Multiple sensor fusion for effective abnormal behaviour detection in counter-piracy operations

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Abstract—**We propose a two-stage method based on multiple distributed sensors for detection of piracy operations at sea. The proposed method is based on fusion of evidence from radar and optical sensors as well as AIS signals. The sensors are land based, air based and space based. In the first stage, a number of detectors perform recognition of low-level events, such as vessel speed, direction, size and identification. Their outputs act as input to the second stage, which performs fusion and disambiguation of the first-stage detections taking into account multiple sensor fusion, multi temporal fusion and distributed fusion. The result should be effective abnormal behaviour detection, by which we mean a method that is able to detect piracy operation at an early stage, i.e. close to the time, or possibly before, the attack has occurred. A numerical example with a pirate attack is presented and discussed.**

Keyword: Sea surveillance, senor network, abnormal behaviour detection, sensor fusion, Hidden Markov Model

I. INTRODUCTION

The sea constitutes an important arena for the international trade; export and import of agricultural products, construction materials, oil, gas, etc. In fact the majority of the international trade is carried out on sea. However, there are threats like piracy, terrorism and sabotage that can hinder a continuous and safe trade. These threats are today generally difficult to detect in time to be able to prevent or mitigate the effects of them. It is therefore very important to continue to explore and develop techniques that can help improving security and safety for the sea-borne trade.

Research on methods for autonomous abnormal behaviour detection on the sea has been an active area for study in recent years. The research includes techniques for analyzing large amounts of data coming from various information sources and also techniques for utilizing and learning from prior knowledge of normal motion patterns that often characterize the movements of commercial vessels.

In this paper we present a two-stage method for automatic abnormal behaviour detection, with special focus on detecting piracy operations. The proposed method is based on fusion of evidences from different types of sensors, including radar, SAR (Synthetic Aperture Radar), electro-optical sensors, infrared sensors and also from AIS (Automated Identification System). The sensors can be deployed on different platforms such as aircraft, UAV, satellite, other vessels and on the coast. The sensors can also be co-located on the same platform.

In the first stage, the sensors perform detection, tracking and classification locally. The outputs act as input to the second stage which performs high-level fusion and disambiguation of the first-stage information. The high-level fusion is performed by using a Hidden Markov Model (HMM). The HMM is a statistical model where the system, that is modeled, is assumed to be a Markov process, i.e. a time-varying random phenomenon that is conditional only on the present state. In this application the HMM calculates the likelihood of normal vessel behaviour, given an observation sequence of features from the different sensors.

The paper is organized as follows: In Section II we briefly overview related work for abnormal behaviour detection and multiple sensor systems for maritime surveillance. In Section III we describe the concept of sensor fusion and discuss the different sensor fusion levels according to the JDL (Joint Directors of Laboratory) model. In Section IV we introduce and explain the HMM and in V we present our algorithm for abnormal behaviour detection (with focus on piracy operation). In Section VI we illustrate the algorithm with a numerical example and in VII we finally report some conclusions and further work.

II. RELATED WORK

In recent years there has been an increased interest in methods for improving security and safety for vessels at sea and in ports. A method for abnormal behaviour detection in port areas is presented in [1]. The method is based on HMM, density map and AIS information. The density map is used to identify important regions in the port area concerning vessel movements. This information will then serve as prior knowledge to the HMM. The routes of the vessels are input data to the HMM to learn how the vessels normally move and to detect abnormal behaviours.

Reference [2] presents different indicators on abnormal behaviours at sea and how they can be formulated in algorithms for automatic abnormal behaviour detection. The authors present the following indicators: deviation from standard route, unexpected AIS activity, unexpected port

arrival, close approach and zone entry. The estimation of anomalies is performed using a Bayesian network.

A way of incorporating human expertise into insufficient databases for maritime surveillance is presented in [3]. The modelling of human expertise in the VTMIS (Vessel Traffic Management Information System) database is used for illustrating the method, and the scenario describes a smuggling activity. The result indicates that human expertise will improve the detection capability considerably.

Reference [4] presents an approach for predicting future vessel behaviours, based on the classification of prevailing behaviours. This approach thus goes a step further in predicting the next step of the vessels behaviours, based on how they behave now. The model includes neural networks for continuous and autonomous learning of the normal situation. Normal changes in the sea area can then be automatically incorporated in the behaviour analysis, and the model will obtain adaptability for changes in the environment.

