesco A.N. Palmieri[1], and Carlo Regazzoni[2]

[1] Seconda Università di Napoli (SUN), DIII, via Roma, 29 - 81031 Aversa (CE), Italy
[2] Università di Genova, DITEN, Via all'Opera Pia, 11 - 16145 Genova (GE), Italy

Abstract. The analysis of vessel behaviors and ship-to-ship interactions in port areas is addressed in this paper by means of the probabilistic tool of Dynamic Bayesian Networks (DBNs). The dimensional reduction of the state space is pursued with Topology Representing Networks (TRNs), yielding the partitioning of the port area in zones of different size and shape. In the training phase, the zone changes of interacting moving vessels trigger different events, the occurrence of which is stored in Event-based DBNs. The interactions are modeled as deviation from the common behavior prescribed by a single-ship normality model, in order to reduce the number of conditional probabilities to calculate and store in the DBNs. Inference on the networks is then carried on to analyze the behavior of various ships and vessels maneuvering in the harbor. The results of the algorithm are showed by using simulated data relative to a real port.

Keywords: Interaction Analysis, Ship-to-Ship Interactions, Dynamic Bayesian Networks, Topology Representing Network.

1 Introduction

The sadly famous Costa Concordia accident [1], as other dramatic crashes happened in recent years in port areas or near the coastlines [2], confirm that the design of monitoring systems able to supervise complex and crowded areas as harbors, coastlines, airports, etc., is very far from being considered a closed issue. Nowadays, these areas are monitored by a great number of high-quality sensors, but the lack of robust methodologies able to combine these volumes of data hinders to analyze and comprehend what is really happening in the area under surveillance.

In this paper, we analyze vessels of different kind during the time they reside in generic port areas. The security of maritime environments may be jeopardized by a great number of different threats: ships moving too rapidly or too slowly, pairs of ships sailing too close to each other, small vessels obstructing the passage for larger ships, and so forth. By understanding and labeling the movements in the area we could build an intelligent system, capable of providing alerts or warnings to the human operators (whose presence is obligatory in ports) when the detected situations are not acknowledged as *normal*. The issue is that in

S. Bassis et al. (eds.), *Recent Advances of Neural Networks Models and Applications*,
Smart Innovation, Systems and Technologies 37, DOI: 10.1007/978-3-319-18164-6_17

crowded harbors it is likely to find many types of ships (motorboats, tugboats, container ships, etc.) interacting in many different ways with the other moving objects in the scene. In general terms, an interaction in maritime environments [3] occurs when a ship comes too close to another ship, or too close to a river, or to a canal bank. We focus on *ship-to-ship interactions* [3] [4] in ports, i.e. when the presence and the movements of one ship affect the behavior of another, and vice-versa. The ships type, the navigation rules [5] of the country in which the port resides, the wind conditions, are all parameters that concur to define a normal interaction between vessels. We assume the interaction to be over when the two ships reach their destinations (for entering ships) or leave the port area (for exiting ships).

In literature the ship-to-ship interaction problem has been mostly approached by analyzing the hydrodynamic phenomena arising when two or more watercraft are slightly spaced from each another [6] [4]. Bayesian reasoning [7] [8] [9] has been extensively used to study the interaction of objects for different applications and in different scenarios, but little has been done for the behavioral analysis of pairs of ships. The reduction of the state space, necessary to carry out the event-based approach described in the paper, is achieved by means of Topology Representing Networks (TRNs), among which we choose the Instantaneous Topological Map [10].

The paper is structured as follows. In Section 2 we analyze the techniques to reduce the state space and partition the area in zones. Section 3 describes the probabilistic approach based on the event detection and identification. In Section 4 we drawn some results by using data generated in a simulated environment that replicates the port of Salerno, Italy. Section 5 is for conclusions and future developments.

