Loitering behaviour detection of boats at sea

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Abstract

We present in this paper a technique for Loitering detection based on the analysis of activity zones of the monitored area. Activity zones are learnt online employing a soft computing-based algorithm which takes as input the trajectory of object mobiles appearing on the scene. Statistical properties on zone occupancy and transition between zones makes it possible to discover abnormalities without the need to learn abnormal models beforehand. We have applied this approch to the PETS2017 IPATCH dataset and addressed the challenge on detecting skiff boats loitering around a protected ship, which eventually is attacked by the skiffs. Our results show that we can detect the suspicious behaviour on time to trigger an early warning.

1. Introduction

The beginning of the 21st century has seen a resurgence of maritime piracy. According to the International Maritime Bureau's (IMB) Piracy Reporting Center, piracy has been rising steadly for years [22]. Some regions in the Gulf of Aden, West Africa, South East Asia and South America have turned into dangerous places for commercial ships. It is of utmost importance for ships in high risk areas to detect piracy threats as early as possible so that the ship master can initiate countermeasures while they are still effective.

Several events are useful indicators of an early warning of a maritime threat. We can cite among them: 'boat speeding up', the sudden acceleration of the mobile object; 'boat loitering', the detected object stands/moves slowly in the same area; 'boat with anomalous direction', an object has a trajectory deviating from normal paths. While some other works have addressed some of these events [4, 7, 21, 23], loitering remains still to be characterised/exploited in the maritime domain.

In this work we focus on the detection of Loitering events, as set in the PETS2017 challenge on the maritime IPATCH dataset. The proposed approach works by first detecting Activity zones. Activity zones are learnt on-line

employing a soft computing-based algorithm which takes as input the trajectory of detected mobile objects. Statistical properties on zone occupancy and transition makes it possible to discover abnormalities without the need to learn abnormal models beforehand.

The remainder of this paper is organised as follows. The next section gives a short overview of the related work. The general system description is presented in Section 3. In Section 4, it is explained how the boat loitering behaviour is addressed. Section 5 presents the main results and evaluation. Finally, Section 6 draws the main conclusions and includes our future work.

2. Related work

Maritime surveillance has become a subject of utmost importance as the beginning of the 21st century has seen a resurgence of maritime piracy. According to the International Maritime Bureau's (IMB) Piracy Reporting Centre, piracy has been rising steadily for years [22]. Some regions in the Gulf of Aden, West Africa, South East Asia and South America have turned into dangerous places for commercial ships.

Different threats have been searched in the literature. Most works are based on the analysis of vessel trajectory provided by AIS and/or radar. Clustering methods have been popular to detect ship traffic-related abnormalities (deviating from normal routes; travelling in an anomalous direction; travelling in a sea lane but at an anomalously high speed; crossing the main sea lane at an anomalous location; stopping in a prohibited anchoring location) [4, 7, 21, 23, 20] or learning contextual areas at sea, such as fishing areas or high piracy risk areas [5]. Detecting piracy attacks has been the subject of some specific works. Garcia, et al. [22] looks to build a reliable surveillance picture based on matching boat tracking information with an ontology and using Belief Theory [24]. The boat features analysed for the threat are speed, direction, type and flag state. Bouejla et al. [3] have addressed piracy attacks against offshore oil infrastructure (oil platforms or oil tankers); the parameters employed to characterise the asset in danger include

the threat itself (the type of ship used by the attackers, its speed and their weapons) and the environmental conditions (the time of day, visibility, sea state, etc.). Lane et al. [13] have employed Bayesian networks to detect threatening behaviours such as 'close approach' or 'unexpected activity' based on location, speed and heading of the suspicious boat. Dabrowski, et al. [6] classify vessels as pirate vessels, fishing vessels or transport vessels based on the tracked trajectory of the vessel.

Loitering itself has been acknowledged to be important for detection of a maritime threat [19]. Loitering refers to a boat spending abnormally long time on the same area or performing slow movements around a bigger area but still without displacing itself a significant distance. This behaviour has been studied extensively in its land-case counterpart as loitering is a suspicious behavior that might lead to abnormal situations, such as pickpocketing, attack to a person or to a valuable asset [2, 11, 9, 17].