Imprecise anomaly detectors for maritime surveillance are introduced in [5]. Imprecise anomaly detectors consider threshold intervals, instead of single thresholds. With single thresholds there is a risk that the wrong decision will be made concerning the classification of low-level events, if the result from the individual anomaly detectors is very close to the single threshold. This problem can often be avoided by using imprecise anomaly detectors.

Reference [6] provides an interactive methodology based on visual representation that involves the user in the anomaly detection process and therefore benefits from the operator's knowledge and experience.

Strategies for how to complement the AIS information to be able to observe also vessels that do not carry or use AIS are discussed in [7]. There are several possible sensor solutions for this purpose, e.g. coastal radars, radar satellites, satellites carrying passive sensors for direction finding and aircraft (or UAV) with active or passive sensors. A complete solution for coastal water surveillance may comprise of AIS and coastal radar chains together with satellite based sensors to cover for beyond the horizon surveillance. Reference [8] presents a model for multisensory fusion based on data from radar, AIS and satellite imagery (SAR). Abnormal behaviour detection is performed by using a Bayesian framework.

Various data fusion architectures for maritime surveillance are discussed and reviewed in [9]. The architectures include the JDL model, the Waterfall model and the extended OODA model. The choice of architecture for maritime surveillance is not always easy. In the maritime case we often have large surveillance areas which introduce problems with data communication as well as timing and accuracy of sensor data. Moreover, there is often a combination of different types of sensors that are deployed on different types of platforms.

III. SENSOR FUSION

The key technique in this approach is sensor fusion. Sensor fusion is the process of combining information from different sources in order to reduce uncertainty in the overall situational picture. As a result of the improved situational picture the operator will, at an earlier stage, be able to take more correct decisions. Sensor fusion can take place at different so-called information levels, ranging from automatic signal processing at the sensor to the cooperation with the operator, who can react on the information and give feedback to the system by e.g. sensor management.

The sensor fusion processes can be explained and understood by using the JDL model. The JDL model differentiates the types of data fusion functions into different fusion levels. The JDL Model has been used to develop an architecture paradigm for data fusion [10] and was originally created by the Data Fusion Group at the JDL Joint Directors of Laboratories in USA. It was first published around 1987-88. The JDL model can contribute will at least the following:

- provides a common frame of reference for discussions and explanations on fusion issues

- facilitates the understanding of data fusion

- facilitates the recognition of the type of problems where data fusion can be applied

- facilitates the recognition of commonality among problems and the relevance of candidate solutions.

The structure of the JDL Model is presented in Fig. 1. Level 0 (signal refinement) refers to the estimations and predictions of signal observable states on the basis of pixel/signal data association and characterization. Level 1 (object refinement) refers to estimation and prediction of entity states on the basis of inferences from observations. Level 2 (situation refinement) refers to estimation and prediction of entity states on the basis of inferred relations among entities. Level 3 (threat refinement) tries to predict the future states of entities and relationships. At Level 2 and Level 3 information comes not only from the sensors but also from other information sources such as expertise knowledge and various databases. At level 4 process refinement aims to improve the monitoring process based on the results from the foregoing levels. The refinement can be performed by using e.g. sensor management.
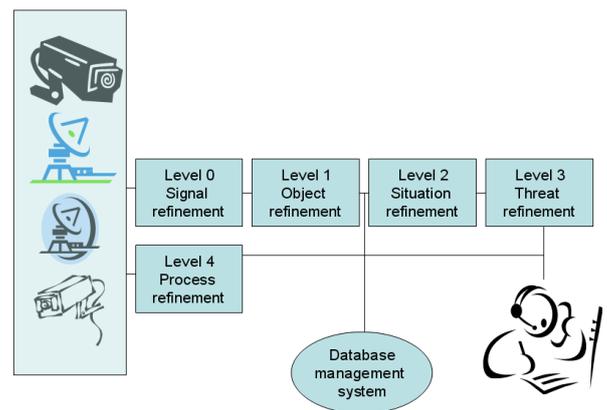

Figure 1. Structure of the JDL model.

The processing at each level is not necessarily performed in order. For example, threat refinement can be performed based on the results directly from object refinement, i.e. the situation refinement can be left out.

In this application we are at Level 1 and Level 2. At Level 1 track fusion and attribute fusion are performed. At Level 2 abnormal behaviour analysis is performed. The focus of the paper is on Level 2.

IV. HIDDEN MARKOV MODELS

The high-level fusion is performed by using a discrete HMM. In brief, the HMM consists of two stochastic processes [11]. The underlying process is defined by a combination of states and probabilities for changing from one state to another. The states represent some unobservable condition of the system, i.e. the underlying process is hidden. The states can however be observed via observation symbols.