2 Reduction of State Space with Topology Representing Networks

In this paper the actors in play, namely ships and vessels of different kinds and shape, are treated as points moving in the 2D space described by the portion of sea included in the port. For the i-th ship we can define the state vector $s_t^i = (x_t^i, y_t^i)^T$, representing the position of the moving object at time t. The analysis of behaviors and interactions between ships (and in general between moving objects) by evaluating the low-level state space trajectories as they are (without any modification) turns out to be quite a challenge, given the great variability of the state space vectors relative to multiple ships in port areas (even in small ones). However, we can exploit the fact that the "features" of a port (i.e. the position and the shape of the docks, the common routes of the ships, etc.) can be easily known a priori and do not change very often. If we are able to construct a *topological map* of the harbor, it is possible to design a higher-level algorithm where behaviors and interactions are emphasized and emerge with more clarity.

The simplest way to build a map is to partition the area in zones of equal size with a rectangular grid. However, this approach ignores that ships and vessels take only certain routes to enter or exit the port. The latter information is precious because we expect an "intelligent" map to be more precise in the zones where many ships pass through, and coarser in places rarely touched by ships. The Topology Representing Networks (TRNs) are an important class of algorithms that exploits at best the positional information of the actors in play, by building a map from a dataset of moving objects exploring the scene. The most famous TRN algorithms are the Self Organizing Maps (SOM) [11], but in recent times other approaches have been proposed, as the Growing Neural Gas (GNGs) [12] or the Instantaneous Topological Maps (ITMs) [10]. In this paper the topological maps are built by means of ITMs, and this is motivated by the fact that ITMs are quite good in handling strongly-correlated data, as the one provided by ships and vessels sailing in the port. We do not report the explanation of the algorithm, as it is a straightforward implementation of the procedure detailed in [10]. In order to build the map, we need to set only two parameters, namely the resolution e_{max} and the smoothing parameter ϵ_{itm}.

Therefore we assume to have the map of the environment, i.e. to have a set of N_n nodes, each of which corresponds to a zone. A zone can be defined as the portion of the space whose points are closer (respect to a fixed distance definition, as for example the Euclidean distance) to the generator node (the "center" of the zone). The Bayesian models defined in Section 3 are based on zones changes triggered by the moving vessels in the area. More in detail, when the i-th vessel moves from zone a to zone b, an event $\epsilon_t^{i^{(a,b)}} = l_a \rightarrow l_b$ is triggered, where l_a and l_b are the labels identifying two neighboring zones and $t \in \mathbb{N}$ is the time at which the event occurs. The events $\epsilon_t^{i^{(a,b)}}$ can be seen as the outcomes of the discrete random variable $\mathcal{E}_t^i$, that will be the state of the Bayesian networks. If the vessel remains in the same zone a for a T_{max} time, a *still* event $\epsilon_t^{i^{(a,a)}} = l_a \rightarrow l_a$ is detected.

3 Bayesian Models

By means of an Event-based Dynamic Bayesian Network (E-DBN) [9] [7], we define a *normality* model Θ^1, relative to a target i-th ship sailing in the port. In the E-DBN we encode the probability of the event ϵ_t^i, given the previous event $\epsilon_{t-\Delta_t^i}^i$ through the following conditional probability (CPD),

$$\Theta^1 = p(\epsilon_t^i | \epsilon_{t-\Delta_t^i}^i). \tag{1}$$

If the target ship is alone in the port (or very far from other ships) and does not behave accordingly to the normality model (zig-zag trajectories, vessels stopping in the middle of the port, etc.), we can infer that the behavior is abnormal and a warning can be send to the operator.

Things are different when other vessels are nearby the target ship, because a deviation from the normality could be due to interactions between the vessels (as for instance a tugboat towing a cargo ship, a motorboat overtaking a sailboat, etc.). For this reason it is useful to define the following parameters: (a) the

Euclidean distances d_j^i (called *influence distances*) between the target i-th ship and the other j-th ships which reside or maneuver in the port area; (b) an *influence threshold* τ_i, that, compared with the d_j^i distances, permits to verify if the target i-th ship and the other j-th ships are close enough to interact ($d_j^i < \tau_i$) or not. Actually, in the experimental part of this paper (Section 4) we will use pairs of ships that, for simplicity, interact with each other during all the time they maneuver in the harbor, but in general the influence distances are very important in a multi-target scenario, where we do not know a priori who interacts with whom.