However, Loitering has generally been addressed as detecting an object on the scene for a period of time that exceeds a given threshold [15, 14, 12]. This means that manual adjustments on setting the threshold have to be done according to the dynamics of the scene under scrutiny. Instead, we propose in this work to learn statistical properties on zone occupancy that will allow automatic detection of Loitering behaviour without the need of setting temporal thresholds beforehand. Our system would then start by extracting the activity zones of the scene. Such zones would be analysed at several resolutions to allow for detection of Loitering on small or larger areas. Our contribution to the literature is thus a methodology for loitering detection applied to the maritime domain, which is based on learning statistical properties on zone occupancy without the need of setting thresholds.

3. System description

In this work we propose an extension to the behaviour analysis framework given in [18]; which is based on Semantic modelling and trajectory analysis. In such framework, the system can learn activity zones (context zones) that characterise the scene dynamics. We extend that system by extracting temporal statistics of object mobiles at each zone to detect the abnormal behaviour of an object Loitering.

The system is composed of three modules applied sequentially. In the first module, Tracklet calculation process (Extraction of points of interest), we study the trajectory speed and direction variations in order to distinguish between the object mobile in a stationary state (stop points) or moving state; between the object mobile in a straight direction or changing direction. The second module is a Zone learning module where we aim here to automatically discover activity zones of the scene. In a first step, points of

interest obtained from the previous calculation process are clustered together to obtain a first set of zones. In a second step zones are refined with a zone merging procedure. Indeed, It is possible that some discovered activity zones are partially overlapping. When this is the case, both regions are most certainly part of a bigger activity zone. Our algorithm will attempt to merge those overlapping activity zones. The third module is the Event Detection module: Statistical confidence levels are applied on zone occupancy measures to discover object mobiles spending suspiciously long periods on a given zone. Note that the system requires a detection and tracking algorithm that delivers trajectories of each mobile object on the scene. The hypothesis is thus that such a system is operational. In this work we employ for our study the trajectories made available on the PETS IPATCH dataset.
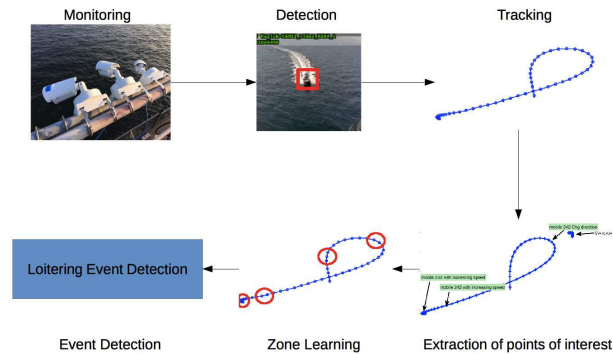

Figure 1. Processing chain for the proposed approach. Note that this work includes only modules displayed in the lower raw. A detection and tracking algorithm is assumed but not considered in this work.

4. Boat Behaviour Analysis

Loitering detection is based on the analysis of activity zones of the monitored area. Statistical properties on zone occupancy and transition between zones makes it possible to discover abnormalities without the need to learn abnormal models beforehand. In our work, activity zones are learnt on-line employing as input the trajectory of object mobiles appearing on the scene. Two essential procedures in our work are thus the trajectory processing and the discovery (learning) of activity zones, which are explained next.