Consequently, in each state of the system (at time t) there is a certain probability of producing any observable system outputs, as described in Fig. 2.

A discrete HMM, λ, is described by a number of states N and a number of discrete observation symbols M. The individual states are denoted $S = \{S_1, S_2,...,S_N\}$. The individual discrete observation symbols are denoted $V = \{v_1, v_2,...v_M\}$. The model λ is described by the following parameter set:

$$\lambda = (\pi, A, B, N, M) \qquad (1)$$

$$\pi = \{\pi_i\} = \{P[q_1 = S_i]\}. \qquad (2)$$

$$A = \{a_{ij}\} = \{P[q_{t+1} = S_j \mid q_t = S_i]\} \qquad (3)$$

$$B = \{b_j(k)\} = \{P[O_t = v_k \mid q_t = S_j]\} \qquad (4)$$

A represents the state transition probabilities, B represents the probability distributions of the discrete observation symbols for all states and π represents the initial probability distribution of the states. a_{ij} denotes the probability of the system to change from state i to state j and $b_j(k)$ denotes the probability distribution of the symbols for a certain state j. The current state is denoted q_t, the current observation is denoted O_t and $1 \leq i, j \leq N$, $1 \leq k \leq M$.

The parameters A, B and π can be estimated by HMM learning. In this work HMM learning is performed by using the Expectation-Maximization (EM) algorithm [11].

Once λ is defined, it can be used to calculate the likelihood L of an observation sequence O, given the specific model λ, i.e.
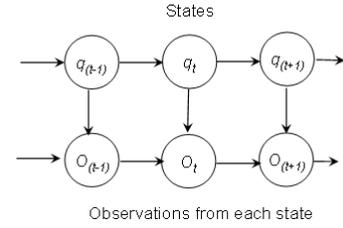
$$L = P(O \mid \lambda). \qquad (5)$$

Figure 2. For each time t, the current hidden state q_t can be observed through O_t.

O consists of observations registered at T points of time, i.e. $O = (O_1 O_2...O_T)$. In a recognition problem (e.g. recognition of abnormal behaviour) the purpose is to compare O to a specific λ and to find out whether O yields a high or low L value. To practically calculate L the forward algorithm is usable [11]:

$$\alpha_t(i) = P(O_1 O_2...O_t, q_t = S_i \mid \lambda). \qquad (6)$$

The forward algorithm describes the probability of observing the partial observation sequence $O_1 O_2...O_t$ in state S_i at time t, given λ. For O_1, α is calculated as follows:

$$\alpha_1(i) = \pi_i b_i(O_1). \qquad (7)$$

For the following observations α is calculated according to:

$$\alpha_{t+1}(j) = [\sum_{i=1}^{N} \alpha_t(1) a_{ij}] b_j(O_{t+1}) \qquad (8)$$

where $1 < t < T - 1$. (8) illustrates how S_j can be reached at time $t + 1$ from the N possible states at time t. The calculation is performed for all states j at time t. The calculation is then iterated for $t = 1, 2,...,T - 1$. The final result is given by the sum of the terminal forward variables $\alpha_T(i)$, i.e.

$$P(O \mid \lambda) = \sum_{i=1}^{N} \alpha_T(i). \qquad (9)$$

During the calculation procedure there are several multiplications with probabilities well below 1, leading to a final result which is close to 0. Problems will arise when the result is less than the smallest number that the computer can represent. The problem can however be solved by introducing the scaling factor c_t.

$$c_t = \frac{1}{\left(\sum_{i=1}^{N} \alpha_T(i)\right)}. \qquad (10)$$

The final equation that is useful for the calculations then becomes:

$$\log[P(O\,|\,\lambda)]=-\sum_{t=1}^{T}\log c_{t}. \qquad (11)$$

V. ABNORMAL BEHAVIOUR DETECTION

A. Low-level Event Detection

To distinguish between normal and abnormal behaviours, and specifically piracy operations, we have selected the following features and motion patterns:

- Non-cooperative vessels.
- Fast vessels/boats, possibly in groups.
- Unexpected AIS activity.
- Heading towards a passenger ship.
- Close approach.
- Deviation from expected and normal route.
- Small boat.
- Rubber boat.