Given these distances, it is possible to see the interactions between ships as deviation from the normality described by the model defined in Equation (1). More specifically, if the j-th ship is very close to the target ship (i.e. $d_j^i < \tau_i$), the following interaction model can be defined

$$\Theta^m = p(\epsilon_t^i | \epsilon_{t-\Delta_t^i}^i, \epsilon_{t-\Delta_t^j}^j), \tag{2}$$

where $m = 2, .., M$ denotes the type of interaction and $\epsilon_{t-\Delta_t^j}^j$ is the event relative to the j-th ship, with $t < \Delta_t^j \leq \Delta_t^i$. Equation (2) can be written as

$$p(\epsilon_t^i | \epsilon_{t-\Delta_t^i}^i, \epsilon_{t-\Delta_t^j}^j) = \frac{p(\epsilon_t^i, \epsilon_{t-\Delta_t^i}^i, \epsilon_{t-\Delta_t^j}^j)}{p(\epsilon_{t-\Delta_t^i}^i, \epsilon_{t-\Delta_t^j}^j)} = \frac{p(\epsilon_{t-\Delta_t^j}^j | \epsilon_t^i, \epsilon_{t-\Delta_t^i}^i) p(\epsilon_t^i | \epsilon_{t-\Delta_t^i}^i)}{p(\epsilon_{t-\Delta_t^j}^j | \epsilon_{t-\Delta_t^i}^i)}, \tag{3}$$

where $p(\epsilon_t^i | \epsilon_{t-\Delta_t^i}^i)$ is the conditional probability defining the normality model of Equation (1). In other words, we can define the interaction as deviation from the normal model Θ^1, by adding two CPDs, namely $p(\epsilon_{t-\Delta_t^j}^j | \epsilon_t^i, \epsilon_{t-\Delta_t^i}^i)$ and $p(\epsilon_{t-\Delta_t^j}^j | \epsilon_{t-\Delta_t^i}^i)$, and in this way we can reduce the number of CPDs to store and use. In this paper we focus on a very common type of ship-to-ship interaction between two vessels, but the proposed approach can be extended to the (unlikely) case of three and more interacting ships by adding the correspondent events in the model defined in (2). For instance, in the case of three ships we may define the CPD $p(\epsilon_t^i | \epsilon_{t-\Delta_t^i}^i, \epsilon_{t-\Delta_t^j}^j, \epsilon_{t-\Delta_t^n}^n)$, where n denotes the third ship and $t < \Delta_t^n \leq \Delta_t^i$.

The Bayesian networks just introduced can be used to infer the behavior of ships maneuvering in the port, but only after an initial training process, in which the conditional probabilities within the models are estimated and stored. The latter CPDs describe the probability of a cause-effect relation between the events of nearby vessels, and are calculated with a maximum likelihood training algorithm [7], equivalent to counting the number of occurrences of the outcomes of the CPDs in the dataset, normalized to the total number of occurrences.

The training of the network is performed with different datasets, related to behavior and interaction models. We point out that in large port areas different normality models (e.g. relative to different docks of the port) could exist, and the same for the interaction models. In such cases the number of models could significantly grow, and this is the main reason we decided to model the interactions as deviation from the normal path prescribed by the normality model.

If we assume to have M models Θ^m, $m = 1, .., M$, in order to calculate the probability that a new target ship behaves accordingly with the Θ^m model, the following cumulative normalized measure is proposed

$$\alpha_k^m = \left(\frac{k-1}{k}\right)\alpha_{k-1}^m + \frac{1}{k}\Theta^m, \tag{4}$$

where $k \in \mathbb{N}$ denotes the number of detected events for the target ship and with $0 < \alpha_k^m < 1$. The normality model Θ^1 can be always evaluated with the data of the target ship, while the interaction models Θ^2,.., Θ^M are used only if at least another vessel is nearby the target ship (information provided by the evaluation of the influence distances d_j^i). Given the vessels trajectories, for each couple of events we calculate α_k^m and compare each model Θ^m with a threshold τ_n. If none of the models is compatible with the trajectory (i.e. the α^m values result above the threshold for each m-model), we can infer that the ship behavior is abnormal. We point out that α_k^m is a function that takes into account the past history along with the probability of the current events, and its trend can be analyzed in real time to infer the behavior of the ship during the time period it resides in the harbor.