4.1. Trajectory Processing

In order to detect boats abnormally staying long periods of time around the protected ship, we analyse the monitored boats speed profile. We aim to extract indicators of movement such as speeding up or staying still in the vicinity of the ship in order to distinguish loitering. We analyse the

boat direction to complement with points of interest indicating a direction change of the boat, and if the boat still remains in the vicinity of the ship this may be a further indication of loitering. Figure 2 shows an example of extracted speed points of interest.
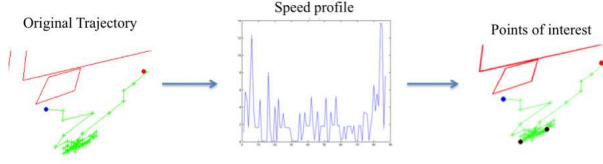

Figure 2. speed-related points of interest are extracted from the analysis of the mobile trajectory

Each mobile trajectory is defined as the set of points $[x_j(t), y_j(t)]$ corresponding to their position on the ground on the t-th frame. The instantaneous speed for that mobile at point $[x_j(t), y_j(t)]$ is then $v(t) = \left(\dot{x}(t)^2 + \dot{y}(t)^2\right)^{\frac{1}{2}}$, and the direction θ that the mobile takes at that point is $\theta(t) = arctan(\dot{y}(t)/\dot{x}(t))$.

Each of these two time series is analysed in the frame of a multiresolution analysis [16] with a Daubichis Haar smoothing function, $\rho_{2^s}(t) = \rho(2^s t)$, to be dilated at different scales s.

In this frame, the approximation A of $v(t)$ by ρ is such that $A_{s-1}(v) = \int v(t)\rho\left(2^{s-1}t - b\right) dt$ is a broader approximation of $A_s v$ and correspondly for $A_{s-1}(\theta)$ and $A_s \theta$. The analysis is performed through six dyadic scales. Speed changing points and direction changing points correspond to those important discontinuities which remain present across scales.

4.2. Zone Learning

Activity zones are computed having inputs of track speed and direction changing points calculated as explained in Section 4.1. These points are first clustered by a fast partitioning algorithm (the Leader algorithm [8, 10]), allowing to quickly create an initial set of zones Zn. In a second step the partition is corrected leading to the final activity zones. To correct the initial partition, different relationships between initial zones Zn are taken into account. For this step, soft computing techniques are employed.

4.2.1 Soft computing relation clustering

Let us consider two different fuzzy binary relations, *R1* and *R2*, linking different sets *X*, *Y*, and *Z* :

- R1 = x is relevant to y

- R2 = y is relevant to z

It is then possible to find to which extent x is relevant to z by employing the extention principle (noted $R = R1oR2$):

$$\mu_{R=R1\circ R2}(x,z) = \max_y \min\left[\mu_{R1}(x,y), \mu_{R2}(y,z)\right]$$

μ_{R1} and μ_{R2} being the membership functions defining *R1* and *R2*. The resulting relation, *R*, is symmetric, $R(x,y) = R(y,x)$, reflexive $R(x,x) = 1$; *R* is also a transitive relation. $R(x,y)$ is a transitive relation if $\exists z \in X, z \in Y/R(x,y) \geqslant \max_z \min\left[R(x,z), R(z,y)\right]$. *R* can be made furthermore closure transitive following the next steps

Step1. $R' = R \cup (R \circ R)$
Step2. If $R' \neq R$, make $R = R'$ and go to step1
Step3. $R = R'$ Stop.

$$(1)$$

R is the transitive closure where

$$R \circ R(x,y) = \max_z \min\left(R(x,z), R(z,y)\right) \qquad (2)$$

4.2.2 Initial zone learning partition

For the first step, the clustering Leader algorithm is employed. It has the advantage of working on-line without needing to specify the number of clusters in advance. In this method, it is assumed that a threshold *T* is given. The algorithm constructs a partition of the input space (defining a set of clusters) and a leading representative for each cluster, so that every object in a cluster is within a distance *T* of the leading object. The first pattern is assigned to a cluster. Then the next pattern is assigned to an existing cluster or to a new cluster depending on the distance between the pattern and the cluster leading representative. The process is repeated until all patterns are assigned to clusters.