There are numerous of different information sources that can be used for maritime surveillance. The radar sensor is used for detection, tracking and classification. The radar is rather robust against different weather conditions but can have difficulties in detecting the objects due to sea clutter and this is especially true for detection of small vessels (or boats). The radar is advantageous in detecting and tracking vessels/boats that do not emit AIS signals (i.e. non-cooperating vessels).

SAR (Synthetic Aperture Radar) is a form of radar that produces high-resolution images. Airborne or space borne SAR can be used to detect non-cooperating vessels.

Electro-optical sensors can be used for classification of non-cooperative vessels/boats during daytime when the light conditions are good. In the same way, infrared sensors can be used for the classification during poor light conditions.

AIS is used for monitoring of cooperative vessels. AIS is an automated broadcast technology that enables tracking of vessels by shore-based stations and by other vessels. AIS receivers record various broadcast attributes of vessels within the transmission range. The attributes include speed, direction and identity. Vessels broadcast AIS data at intervals specific to the current status of the vessels; for example in transit, at anchor and conducting maneuvers. The AIS signals are expected to be continuous in time within the transmission range. Any unrealistic changes in AIS signals, within this range, may be an indication of suspicious activities. The AIS transmitter could have been switched off or it could have been manipulated to send incorrect information about the vessel.

VTS (Vessel Traffic service) is a marine traffic monitoring system that keeps track of vessel movements within a limited geographical near the ports. VTS typically uses radar sensors, visual cameras and AIS. The VTS integrates all of the information into a single operational picture to be used for effective vessel traffic organization. Like AIS, VTS can deliver data to the abnormal behaviour detection if the sea area is covered by VTS.

B. High Level Fusion

Fig. 3 illustrates the suggested sensor fusion architecture, which is based on the same principle as the JDL model. Sensor data in each sensor undergoes signal processing, detection, tracking and feature classification (Level 0 and Level 1). The analyzed data is then sent to the Ground Control Station (GCS) for further object refinement and situation refinement (Level 1 and Level 2). At the GCS the sensor coordinates are transformed from the sensors' local coordinate systems to a common coordinate system representing the multiple sensor system. After coordinate translation track and attribute fusion are performed in order to get a common and consistent situational picture. For track association the statistical distance can be used and for track fusion the covariance intersection can be used [12]. For the attribute fusion the Bayes theorem can used [12]. In the common and consistent operational picture all objects within the area of interest have been detected, tracked and classified. From this information we derive the specific features, O_t, for the HMM observation sequence O.

Data in the different sensors are collected with different time intervals. For example, a satellite-based sensor collects data with relatively long intervals (the satellite may monitor the area perhaps only one time per day). The land-based sensors can collect data continuously (if the area of interest is close enough to the coast) and can therefore give a more detailed situational picture. These aspects will have to be considered for the track and attribute association and fusion in the GCS to give realistic observations O_t. In this case we assume that the association and fusion in the GCS can be accurately performed to create representative O_t values.
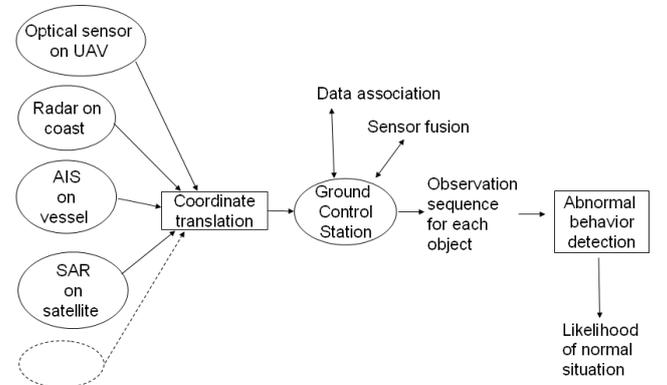

Figure 3. The sensors perform data processing, detection, tracking and feature classification. The Ground Control Station (GCS) performs track association, track fusion, attribute fusion and abnormal behaviour detection.

The features are defined as follows and included in the observation sequence O according to (12):

- Change in distance between the vessel and other objects (Δd). This could indicate that a vessel is approaching another vessel. Δd describes a relation between the vessel and another object in the vicinity of the vessel. It is necessary to limit the area in which the

vessel is compared to other objects; otherwise there is a risk that there is a large amount of combinations that has to be calculated.

- Change in vessel size (Δs). This could indicate that there are two vessels close to each other

- Change in vessel identification (ΔID). If no ID information is obtained the AIS transmitter could have been switched off or the distance between the vessel and AIS receiver is too long. If AIS information is changed to unrealistic values then the AIS may have been manipulated to send misleading information.