4 Preliminary Results

In the following we report results of behavior analysis of ships in the Port of Salerno, Italy. The data are provided by a realistic simulator of trajectories, which reproduces the real structure of the port and generates the movements of ships entering the port (for simplicity we assume only entering ships, but the same reasoning can be applied when we have at the same time exiting ships). Figure 1 left depicts an image of the harbor of Salerno, and indicates in black the dock on which we focus our behavioral analysis. Figure 1 right depicts a frame of the simulator.

As explained in Section 3, the first step is to build the normality model Θ^1. This is accomplished with $N_{itm} = 150$ noisy trajectories of vessels heading to the dock. These trajectories are used at first to build the Instantaneous Topological Map defined in Section 2, with $e_{max} = 5$ and $\epsilon_{itm} = 0.1$, and then to store the CPDs of Equation (1) for different consecutive events. In Figure 1 left the ITM is superimposed to the port image.

Given the normality model, it is possible to construct ship-to-ship interaction models Θ^m, $m = 2, .., M$, that are allowed in the portion of the port under surveillance. For simplicity, we build a single interaction model, and show how interactions not compatible with that model are robustly recognized. Given the European maritime rules in harbors [13] [14], we define an interaction model Θ^2 relative to a sailboat and a motorboat trying to enter the port area at the same time. The navigation rules prescribe that the ship with the highest level of maneuverability (in this case, the motorboat) stops its engine, lets the other

Fig. 1. Left: Satellite photo of the port of Salerno. We focus our attention to the right dock (indicated with black lines) where small vessels as motorboats and sailboats are allowed to land or depart (the other two major docks on the left are only for container or cargo ships). On the same image the ITM on which the events are gathered is superimposed. The green lines connect the neighbor nodes, and for each node we define the correspondent zone as the locus of points that are closer to that node, with respect to the others. Right: A picture taken from the simulator used in this paper, that accurately reproduces the shape of the port and generates realistic trajectories of ships in the area.

ship pass through the entrance and only after enters the port. We call this a *motorboat-sailboat* interaction, because the target ship is always the motorboat and the other ship is always the sailboat, and we generate the model by using $N_{ms} = 300$ noisy trajectories extracted from the simulator. We remark again that other interactions (for instance two motorboats entering the port in the same moment, a tugboat towing a container ship, etc.) are possible and can be easily built in different Θ^m models. We have chosen empirically the value of $\tau_i = 0.4$ and $T_{max} = 3$.

Once the ITM is created and models are assembled, inference on the data can be carried on. More in detail, a high-quality system has to guarantee two features: (a) low false alarm rates; (b) robust recognition of uncommon and abnormal behaviors or interactions. In order to assess the first feature, in the first experiment we test the Bayesian models with $N_{t_1} = 200$ noisy trajectories of two nearby ships that act as motorboat and sailboat of the interaction model Θ^2. The single trajectories of these ships are compared with the normality model Θ^1, while at the same time the data from the two vessels are combined and compared with the Θ^2 model. In Figure 2 we depict the trend over the events of the cumulative measure defined in Equation (4). The analysis of the figure permits to draw the following conclusions: (a) the two trajectories singularly are almost always recognized as belonging to the normality model (their trends in very few cases and for little time are below the recognition threshold τ_i). This is true because in the model there is no indication of the time spent during

