Semantic Modelling for Behaviour Characterisation and Threat Detection

Luis Patino and James Ferryman
University of Reading, Computational Vision Group
Whiteknights, Reading RG6 6AY, United Kingdom
{j.l.patinovilchis, j.m.ferryman}@reading.ac.uk

Abstract

Threat detection in computer vision can be achieved by extraction of behavioural cues. To achieve recognition of such cues, we propose to work with Semantic Models of behaviours. Semantic Models correspond to the translation of Low-Level information (tracking information) into High-Level semantic description. The model is then similar to a naturally spoken description of the event. We have built semantic models for the behaviours and threats addressed in the PETS 2016 IPATCH dataset. Semantic models can trigger a threat alarm by themselves or give situation awareness. We describe in this paper how semantic models are built from Low-Level trajectory features and how they are recognised. The current results are promising.

1. Introduction

In the PETS2016 IPATCH dataset, threat event detection corresponds to the automatic recognition of suspicious behaviours or clear indications of attack from boats in the near or long range vicinity from the main vessel. The dataset contains acted scenarios from maritime-domain real end-user piracy experiences. As expected, piracy attacks occur in a large variety of forms. Sometimes pirates disguise themselves as fishermen; sometimes pretending to follow an unrelated course to the main vessel before deviating to attack and sometimes devising a slow-approach to their attack. Despite the different forms of attack, the contextual area of the attack, possible weather and other conditions, recorded sequences consistently contain threat behaviours such as a skiff speeding up towards the ship, suddenly heading towards the ship, approaching at high speed, for which, although we cannot recover the boat movements and timing, the conveyed semantic is clear and leaves no doubt of a potential threat to the main vessel. To achieve threat recognition in the PETS2016 IPATCH dataset we propose to work with Semantic Models of threats. Semantic Models correspond to the translation of Low-Level information (tracking information) into High-Level semantic description. The model is then similar to a naturally spoken description of the event. This translation and building of models have been first proposed by Patino et al [10] to translate trajectory information from people walking around in a scene to a semantic model. Learning the model is based on the learning of activity zones of the scene; extracting semantics from key points in the trajectory and expressing the trajectory as a sequence of visited zones. Semantic models in IPATCH can trigger a threat alarm by themselves or give situation awareness as input to further analysis or processing by the end-user. We describe next how semantic models are built from Low-Level trajectory features; which threats we address and how they are recognised.

2. Related work

Threat detection and suspicious behaviour recognition has been widely researched for surveillance of human activities. Depending on the application domain, such systems may specialise in the detection of some targeted events. Infrastructures with valuable assets are interested in detecting a person in a forbidden or sensitive area [13]. Counting people is an important feature in space/ environment planning in ambient intelligence applications [9]; this can increase management efficiency in public spaces making system operators aware of areas with high congestion or signalling areas that need more attention. This has led to a research interest on behaviours such as panic, fighting, and vandalism.

In the maritime case, threat and behaviour analysis has been less developed. The event detection and raising of an alarm has focused on detection of boat behaviour abnormalities. By abnormalities we understand anomalous events occurring infrequently in comparison to normal events; or anomalous events that have significantly different characteristics from normal events. This links to suspicious behaviour detection, where we search for events which have specified different characteristics from normal events. Well known abnormal behaviours are related to AIS transmission. These include the switching on or off of AIS systems and spoofing a ship's name or other details. However, the most common researched abnormalities are related to the vessel route and associated kinematics (still with AIS and/or radar-based datasets as inputs). These correspond to abnormal traffic patterns that could be related to a vessel traveling in an anomalous direction, a vessel traveling in a sea lane but at an anomalously high speed, a vessel crossing the main sea lane at an anomalous location or a vessel at a prohibited anchoring zone. Trajectory analysis has been widely used in these cases. Spline-based trajectory clustering [3]; Kohonen maps [12], Gaussian mixture model, or multivariate analysis [14, 11], have been for instance employed to model normal sea lanes and discover abnormalities. Probabilistic models based on Markovian and Bayesian theory have also been researched particularly for its intrinsic nature to handle uncertainty. Bayesian networks are used to combine individual probabilities and calculate the overall probability of facing an abnormal event [2]. Good success has been reported on using Hidden Markov models HMMs [15]; these are particularly interesting to model sequences of events (e.g. the sequence of ship port arrivals). Suspicious behaviour detection capabilities implemented in real maritime control rooms are must commonly rule-based systems. Such systems are set by experts that create rules that will trigger an alarm. Rule-Based Expert Systems with rules defined by experts have been proposed for the deduction of different situations, e.g. dangerous area, smuggling, hijacking, close approach [4, 6, 5, 16]. Such systems employ input data regarding vessel type, speed, location, report time and heading, as well as environmental information such as tides, wind speed and direction.