- Change in vessel speed ($\Delta \upsilon$). This could indicate a first step in an attack.

- Change in vessel heading ($\Delta \delta$). This could indicate deviation from normal route.

$$O = [\Delta d, \Delta s, \Delta ID, \Delta \upsilon, \Delta \delta] \qquad (12)$$

Each feature will be represented in (12) by the values 1, 2 or 3. If $O_t = 1$ there *is* information available at the GCS and it has not changed compared to (t-1). If $O_t = 2$ there is information available, but it has been changed compared to (t-1). If $O_t = 3$ there is no information available at the GCS at time t. Table 1 presents and defines the observation symbols.

Δd, $\Delta \upsilon$ and $\Delta \delta$ are obtained from radar sensors, AIS and/or VTS. Δs is obtained from electro-optical sensors, infrared sensors and/or SAR. If the features/attributes are obtained from several sensors and information sources the corresponding O_t is derived after the association and fusion at the CGS. ΔID is obtained from AIS.

TABLE I. OBSERVATIONS AND THEIR POSSIBLE VALUES

Feature	$O_t = 1$	$O_t = 2$	$O_t = 3$
Δd	$\Delta d \approx 0$	$|\Delta d| > 0$	No information
Δs	$\Delta s \approx 0$	$|\Delta s| > 0$	No information
ΔID	$\Delta ID \approx 0$	$|\Delta ID| > 0$	No information
$\Delta \upsilon$	$\Delta \upsilon \approx 0$	$|\Delta \upsilon| > 0$	No information
$\Delta \delta$	$\Delta \delta \approx 0$	$|\Delta \delta| > 0$	No information

We use λ with the purpose of describing normal vessel behaviours. The observation sequence O is however formulated in such a way that it represents a pattern of observations O_t that is typical for piracy operation.

We select two states S_1 and S_2. S_1 refers to continuous vessel motions, predominantly in a straight line and with no major changes in AIS signals or other features. There should be no apparent reduction in distance between the vessel and other detected vessels in the vicinity of the vessel. S_2 refers to minor changes in one or possible two features, but can still refer to normal behaviours. S_2 can represent for example maneuvers, where direction and speed are changed, or that the vessel is outside the range of the AIS receiver or can not be observed by another sensor.

A number of normal vessel routes were defined in order to obtain training data for the HMM learning to the numerical example presented in Section VI. The observation sequence (12) was used as a base for the training data. It is of course advantageous to collect data for a long time period to include variations in motion patterns over the day, the week and the year. In this case the EM algorithm gave the following HMM parameters for prior state distribution (π), state transition probabilities (A) and observation distribution probabilities (B):

$$\lambda = (\pi, A, B, 2, 3) \qquad (13)$$

$$\pi = \left\{ \begin{array}{c|c} \pi_1 & 0.56 \\ \pi_2 & 0.44 \end{array} \right\} \qquad (14)$$

$$A = \left\{ \begin{array}{c|cc} & a_1 & a_2 \\ \hline a_1 & 0.62 & 0.38 \\ a_2 & 0.60 & 0.40 \end{array} \right\} \qquad (15)$$

$$B = \left\{ \begin{array}{c|ccc} (b_j(k)) & k=1 & k=2 & k=3 \\ \hline (b_1(k)) & 0.77 & 0.13 & 0.10 \\ (b_2(k)) & 0.70 & 0.28 & 0.02 \end{array} \right\} \qquad (16)$$

We then simulated some vessels with normal behaviours in order to investigate what threshold we can use for distinguishing between normal and abnormal behaviours. Fig. 4 shows the L values for the simulation.
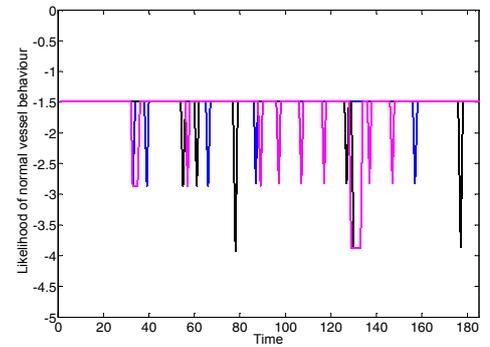

Figure 4. L values for three vessels (represented by black, mangenta and blue lines) that show normal behaviours.

Based on these L values we choose the following threshold:

- If $L > -4$ then we assume the vessel behaviour to be normal.

- If $L < -4$ then we assume the vessel behaviour to be abnormal (and in this case indicating a piracy operation).