In this application, when a point is designed as cluster leader (or leading representative), *L*, the cluster influential zone, *Zn*, is defined by a radial basis function (RBF) centered at the position *L*; and the membership of a new point *p(x,y)* to that zone is given by:

$$Zn(L,p) = \phi(L,p) = exp(-\|p-L\|^2 T^2) \qquad (3)$$

The RBF function has a maximum of 1 when its input is *p=L* and thus acts as a similarity detector with decreasing values outputted whenever *p* strides away from *L*. An object element will be included into a cluster if $Zn(L,p) \geqslant 0.5$. The cluster receptive field (hypersphere) is controlled by the learnt parameter *T*. In this work we employ the same settings as in [18]

4.2.3 Final zone learning partition

The final activity areas are found by merging similar initial zones Zn. They are established by the fulfilment of different relations between zones Zn. This procedure is achieved by setting soft computing relationships between zones.

The first relation indicates if zone Zn_i overlaps zone Zn_j. This relation is defined as follows:

$R1_{ij}$: Zone Zn_i overlaps Zone Zn_j

$$R1_{ij} = \sum_{k=1}^{3} \left[\sum_{p(x,y) \in (X_{ik}, Y_{ik})} Zn_j(L_j, p(x,y)) \right] \quad (4)$$

and $(X_{ik}, Y_{ik}) = \left\{ \frac{(k+1)}{3} T \cos(\theta) + L_i \right\}$ with $\theta = 0, ..., \frac{\pi}{8}, ..., 2\pi$

That is, points $(x,y) \in (X_{ik}, Y_{ik})$ belonging to Zn_i centered at L_i are tested to verify the overlap/similarity between Zn_i and Zn_j.

Similar relations that we have introduced are as follows:

$R2_{ij}^t$: zone Zn_i and zone Zn_j are destination zones for mobiles departing from the the same activity zone Zn_k

$R3_{ij}^t$: zone Zn_i and zone Zn_j are origin zones for mobiles arriving at the the same activity zone Zn_k

$R4_{ij}^t$: zone Zn_i and zone Zn_j have about the same number of detected mobiles stopping at the zone

$R5_{ij}^t$: zone Zn_i and zone Zn_j have about the same mobile interaction time. The mobile interaction time is the mean time a mobile spends in that zone.

All relations can be aggregated employing a soft computing aggregation operator such as

$R = R1 \cap R2 \cap R3 \cap R4 \cap R5 = \max(0, R1 + R2 + R3 + R4 + R5 - 4)$ and made transitive with the formulae given in Equation 1.

R then indicates the strength of the similarity between Zn_i and Zn_j. If we define a discrimination level α in the closed interval [0,1], an $\alpha - cut$ can be defined such that

$$R^\alpha(x,y) = 1 \Leftrightarrow R(x,y) \geqslant \alpha \quad (5)$$

From the classification point of view, R^α induces a new partition π^α with a new set of clusters $\pi^\alpha = \left\{ AZn_1^\alpha, \cdots, AZn_k^\alpha, \cdots, AZn_{|\pi^\alpha|}^\alpha \right\}$ such that cluster $AZn_k{}^\alpha$ is made of all initial zones Zn_i which up to the alpha level fulfil the relations set above and can thus be merged to form the final activity zone AZn_k^α.

4.3. Boat loitering detection

Loitering detection corresponds essentially, in this work, to measuring the amount of time boats may stay stationary on a given area (activity zone), and determine whether it is significantly different from the normal amount of time boats usually stay around the protected ship. More specifically, we want to establish an statistical measure indicating a boat

'Unusually (abnormally) stays long at any zone' around the protected ship. The decision on abnormality is based on the calculation of statistical confidence levels.

This statistics-based methodology is based on the idea that 'normal' data objects follow a generating mechanism, e.g. some given statistical process (distribution model). 'Abnormal' objects deviate from this generating mechanism.

Such statistical measure is mathematically defined with the following equation:

$$CL = 1.96 * \left(\frac{\sigma}{\sqrt{n}} \right) \quad (6)$$

where σ is the standard deviation of the measured parameter, μ, and n is the number of observations of such parameter. The confidence level can be interpreted as having 95% confidence that the true value of μ lies between $[\overline{\mu} - CL, \overline{\mu} + CL]$. Such statistical bounds are employed as a reference to decide whether a measurement could be considered suspicious by comparing whether it lies inside or outside such statistical bounds. The abnormality of a given measurement is graded depending on how far it lies from these statistical bounds.

