Making Sense of Heterogeneous Maritime Data

Manolis Pitsikalis Department of Computer Science University of Liverpool Liverpool, United Kingdom e.pitsikalis@liverpool.ac.uk Alexei Lisitsa Department of Computer Science University of Liverpool Liverpool, United Kingdom a.lisitsa@liverpool.ac.uk

Simon Lee Denbridge Marine Ltd. Liverpool, United Kingdom simon.lee@denbridgemarine.com Patrick Totzke Department of Computer Science University of Liverpool Liverpool, United Kingdom p.totzke@liverpool.ac.uk

Abstract—While an abundance of real-time maritime information exists and is readily available to monitoring authorities, there are still many instances in which ships are found to be engaged in dangerous or illegal activities. In order to prevent such activities, authorities employ Vessel Traffic Services systems since they promote safety at sea while also assisting in management of ports. In this paper we report on research done in cooperation with Denbridge Marine Ltd., a global provider of maritime solutions, and present an application integrated in a Vessel Tracking Services system that allows the detection of normal vessel activity as well as dangerous or illegal situations in real-time, using information from the Automatic Identification System, a radar sensor and other information. We use a set of phenomena representing maritime activities of interest in the language of Phenesthe, our Complex Event Processing engine, and detect them on real maritime data streams from the area of Liverpool, United Kingdom. We evaluate our application and show that our system is capable of detecting and visualising maritime activities on the map in real time. Finally, we study and demonstrate the significance of using data from the Automatic Identification System along with radar data for maritime monitoring.

Index Terms—maritime monitoring, complex event processing, temporal logic, AIS, RADAR

I. INTRODUCTION

Shipping is an important pillar of world trade, it allows the transportation of goods between countries and continents. Consequently, in order to safeguard shipping there are a lot of technologies that can provide maritime data for vessel monitoring. For example, the Automatic Identification System (AIS) allows the transmission of timestamped positional and identity information from vessels, radar systems produce positional data from vessel targets in range, CCTV cameras in ports record high resolution vessel footage and so on. However, vessels are still found to be involved in dangerous situations or illegal activities that need immediate intervention. For instance, while AIS is a popular and valuable source of information in maritime monitoring systems, it is typical for vessels involved in illegal activities to turn off their AIS transceivers or spoof their information. As a result, systems that rely solely on AIS information are inadequate when it comes to dark ships i.e., ships that don't transmit AIS information and are involved in illegal activities. Therefore, in order to be fully effective, maritime monitoring systems need to use multiple sources of often heterogeneous data and be capable of providing in real-time useful intelligence.

In this paper we report on work that has been conducted as part of a collaboration between the University of Liverpool and Denbridge Marine Ltd¹, a provider of Vessel Traffic Services (VTS) systems to ports and harbours. VTS systems act to facilitate safety of life at sea as well as assisting in the management of ports. Port management includes, but is not limited to: collision avoidance, berth management, surveillance of unidentified vessels and monitoring of speed and direction of maritime traffic. We present an application integrated in a VTS system that uses radar and AIS information as its main input source along with a collection of indicative maritime phenomena definitions specified in the language of Phenesthe [1], our Complex Event Processing engine. Finally, we evaluate the efficiency of our application with real maritime data streams and study the significance of fusing multiple sources of vessel data for maritime monitoring. Therefore, the contributions of this paper are the following:

- a maritime monitoring application that uses several sources of heterogeneous data (e.g., AIS, radar, maritime areas of interest, static vessel data etc.),
- an evaluation of the efficiency of our application and a study of the significance of using radar as an additional source of information.

This paper is organised as follows. In Section II we discuss work related to ours, while in Section III we present the background for our setup. In Section IV we present a collection of indicative maritime phenomena definitions, next in Section V we evaluate our maritime monitoring application. Finally, in Section VI we summarise our contribution and discuss future work.

¹https://www.denbridgemarine.com

This work has been funded by the Engineering and Physical Sciences Research Council (EPSRC) Centre for Doctoral Training in Distributed Algorithms at the University of Liverpool, and Denbridge Marine Limited, United Kingdom.