Compared to the state of the art, the proposed approach has the advantage to recognise threats in the semantic domain, thus allowing recognition of threatening situations that may occur in a large variety of forms and whose complexity would grow when focusing only on Low-Level trajectory data. Employing semantics, an operator can also easily specify behaviour patterns of interest, which allow for system flexibility.

3. Concept description

Semantic modelling is achieved through trajectory analysis. By employing clustering techniques, activity zones (context zones) can be learnt characterising the scene dynamics. Detected mobile object activities are extracted by relating mobile trajectories to the learned zones. The activity of a mobile object can then be summarised as the series of zones that the person has visited. Semantics are automatically attributed to activity zones and to key points in the mobile trajectory, allowing expressing activities themselves with semantics. Figure 1 shows the steps employed to build the semantic model and to employ them for the recognition of targeted threats. The assumption is that a fusion module is generating trajectories from detected objects from a series of heterogeneous sensors. These could correspond to objects observed on different types of camera (visible, thermal) or other tracking systems (such as radar or AIS). The proposed system would then start by the analysis of detected mobile trajectories and extracting trajectory points of interest indicating mobile change of speed or direction (Extraction of points of interest module). Points of interest are those trajectory points that can give behavioural information allowing the recognition of targeted behaviours. We are interested to extract points indicating an object mobile 'has stopped', 'speeds up' or 'stands waiting'. As previously mentioned, the proposed semantic models employ learned activity zones where mobiles evolve in the scene. This is the second step in the proposed system. The input, to the zone learning procedure, is the extracted trajectory points of interest. Activity zones are built by running a soft computing clustering algorithm on those points. Activity zones are important because they allow understanding frequent behaviours. Meeting zones, waiting zones, queuing zones and user-defined zones are meaningful for this. In an offline step, semantic models are built by characterising mobile object movements as a series of visited activity zones (activity extraction module). Such characterisation allows recognition of the targeted threats. Different threats are considered: boats suddenly changing direction or involving suspicious fast movements. Detected mobiles can then be inferred as having a normal, or a threat activity.

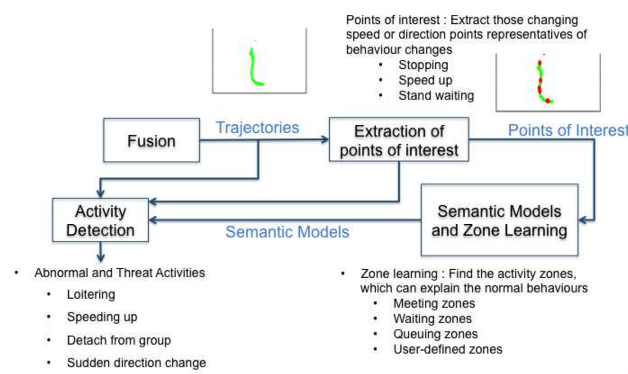

Figure 1. Processing chain for the proposed approach

3.1. Addressed behaviours

Specifically we target the recognition of the following behaviours: 'boat Meeting', 'boat Splitting', 'boat suddenly detaching from group', 'boat chasing/catching up', 'boat suddenly changing direction'. While the first two behaviours are normal group behaviours, the next ones represent clear indications of an abnormal activity (potentially an attack towards the main vessel). We define:

- Skiff (boat) speeding up: Sudden acceleration of the mobile object.

- Skiff group formation: A mobile comes close to another and holds an interaction.
- Skiff group separation: A mobile departs from a group.
- Skiff suddenly changing direction: Mobile object suddenly changes trajectory.

4. Setting semantic models

As mentioned in the previous section, semantic models are built from two key stages: Extraction of semantics from points of interest and learning of scene context (activity zones). We now describe each of these processes.

4.1. Extracting semantics from trajectory

Behavioural indicators for meeting situations are for instance 'tracked objects stopping to meet ' or tracked objects which 'change direction' to approach another one. Information of this type can be extracted from both the analysis of the mobile trajectory speed and direction profile. There are thus two parallel processes: The first is to analyse the mobile speed profile and obtain those speed changing points. The second is to analyse the mobile direction profile and obtain those direction changing points.

Each 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 $v\left(t\right) = \left(\dot{x}\left(t\right)^2 + \dot{y}\left(t\right)^2\right)^{\frac{1}{2}}$, and the direction θ that the mobile takes at that point is $\theta\left(t\right) = arctan\left(\dot{y}\left(t\right)/\dot{x}\left(t\right)\right)$.

Each of these two time series is analysed in the frame of a multiresolution analysis [7] with a Daubichis Haar smoothing function, $\rho_{2^s}\left(t\right) = \rho\left(2^s t\right)$, to be dilated at different scales s.

In this frame, the approximation A of $v\left(t\right)$ by ρ; where b is a translation parameter spanning the time domain of $w(t)$, is such that $A_{s-1}\left(v\right) = \int v\left(t\right)\rho\left(2^{s-1}t - b\right)dt$ is a broader approximation of $A_s v$ and correspondingly for $A_{s-1}\left(\theta\right)$ and $A_s\theta$. The analysis is performed through six dyadic scales. The effect at performing a broader approximation is to smooth out signal variations at each scale. We select as speed changing points and direction changing points those points seen as sharp discontinuities which remain present across scales despite the smoothing procedure.