It is assumed in this work a normal distribution of the data for abnormality detection, that is, it is assumed 'normal activities' ('staying in a zone', 'undertaken path frequencies') can be characterised by a mean value and symmetrical tolerance intervals around it. Furthermore, the central limit theorem states that even if the population distribution is unknown, the sampling distribution of the mean will be approximately normally distributed if the sample size is large.

Let $stayinZntime(tr_j, AZn_k^\alpha)$ be the time a mobile spends in the given activity zone AZn_k^α. A mobile trajectory is considered to suspiciously stay long in that activity zone at resolution α if its $stayinZntime$ measure lies outside the confidence values; grading the abnormality by calculating the ratio

$$R = \frac{stayinZntime(tr_j, AZn_k^\alpha)}{stayinZntime\left(\sum_j tr_j, AZn_k^\alpha \right) + CL} \quad (7)$$

5. Experimental Results

We have addressed the challenge set in PETS2017 [1] regarding the Loitering behaviour recognition of a boat in the vicinity of a protected ship. As such, we have evaluated the two sequences from the PETS dataset containing this behaviour. The two test sequences are namely Sc3_Tk1 and Sc3_Tk3. Scenario 3 corresponds in the dataset to a slow approach from two skiffs to a protected ship equipped with

Figure 3. Sc3_Tk1 of the IPATCH-PETS dataset. A) The schematic representation of the scenario indicates two skiffs loitering before speeding up to attack a vessel. B) Two skiffs observed stationary (Loitering) by one of the ship cameras. C) The two skiffs observed speeding up for an attack against the vessel.
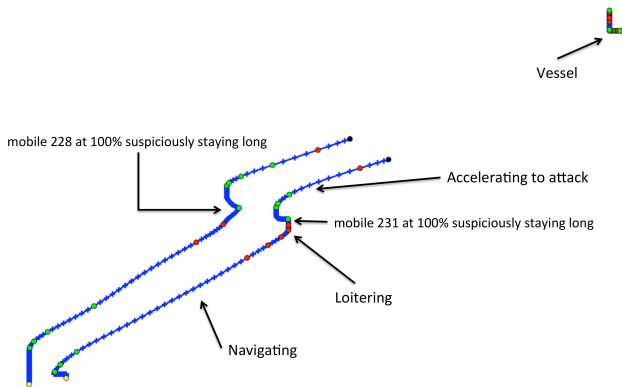

Figure 4. Sc3_Tk1 of the PETS-IPATCH dataset. The two skiffs have a loitering period before performing an attack to the ship. Red points indicate boat decreasing speed. Green points indicate boat increasing speed.
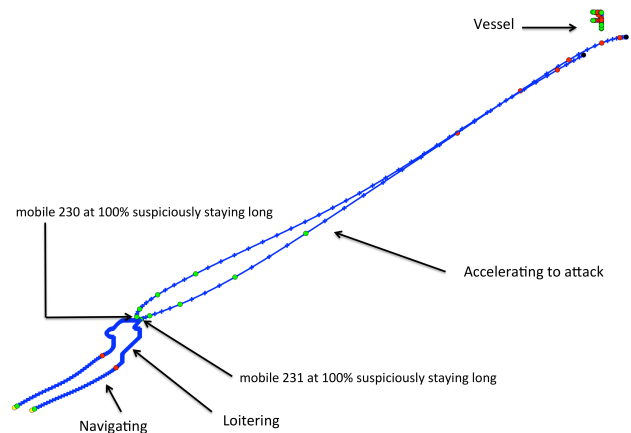

Figure 5. Sc3_Tk3of the PETS-IPATCH dataset. The two skiffs have a loitering period before strongly speeding up to attack the ship. Red points indicate boat decreasing speed. Green points indicate boat increasing speed.

cameras to monitor the close range space. The skiffs first remain long periods stationary, simulating being fishermen, before speeding up to attack the ship. These two sequences are appropriate for test as they contain long periods of stationary not far from the protected ship that can be considered as loitering activity. Figure 3 shows the schematic interpretation of scenario 3 and provides some examples of the skiffs captured by one of the ship cameras, first in stationary state (Loitering) and then approaching the ship at high speed to perform an attack.