II. RELATED WORK

There is a considerable amount of literature focusing in maritime safety and maritime surveillance. For example, works such as [2]–[4] utilise vessel related information (e.g., AIS data, vessel images, SAR images) for ship type classification. Other works, such as ours, focus on detecting maritime activities of interest. For instance, Kontopoulos I. et al. in [5] convert vessel trajectories into images and employ deep neural networks for classifying vessel activities. In another work, Zhou Y. et al. [6], use natural language analytics techniques on a textual representation of trajectories for detecting maritime anomalies. While the aforementioned approaches can detect specific maritime activities or anomalies with some success, they don't allow the integration of an expert's knowledge into their models.

Roy J. in [7] argues that human experts understand much better the nature of surveillance data, therefore it is very important to allow domain experts express their knowledge into the models in use. This direction follow the approaches presented in [8], [9]. In detail, Pitsikalis M. et al. in [8] present a composite maritime event recognition system where maritime activities are formalised in the language of the Run-Time Event Calculus (RTEC). However, in both [8], [9], the main source of dynamic maritime vessel data is AIS, consequently vessels that switch off their AIS transponders on purpose can evade possible detections. Moreover, while the language of RTEC allows the definition of several maritime activities, it does not offer Allen's algebra [10] relations on intervals. Allen's algebra relations on intervals are particularly useful in phenomena definitions since they allow the specification of the temporal arrangement of phenomena when it's known. For example, as we will present later in Section IV, a phenomenon formalising vessel trips can be defined with little effort using relations from Allen's interval algebra. In this paper, we present a maritime monitoring system that allows maritime domain experts with no previous programming knowledge to write definitions describing maritime phenomena of interest. Furthermore, instead of relying in only one source of dynamic vessel information, we use both AIS and radar data.

III. PRELIMINARIES

We perform maritime monitoring using maritime data transmitted over AIS, and data coming from a radar system placed in the area of Liverpool, United Kingdom. Additionally, we use a stream of zone interaction events produced when vessels enter or leave a zone of interest (e.g., a port, an anchorage etc.). We combine all dynamic information into a single stream and feed it in Phenesthe which in turn produces a stream of detected time-associated maritime phenomena. In this Section we will present briefly the input data sources, Phenesthe, and the architecture of our application.

A. Fused maritime data stream

Our input stream provides the relevant dynamic information of vessels derived from the use of a radar sensor and the AIS. The radar sensor allows the use of Kalman-based filters [11] on

TABLE IPhenomena of the input stream.

Input Phenomenon	Description
pos(TID, LA, LO, V, C, S)	A position message. <i>TID</i> , <i>LA</i> , <i>LO</i> , <i>V</i> , <i>C</i> and <i>S</i> stand for track id, latitude, longitude, speed (knots), course over ground, and information source.
$zone_interaction(TID, Z, IT)$	An input phenomenon occurring when a target (TID) enters or leaves a zone (Z). IT can be either 'entry' or 'exit'.

vessel tracks; hence when radar detected, the radar components of the track stream provide filtered dynamic information of position, course and speed every 3 seconds. On the other hand, AIS transmitted data contains the self-reported dynamic parameters of position, speed and heading (provided that the vessel is equipped with an electronic compass), plus ancillary static/voyage-related information that includes the length, the beam, the Maritime Mobile Service Identity (MMSI) number and International Maritime Organisation (IMO) number. The reporting time frequency for dynamic information transmitted over AIS ranges from 2 seconds to 3 minutes for Class A transponders or 3 seconds to 3 minutes for Class B transponders, depending upon the vessel's speed. The ancillary data is reported roughly every 6 minutes per vessel. In our case, the coverage of the AIS basestation is approximately 30 nautical miles, while for the radar sensor, an IALA target type 4 in good weather conditions can be detected in approximately 9.7 nautical miles [12].