VI. NUMERIACL EXAMPLE

We assume there are four vessels within the area of interest, see Fig. 5. There are two vessels moving along normal routes (i.e. predominantly continuous motion in straight lines). Then there is a third vessel approaching a forth vessel in a relatively high speed. The third vessel does not emit AIS signals. The fourth vessel initially emits AIS signals, but after a while the AIS signals show abnormal change. After a while both vessels changes directions and speed.

We have coastal radars, long endurance UAVs and AIS. Two UAVs are equipped with radar sensors. Two other UAVs are equipped with electro-optical sensors and infrared sensors, so that they can classify the vessels (estimate their sizes) both during day and night. We also have access to satellite images from SAR and electro-optical sensors. The sensors on the satellite observe the event occasionally and the data will be used to get information on the event after the suspected pirate attack.

Figure 5.   The scenario showing the area of interest and the four vessels moving in different directions.

The coastal radars and UAVs are able to continuously send data to the GCS, while the sensors on the satellite send data less often. At the GCS a consistent operational picture is calculated. Since each sensor delivers tracks and feature classification we only have to perform track fusion and attribute fusion at the GCS. This enables for a rather flexible algorithm for abnormal behaviour detection where we can use data that is available at the time, almost independently on the type of sensor that has created the track or feature/attribute.

After the track and attribute fusion the observation sequences O are continuously formed at the GCS and then sent for abnormal behaviour detection in the HMM. If a certain type of feature is not available for O at time t, then this is reported as $O_t = 3$ (see Table 1). The HMM results are compared to the threshold for normal behaviour to find out if there are vessels that may be involved in piracy operations.

Fig. 6 presents L values for the four vessels for a time period of 90 minutes. Two of the vessels (represented by black and red lines) show $L < -4$ part of the time. Besides, they have their lowest L values at approximately the same time. This may

indicate that they are involved in the same event. In this case it represents the event that vessel three is close to vessel four and vessel four has been attacked. The other two vessels (represented by magenta and blue lines) show normal behaviours since $L > -4$ during the whole time.
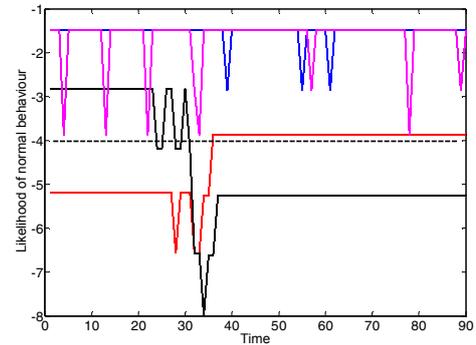

Figure 6.   The likelihood of normal behaviours. Two vessels (black and red) show $L < -4$ during at least part of the time period. Besides, they have their lowest L values at approximately the same time. This may indicate that they are involved in the same event. The other two vessels (mangenta and blue) show normal behaviours during the whole time since $L > -4$.

VII. CONCLUSIONS AND FURTHER WORK

This paper has presented initial work on an algorithm for calculating the probability that a piracy attack is about to take place, or has taken place. The method can give a rough indication of abnormal events and will increase the chances of detecting these events at an early stage. The method can be used for alerting an operator in an earlier stage, close to the time when the attack took place, or possibly even before. The operator then needs to investigate the selected vessel in more detail and make a decision whether to intervene or not.

The HMM parameters that are obtained from learning should be based on training data for the sea area in which the algorithm will be used, in order to get the best results. The algorithm is thus dependent on the current context, described by e.g. islands, normal vessel routes, normal vessel flows, normal weather conditions, expected threats, etc.).

There is a risk that there can be many false alarms in such automatic systems. However, by using multiple sensors the risk for false alarms will be reduced. Each sensor will obtain a unique situational picture and the combination of different unique situational pictures will reduce uncertainty and number of false alarms in the final and common situational picture.

Due to the complexity of the surveillance and anomaly detection in maritime environment, it is likely that a combination of several technical, and also organizational, measures will be required to improve situational awareness. In this paper an algorithm has been presented that can be one component, together with other measures, to improve safety and security on the sea.

Further work will include the introduction of grid-based fusion, where we can consider different sub areas (within the area of interest) with different importance. We will also in more detail investigate the significance of the different time

intervals for data collection (e.g. data from satellites that come rather seldom compared to data from AIS). Finally, more simulations will be performed in order to evaluate the algorithm to a larger extent, and compare the algorithm to other methods.

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