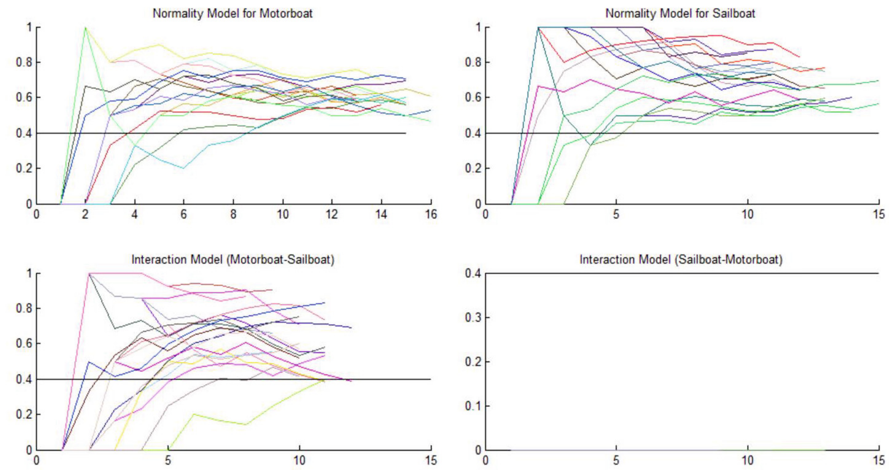

Fig. 2. This figure depicts the cumulative trends over the trajectories of interacting motorboats and sailboats. The two plots on top are relative to the single trajectories compared with the normality model Θ^1, while the bottom plots are for the interaction model Θ^2.

the transition between events, therefore the fact that the motorboat stops at the entrance is not captured by the normality model; (b) the interaction model recognizes in most cases the motorboat-sailboat coupled behavior. Of course this is true when the first ship is the motorboat and the other is the sailboat (bottom left of Figure 2), and not when the ship roles are switched (bottom right of Figure 2).

In the second experiment we assess the ability of the system to alert the operator of strange or dangerous behaviors. We generate $N_{t_2} = 100$ trajectories relative to an interaction named *tugboat-cargo*, representative of the situations in which a large cargo ship is towed in the port by a tugboat. This type of interaction is not allowed in the dock we are monitoring, therefore it is a dangerous situation that should be recognized. Even if the two ships are not a cargo and a tugboat but two motorboats or sailboats traveling together, this can be considered still a noteworthy situation because two different ships so close in the port area could collide and cause relevant damages to the harbor structures. In Figure 3 are depicted the results, that are quite good and can be interpreted as follows: the two trajectory, taken singularly, are compatible with the Θ^1 model, but their interaction is not recognized by the Θ^2 model, except for very few cases and only for a few number of events. Such situation (two ships behaving in a normal way singularly but not interacting in a known way) can be easily reported to the operator, that can decide to intervene or not.

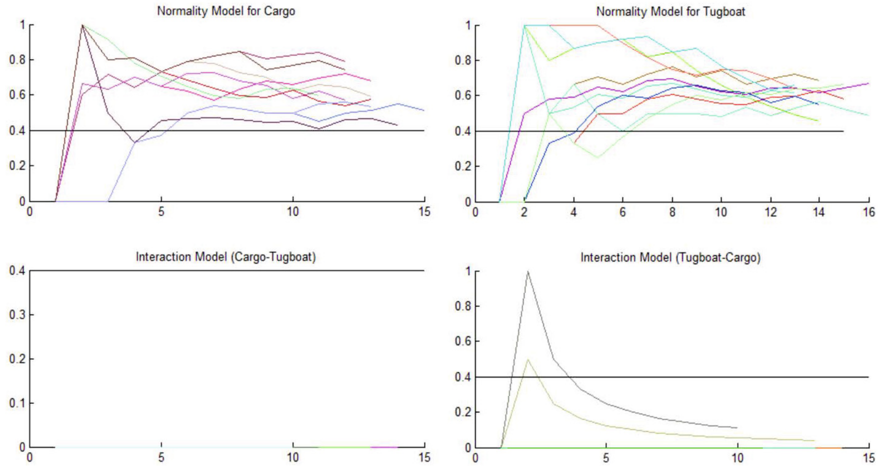

Fig. 3. In this figure the models are compared with the data of ships interacting according to the tugboat-cargo model, in which one ship (the tug) tows the other (the cargo) into the port. While singularly the two ships are behaving correctly, this interaction is not allowed in the small dock we are observing, and the trends of the various cumulative measures permit to automatically evaluate such situation and to report it to the operator.