Both radar and AIS information, is combined by the track manager module of Denbridge Marine Ltd. which produces the fused input track stream. Within the fused input track stream, targets may be radar-tracked only, AIS only, or correlated radar and AIS, depending on the vessel's location within the coverage area. In contrast with the original reporting frequencies, the fused input track stream reports the last known dynamic information of all tracks every 2 seconds. This ensures that no changing dynamic track data is ever lost but does mean repetition of the track reports for vessels that have a low repetition rate due to being moored or being equipped with a Class B transponder. We produce the final input stream of our architecture by merging into the fused input stream zone interaction events denoting the entry or the exit of vessels from specific zones (e.g., a port, an anchorage area etc.). These zone interactions events are produced by applying point in polygon algorithms on the vessels' positions and the relevant zones. Consequently, the final input stream (AIS + RADAR)is composed of temporally sorted instantaneous events that may contain either dynamic vessel information, or a zone interaction. A description of the input phenomena is available in Table I.

B. Complex Event Processing with Phenesthe

We detect maritime temporal phenomena with our publicly available Complex Event Processing engine Phenesthe [1]. Phenesthe, allows the definition of instantaneous and durative temporal phenomena and the relations between them. Given an input stream and a set of temporal phenomena definitions, Phenesthe will produce a stream of time associated temporal phenomena. In this section we will briefly describe the language of Phenesthe and its processing principles. A complete presentation of Phenesthe is available in [1] while a summary of the syntax of the language is presented in Table II.

1) Language: Time, in Phenesthe, is represented by an infinite non empty set $T = \mathbb{Z}_0^+$ of non-negative integers ordered via the '<' relation. Temporal phenomena are divided into three types events, states, and dynamic temporal phenomena. Similar to temporal phenomena, the formulae of the language, are divided in three types: Φ ', Φ^- and $\Phi^=$. Formulae of Φ ' are true on instants of time, formulae of Φ^- hold in disjoint intervals, while formulae of $\Phi^=$ hold in possibly non-disjoint intervals. The three types of formulae allow the definition of phenomena as follows:

- Events are defined using formulae of Φ^{*}. Formulae of Φ^{*} are true on instants of time and utilise the logical connectives of conjunction (∧), disjunction (∨), and negation (¬). Additionally, Φ^{*} formulae may use the start and end predicates to refer to the starting or the ending time of intervals where formulae of Φ⁻ hold. Finally, Φ^{*} formulae may use the newly introduced '∈' connective between a formula that is true on instants (Φ^{*}) and a formula that is true on disjoint intervals (Φ⁻).
- States are defined using formulae that hold in disjoint maximal intervals, i.e., formulae of Φ⁻. Formulae of Φ⁻ may utilise the temporal operators of temporal union (□), intersection (□) and complement (\) between formulae that hold on disjoint intervals (Φ⁻). Moreover, they may utilise the maximal range operator (→) between two formulae of Φ⁻. Finally, we extend the temporal operators for defining states, presented in [1], with an iteration operator (@) and an operator for filtering intervals (filter) based on their size. We will describe these extensions in Section IV.
- Dynamic temporal phenomena are defined using formulae that hold in possibly non disjoint intervals (Φ⁼). Formulae of Φ⁼ allow the specification of the temporal relations between events, states and dynamic temporal phenomena. In detail, formulae of Φ⁼ may use the seven basic relations of Allen's interval algebra [10], before, overlaps, contains, meets, starts, finishes, and equals.

2) Processing: Phenesthe uses time-windows, in other words, it performs temporal queries at equally distanced query times t_q , with a step s (i.e., $t_{q+1} - t_q = s$) over a window ω of a user specified size $|\omega|$. At each temporal query time Phenesthe processes the temporal phenomena definitions according to their dependencies and in parallel if possible. When a temporal phenomenon is processed, a list of the instants or the intervals at which it is true or holds is stored for possible later use. Consequently, phenomena definitions are processed only once without recomputations in a bottom up manner. At the same time, Phenesthe uses a redundancy

TABLE II Syntax summary of the language used by Phenesthe. 'L, R' correspond to left and right operands, while the \Box may be one of the following symbols $\{<, \geq, =\}$.