Our results to detect the Loitering state are summarised in Table 1 respectively for scenarios Sc3_Tk1 and Sc3_Tk3. Visual validation is used to verify if the result is a True Positive (TP), False Positive (FP), True Negative (TN) or False Negative (FN). The real trajectories for the corresponding sequences are shown in Figures 4 and 5 for each of the processed sequences together with the detected loitering event. Note that although in the figures the loitering event is de-

picted at the end of the stationary state, the system assessing the situation around the ship continously and giving the likelihood of loitering as calculated from equations 6 and 7. In Table 1, it can be observed that loitering events are given with gradual levels of warning. It could be argued that possibly when the threat or warning level is low (probably less than 50%) no event warning should be given and as such we have marked produced events under 50% confidence as FP and could probably not be forwarded to the end user. The remaining of the produced events are marked as definite True Positives as they carry a high level of confidence and can be visually validated.

6. Conclusions

In this work we have addressed the challenge set on PETS 2017 regarding loitering detection of boats around

Sequence	trackid	eventhhmmss	event	Visual Evaluation
Sc3_Tk1	Boat 2	21/04/15 12:00:00	mobile 228 at 28% suspicsously staying long	FP
Sc3_Tk1	Boat 1	21/04/15 12:00:00	mobile 227 at 28% suspicsously staying long	FP
Sc3_Tk1	Boat 1	21/04/15 12:00:40	mobile 227 at 87% suspicsously staying long	TP
Sc3_Tk1	Boat 2	21/04/15 12:00:40	mobile 228 at 87% suspicsously staying long	TP
Sc3_Tk1	Boat 1	21/04/15 12:01:20	mobile 227 at 100% suspicsously staying long	TP
Sc3_Tk1	Boat 2	21/04/15 12:01:20	mobile 228 at 100% suspicsously staying long	TP
Sc3_Tk1	Boat 1	21/04/15 12:01:36	mobile 227 at 100% suspicsously staying long	TP
Sc3_Tk1	Boat 2	21/04/15 12:01:36	mobile 228 at 100% suspicsously staying long	TP
Sc3_Tk3	Boat 1	21/04/15 12:16:45	mobile 230 at 28% suspicsously staying long	FP
Sc3_Tk3	Boat 2	21/04/15 12:16:45	mobile 231 at 28% suspicsously staying long	FP
Sc3_Tk3	Boat 1	21/04/15 12:17:17	mobile 230 at 75% suspicsously staying long	TP
Sc3_Tk3	Boat 2	21/04/15 12:17:17	mobile 231 at 75% suspicsously staying long	TP
Sc3_Tk3	Boat 1	21/04/15 12:17:57	mobile 230 at 100% suspicsously staying long	TP
Sc3_Tk3	Boat 2	21/04/15 12:17:57	mobile 231 at 100% suspicsously staying long	TP
Sc3_Tk3	Boat 1	21/04/15 12:18:37	mobile 230 at 100% suspicsously staying long	TP
Sc3_Tk3	Boat 2	21/04/15 12:18:37	mobile 231 at 100% suspicsously staying long	TP

Table 1. Recognised behaviours in the PETS-IPATCH dataset.

a protected ship. The approach is based on the analysis of real trajectories provided in the IPATCH dataset. First, activity zones are learnt online employing a soft computing-based algorithm which takes as input the trajectory 'change of speed' or 'change of direction' points, extracted from the object trajectories. Statistical properties on zone occupancy will allow automatic detection of Loitering behaviour. Contrasting with state of the art algorithms, we can perform loitering detection without the need of setting temporal thresholds beforehand. The results obtained on the PETS2017 IPATCH dataset are encouraging and to our knowledge this is a pioneering work on loitering detection on the maritime domain. Our future work will include the analysis of tracks fusing different sensors such as Radar, AIS and camera tracking.

Acknowledgement

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