5 Conclusion

This paper has presented an application of Bayesian networks for behavioral analysis of multiple ships in port areas. The idea is to preserve the port safety by classifying the movements of the different actors in the scene. The analysis is complicated by the fact that multiple ships can interact in many ways, with a number of interaction models that could become very large: the idea pursued in this paper is to relate the interactions to normality models, i.e. by modeling the interaction as deviation from the normal path taken by a ship maneuvering without other vessels in the port area. In this way we construct interactions starting from the normality model, reducing in this way the probabilistic data we have to gather and use for inference. The computational load of the algorithm is quite low, because after the training step the inference is carried on by simply updating the cumulative measure for the normality and interaction models.

Other information can be gathered from moving ships and used to enhance the probabilistic model. For instance, the travel time of the ships into the zones can be saved along with the zone changes, and this information could be precious to recognize abnormal behaviors strictly connected with the vessel speed (i.e. ships that are too fast or slow, that stop into the middle of the port, etc.). Another useful information could be the initial position of the ship entering in a zone (i.e. from which part of the zone the ships usually enter), that could be used to construct, within the zone, a low-level tracking model by which follow the ship.

The latter information could be used to anticipate the behavioral analysis at the level of the tracker instead of waiting for consecutive events (that for large zones could be triggered after quite long times).

References

1. Costa concordia: What happened,
   http://www.bbc.com/news/world-europe-16563562
2. Cargo ship crashes into port control tower in genoa killing three,
   http://www.theguardian.com/world/2013/may/08/italian-cargo-ship-crashes-genoa
3. Barrass, B.: Ship Design and Performance for Masters and Mates. Elsevier Science (2004), http://books.google.it/books?id=2KaLDCpZgbQC
4. Eloot, K., Vantorre, M.: Ship behaviour in shallow and confined water: an overview of hydrodynamic effects through efd. In: Assessment of Stability and Control Prediction Methods for NATO Air and Sea Vehicles. NATO. Research and Technology Organisation (RTO), p. 20 (2011)
5. U. N. E. C. for Europe. Working Party on Inland Water Transport. CEVNI:, ser. TRANS/SC. 3/115/Rev. 2. UN (2002),
   http://books.google.it/books?id=RVVsQticMUgC
6. The Second International Conference on Manoeuvring in Shallow & Confined Waters: Ship to Ship Interaction (May 2011)
7. Barber, D.: Bayesian Reasoning and Machine Learning. Cambridge University Press (2012)
8. Koller, D., Friedman, N.: Probabilistic Graphical Models: Principles and Techniques. MIT Press (2009)
9. Murphy, K.: Dynamic bayesian networks: Representation, inference and learning. Ph.D. dissertation, UC Berkeley, Computer Science Division (July 2002)
10. Jockusch, J., Ritter, H.: An instantaneous topological mapping model for correlated stimuli. In: International Joint Conference on Neural Networks, IJCNN 1999, vol. 1, pp. 529–534 (1999)
11. Kohonen, T.: Self-organized Formation of Topologically Correct Feature Maps. In: Anderson, J.A., Rosenfeld, E. (eds.) Neurocomputing: Foundations of research, pp. 509–521. MIT Press, Cambridge (1988),
    http://dl.acm.org/citation.cfm?id=65669.104428
12. Fritzke, B.: A growing neural gas network learns topologies. In: Advances in Neural Information Processing Systems 7, pp. 625–632. MIT Press (1995)
13. I. M. Organization, International Convention for the Safety of Life at Sea: consolidated text of the 1974 SOLAS Convention, the 1978 SOLAS Protocol, the 1981 and 1983 SOLAS Amendments, ser. IMO Publication. IMO (1986),
    http://books.google.it/books?id=_5oTAAAAYAAJ
14. I. M. Organization, ISPS Code: International Ship and Port Facility Security Code and SOLAS Amendments 2002 Adopted 12 December 2002, ser. IMO publication. International Maritime Organization (2003),
    http://books.google.it/books?id=MdUQAQAAIAAJ