Туре	Symbol	Φ	Φ^-	$\Phi^{=}$	Duration
Φ.	\wedge	1, r			
	\vee	1, r			
	_ ata⊭t	r			
	start		r		
	ena	1	r		
	e		r		
	\rightarrow	1, r			
	\Box		l, r		
Φ^-	Π		l, r		
))		l, r		
					r
	filter□		1		r
	before	1, r	l, r	1, r	
$\Phi^{=}$	overlaps		l, r	l, r	
	contains	r	l, r	l, r	
	meets		l, r	l, r	
	starts	1	l, r	1, r	
	finishes	1	l, r	l, r	
	equals		1, r	1, r	



Fig. 1. Architecture of our maritime monitoring system.

handling mechanism for bookkeeping. During this process, instants or intervals are classified as redundant and nonredundant. Redundant information, refers to data that will be outside the next temporal window and will not contribute to any further detections, while non-redundant information refers to information that will be outside the next temporal window but will possibly contribute in detections in a future query. Redundant information is discarded, while non redundant information is kept until classified otherwise.

C. Architecture

The complete architecture of our maritime monitoring system can be divided in three components, the input component, the processing component, and finally the visualisation component. Figure 1 shows these components. The input component contains the input sources (AIS and radar), the track manager and the reporting database. The reporting database contains ancillary AIS information and 'entry' or 'exit' events to specific zones as well as other information that does not change frequently. The processing component contains, Phenesthe, which has access to a set of maritime phenomena definitions,



Fig. 2. Three moored vessels. The vessels and the detections are depicted on the map of the iVision VTS system of Denbridge Marine Ltd. The first line of the label contains the ship's name, the second line shows the track id, and finally the third line shows the phenomenon detected.

the stream produced from the input component, and other information such as ship types, vessel names etc. provided by the reporting database. Finally the visualisation component contains the graphical interface of Denbridge Marine Ltd. VTS system (iVision) which consumes the output stream of Phenesthe and shows relevant information on the map.

IV. MARITIME PHENOMENA DEFINITIONS

Maritime phenomena may concern regular maritime traffic, dangerous situations or illegal activities. In this section, we present a subset of the maritime phenomena definitions included in our maritime monitoring application.

A. Stationary vessels

Vessels can be stationary for several reasons. In this section we present phenomena definitions related to stationary vessels.

1) Moored vessel: According the IMO [13], mooring refers to securing a vessel in a particular place by means of wires or ropes made fast to the shore. Taking into account that it's important for authorities to know the ports a vessel has been to we provide the definition below:

state_phenomenon
$$in_zone(TID, Zone)$$
:
 $zone_interaction(TID, Zone, entry) \rightarrow$
 $zone_interaction(TID, Zone, exit).$
state_phenomenon $moored(TID, Port)$:
 $stopped(TID, _, _) \sqcap$
 $(in \ zone(TID, Port) \land port(Port)).$
(1)

In order to define among others, the moored (TID, Port) state, we define first the state $in_zone(TID, Zone)$. The in_zone state is defined using the maximal range operator (\rightarrow) between two $zone_interaction(TID, Zone, Type)$ events corresponding to the entry or the exit respectively of a vessel with track id *TID* in a zone *Zone* (e.g., a port, an anchorage area, an operator defined area or other areas). According to the first rule of rule set (1), in_zone holds for the maximal time intervals that start when a vessel enters a *Zone* and end when it exits. The *stopped*(*TID*, *Lat*, *Lon*) state, included in



Fig. 3. Two vessels at anchor (lower part), and a vessel underway (top part). The red polygon corresponds to an anchorage area, while the shapes around the vessels correspond to radar blobs.

the definition of the *moored*/2 state, is a user defined state that holds when a vessel's speed is less than an operator defined threshold (e.g., 0.5 knots) for more than an operator defined temporal threshold (e.g., 10 minutes). Additionally, the *stopped*/3 state stores the coordinates (*Lat*, *Lon*) of the position where the vessel started its stop. *port*(*Zone*) is an atemporal predicate that is true if *Zone* is a port. Finally, the \sqcap temporal operator computes the intervals at which both formulae (left and right) hold². Therefore, a vessel will be detected as *moored* at a *Port* if it is stopped inside a port zone. Figure 2 shows an example of three moored vessels, detected using the above pattern.

2) Vessel at anchor: Vessels when there is limited space in ports or due to other reasons may get anchored in designated anchorage areas. In our case, we extract anchorage areas around Liverpool from S-57 ACHARE objects³. When a vessel is anchored, due to strong weather or other reasons it may perform an anchor watch violation. An anchor watch violation is a dangerous situation that involves an anchored vessel exiting without permission, an operator defined perimeter around its anchorage point. Here we present a definition for detecting anchored vessels and anchor watch violations.

state_phenomenon
$$at_anchor(TID, Zone, Lat, Lon)$$
:
 $stopped(TID, Zone, Lat, Lon) \sqcap$
 $(in_zone(TID, Zone) \land anchorage(Zone)).$
event_phenomenon $aw_violation(TID, Zone)$:
 $(pos(TID, Lat_1, Lon_1, _, _, _) \in$
 $at_anchor(TID, Zone, Lat_2, Lon_2)) \land$
 $distance(Lat_1, Lon_1, Lat_2, Lon_2, D) \land$
 $anchor perimeter(Zone, A_{thr}) \land D < A_{thr}.$
(2)

The anchored/4 state as defined in the first rule of rule set (2) holds for the time periods a vessel is stopped within an anchorage area. Next, we define anchor watch violation as an event, i.e., it is true in instants of time. According to the second rule of rule set (2) an anchor watch violation occurs

²A detailed description of the intersection operator is available in [1]. ³http://www.s-57.com/

while the vessel is anchored and a position message is received with coordinates exceeding the perimeter threshold set for that anchorage area. The perimeter thresholds are defined by the operators of the system.

B. Moving vessels

In the previous section, we presented definitions describing maritime phenomena involving stationary vessels. Here, we present a set of definitions involving moving vessels.

1) In range: In general, but especially in ports, it is important to know which vessels are in range and for how long. Below we present a definition describing vessels in range.

state_phenomenon
$$in_range(TID)$$
:
 $pos(TID, Lat, Lon, _, V_1, _) @< 600.$
(3)

 $in_range/1$ is defined using the iteration operator ($@_<$). A formula $\phi @_\square d$, where $\phi \in \Phi^{\cdot}$, $\square \in \{<, \geq, -\}$ and $d \in \mathbb{Z}^+$ holds for a time interval that starts when ϕ is true at a t_0 , continues to hold if the next occurrences of ϕ at t_i (i > 0) satisfy the constraint $t_i - t_{i-1} \square d$ and finally ends at a t_n if the constraint $t_{n+1} - t_n \square d$ is not satisfied. For example, as specified in rule (3), the state in_range holds for the disjoint time intervals where position messages are received and the distance between each consequent pair does not exceed 600 seconds.

2) Vessel underway: According to IMO a vessel is underway if it is not at anchor, or made fast to the shore, or aground [13]. We define underway in a similar manner as in [8]. Below is the definition of underway in the language of Phenesthe:

state_phenomenon
$$underway(TID)$$
:
 $(pos(TID, _, _, _, V_1, _) \land V_1 > 2.7 \rightarrow$ (4)
 $pos(TID, _, _, _, V_2, _) \land V_2 \le 2.7$) filter> 300.

The underway/1 state is defined using the maximal range operator and filtering. A formula ϕ filter $\Box d$ where $\Box \in \{<, \geq, =\}, \phi \in \Phi^-$ and $d \in \mathbb{Z}^+$, holds for the intervals where ϕ is true, and the size of the intervals is $\{<, \geq, =\} d$. In the case of rule (4), the intervals at which underway holds, start when a position message has speed greater than 2.7 knots, end when a position message is received with speed ≤ 2.7 knots, and the duration is greater than 300 seconds. An example detection of vessels underway is available in Figure 3 (top right).

3) Vessel trip: In order to ensure abidance to regulations and safety, authorities must monitor vessel trips. A trip starts when a vessel stops being moored or anchored, then gets underway, and finally reaches its destination port or anchorage area. We define vessel trips as follows:

$$\begin{array}{l} \text{dynamic_phenomenon } trip(TID, ZoneA, ZoneB):\\ & \text{end}(moored(TID, ZoneA)) \lor \\ & \text{end}(anchored(TID, ZoneA, _, _)) \text{ before} \\ & (underway(TID) \text{ before} \\ & (\text{start}(moored(TID, ZoneB)) \lor \\ & \text{start}(anchored(TID, ZoneB, _, _)))). \end{array} \tag{5}$$

TABLE III Maritime phenomena.

Phenomenon	Description
$stop_{start, end}(TID)$	Vessel's speed is $\{<,\geq\}$ 0.5 knots.
$aw_violation(TID, Z)$	Anchor watch violation in zone Z .
stopped(TID)	A vessel is stopped.
stopped(TID, LA, LO)	A vessel is stopped with
	initial coordinates (LA, LO).
anchored(TID, Z, LA, LO)	A vessel is anchored in anchorage Z , with initial coordinates (LA, LO) .
moored(TID, P)	A vessel is moored in port P.
$stopped_in_zone(TID, Z)$	A vessel is stopped in zone Z .
underway(TID)	A vessel is underway.
trip(TID, A, Z)	Vessel trip from area A to area B .

trip/3 is defined as a dynamic temporal phenomenon. As defined in rule (5) the *trip* dynamic temporal phenomenon holds for the intervals that start when a vessel stops being moored or anchored at a *ZoneA*, next the vessel is underway, and finally end when the vessel starts being moored or anchored at *ZoneB*.

V. EVALUATION

We evaluate the efficiency of our maritime monitoring system using a real stream of maritime data that is composed of both AIS and radar information. Additionally, we study the significance of using both AIS and radar information by comparing the detected phenomena when consuming positions signals originating from AIS with the detected phenomena produced when consuming both information sources.

A. Setup

We evaluate the efficiency of our application using the phenomena definitions presented in Table III. In detail, we feed the AIS + RADAR stream to Phenesthe for 8 days, starting from the 1st of April 2022, with the query step set to 3 minutes and the window size increasing every 48 hours in an exponential manner ($\omega = 1, 2, 4, 8$ hours). At any given time during that period there were around 80 to 160 AIS or radar tracks for consideration within the system. Moreover, in order to study the significance of radar information we execute Phenesthe for 48 hours on the following input streams: (a) the AIS + RADAR stream (b) the AIS stream which contains the same events as the AIS + RADAR stream minus radar positional messages. All experiments were conducted under SWI-Prolog 7.6.4, on a machine with an Intel Core i7-8700 Processor and a DDR4-2666 8GB RAM, running openSUSE Leap 15.2.

B. Results

The results of our evaluation are available in Figure 4. Subfigures 4a and 4b show the average number of input events and the average processing time per recognition query for $|\omega| \in \{1, 2, 4, 8\}$ hours and s = 3 minutes, while Subfigures 4a and 4d illustrate the number of input events



Fig. 4. Results of our evaluation. The experiments, regarding efficiency were conducted for $|\omega| = \{1, 2, 4, 8\}$ hours while the window sliding step was set to 3 min. The experiments regarding the significance of RADAR were conducted with $|\omega| = s = 1$ hour. Plots (a) and (c) show the average number of input events (thousands), plot (b) shows the average processing time (sec) per temporal query, while plot (d) shows boxplots describing the number of instants/intervals at which user defined phenomena are true.

and the number of instants/intervals at which user defined phenomena are true or hold per query via boxplots when the input stream is AIS + RADAR or AIS, with $|\omega|$ and s set to 1 hour.

Concerning efficiency, it can be seen from Subfigures 4a and 4b that Phenesthe is able to produce detections of maritime phenomena in approximately 2.5 seconds when the window size is set to 1 hour (\approx 140K input events) or approximately 16 seconds when the window size is set to 8 hours (\approx 820K input events). Considering the above, we can safely say that Phenesthe is able to handle significant load of maritime information without sacrificing efficiency.

Regarding the significance of radar in maritime monitoring, results show (Subfigures 4c and 4d) that when using the AIS + RADAR stream, position signals originating from radar only, constitute around 26% of the input stream. Similar behaviour is observed on the number of instants at which user event definitions are true when using as input the AIS + RADAR and the AIS streams. While the number of intervals at which user defined states and dynamic temporal phenomena hold on average per query are not significantly different when using each stream respectively, in both phenomena types, there are more phenomena detections when using the AIS + RADAR stream as opposed to the AISstream. Conclusively, the results of this study show that radar information can be a valuable source of information when it comes to maritime monitoring.

VI. SUMMARY

We presented a maritime monitoring application along with a set of indicative maritime phenomena definitions specified in the language of Phenesthe. We evaluated our system on real maritime streams containing information from AIS, a radar sensor and other contextual information. Regarding efficiency, the results of our evaluation show that our application is capable of providing maritime phenomena detections in realtime. Furthermore, our study on the significance of radar as an additional source of information shows that a radar sensor can provide useful maritime data that is otherwise unavailable if relying only on AIS.

Our future work involves an extension of Phenesthe for the learning of temporal phenomena definitions from ground truth data. Moreover, we aim to compare Phenesthe, both theoretically and experimentally, to other CEP systems.

REFERENCES

- M. Pitsikalis, A. Lisitsa, and S. Luo, "Representation and processing of instantaneous and durative temporal phenomena," in *LOPSTR*, E. De Angelis and W. Vanhoof, Eds. Cham: Springer International Publishing, 2022, pp. 135–156.
- [2] D. Nguyen, R. Vadaine, G. Hajduch, R. Garello, and R. Fablet, "A multitask deep learning architecture for maritime surveillance using ais data streams," in 2018 IEEE DSAA, 2018, pp. 331–340.
- [3] M. Pitsikalis, T.-T. Do, A. Lisitsa, and S. Luo, "Logic rules meet deep learning: A novel approach for ship type classification," in *Rules and Reasoning*, S. Moschoyiannis, R. Peñaloza, J. Vanthienen, A. Soylu, and D. Roman, Eds. Cham: Springer International Publishing, 2021, pp. 203–217.
- [4] U. Kanjir, H. Greidanus, and K. Oštir, "Vessel detection and classification from spaceborne optical images: A literature survey," *Remote Sensing of Environment*, vol. 207, pp. 1–26, 2018.
 [5] I. Kontopoulos, A. Makris, and K. Tserpes, "A deep learning streaming
- [5] I. Kontopoulos, A. Makris, and K. Tserpes, "A deep learning streaming methodology for trajectory classification," *ISPRS International Journal* of *Geo-Information*, vol. 10, p. 250, 04 2021.
- [6] Y. Zhou, J. Wright, and S. Maskell, "A generic anomaly detection approach applied to mixture-of-unigrams and maritime surveillance data," in 2019 SDF, 2019, pp. 1–6.
- J. Roy, "Rule-based expert system for maritime anomaly detection," in Sensors, and Command, Control, Communications, and Intelligence (C31) Technologies for Homeland Security and Homeland Defense IX, E. M. Carapezza, Ed., vol. 7666, International Society for Optics and Photonics. SPIE, 2010, pp. 597 – 608.
- [8] M. Pitsikalis, A. Artikis, R. Dreo, C. Ray, E. Camossi, and A.-L. Jousselme, "Composite event recognition for maritime monitoring," in *DEBS (2019)*. New York, NY, USA: Association for Computing Machinery, 2019, p. 163–174.
- [9] C. Ray, A. Grancher, r. Thibaud, and L. Etienne, "Spatio-temporal rulebased analysis of maritime traffic," 10 2013.
- [10] J. F. Allen, "Maintaining knowledge about temporal intervals," Communications of the ACM, vol. 26, no. 11, p. 832–843, Nov 1983.
- [11] R. E. Kalman, "A New Approach to Linear Filtering and Prediction Problems," *Journal of Basic Engineering*, vol. 82, no. 1, pp. 35–45, 03 1960.
- [12] International Association of Marine Aids to Navigation and Lighthouse Authorities, "G1111 PREPARATION OF OPERATIONAL AND TECHNICAL PERFORMANCE REQUIREMENTS FOR VTS SYS-TEMS," Tech. Rep. urn:mrn:iala:pub:g1111:ed1.1, January 2022.
- [13] International Maritime Organization, "IMO STANDARD MARINE COMMUNICATION PHRASES," Tech. Rep. Resolution A.918(22), November 2001.