Speed changing points are then labelled according to the direction of the speed change : 'with decreasing speed', 'with increasing speed', 'with normal speed', 'stopping'. Change direction points are labelled on a single category: 'Change direction'.

4.2. Extracting scene context information

A fuzzy set is a set of ordered pairs such that $A = \{(x, \mu_A\left(x\right)) \mid x\epsilon X\}$. Any relation between two sets *X* and *Y* is known as a binary relation *R*:

$$R = \{((x, y), \mu_R\left(x, y\right)) \mid (x, y)\,\epsilon X \times Y\}$$

and the strength of the relation is given by $\mu_R\left(x, y\right)$

Let's consider now two different binary relations, *R1* and *R2*, linking three different fuzzy 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 $R = R1oR2$):

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

It is interesting to verify whether the resulting relation is symmetric, $R\left(x, y\right) = R\left(y, x\right)$, reflexive $R\left(x, x\right) = 1$, which make of R a compatibility relation and occurs in most cases when establishing a relationship between binary sets. Because R was calculated employing the extention principle, R is also a transitive relation. $R\left(x, y\right)$ is a transitive relation if $\exists z \in X, z \in Y / R\left(x, y\right) \geqslant \max_z \min\left[R\left(x, z\right), R\left(z, y\right)\right]$

R can be made furthermore closure transitive following the next steps

$$\begin{aligned} &\text{Step1. } R' = R \cup (R \circ R)\\ &\text{Step2. If } R' \neq R, \text{ make} R = R' \text{ and go to step1}\\ &\text{Step3. } R = R' \text{ Stop.} \end{aligned} \tag{1}$$

R is the transitive closure where

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

R is now a transitive similarity relation with R indicating the strength of the similarity. If we define a discrimination level α in the closed interval [0,1], an $\alpha - cut$ can be defined such that

$$R^\alpha\left(x, y\right) = 1 \Leftrightarrow R\left(x, y\right) \geqslant \alpha \tag{3}$$

From the classification point of view, R^α induces a new partition π^α with a new set of clusters $\pi^\alpha = \left\{CL_1^\alpha, \cdots, CL_k^\alpha, \cdots, CL_{|\pi^\alpha|}^\alpha\right\}$ such that cluster $CL_k{}^\alpha$ is made of all initial elements x, y, z which up to the alpha level fullfill the final similarity relation in equation 2. It should be noted that this relation clustering was first proposed by Patino et al. [8] for the learning of activity zones.

4.3. Relation setup for activity zone computation

Activity zones are computed having as input the track speed (or direction) changing points calculated as explained in Section 4.1. These points are first clustered by a fast partitioning algorithm. In a second step the partition is corrected leading to the final activity zones.

Computing Initial Activity Zones. The algorithm works on-line without needing to specify the number of clusters in advance. The first point is assigned as Leader representative of a new cluster. Then the next point is assigned to an existing cluster or defines a new cluster depending on the distance between the point and the cluster leading representative. The process is repeated until all input points are assigned to clusters. In our application, the cluster influential zone, Z_n, is defined by a radial basis function (RBF) centered at the position of the point designed as cluster leader (or leading representative), L; and the membership of a new point $p(u, v)$ to that zone is given by:

$$Z_n(L,p) = \phi(L,p) = exp(-\frac{\|p-L\|^2}{T^2}) \quad (4)$$

The RBF function has a maximum of 1 when its input is $p = L$ and thus acts as a similarity detector. An object element will be included into a cluster Z_n if $Z_n(L,p) \geq 0.5$; the cluster receptive field (hyper-sphere) is controlled by parameter T.

Final Activity Zone calculation. To calculate the final zone partition, the following relationships are set: $R_{1_{ij}}$: Zone Z_{n_i} overlaps Zone Z_{n_j}. $R_{2_{ij}}$: zone Z_{n_i} and zone Z_{n_j} are destination zones for mobiles departing from any same activity zone Z_{n_k}. $R_{3_{ij}}$: zone Z_{n_i} and zone Z_{n_j} are origin zones for mobiles arriving to the the same activity zone Z_{n_k}. $R_{4_{ij}}$: zone Z_{n_i} and zone Z_{n_j} have about the same number of detected mobiles stopping at the zone. $R_{5_{ij}}$: zone Z_{n_i} and zone Z_{n_j} have about the same mobile interaction time. All relations are aggregated employing a bounded product T-norm soft computing operator $R = \max(0, R_1 + R_2 + R_3 + R_4 + R_5 - 4)$. New zones $AZn_k{}^{\alpha}$ are learned employing equation 1. Final activity zones AZn_k^{α} are made of all initial zones Zn_i which up to the alpha level fullfill the relations set above. Note that unlike [8], we employ an extended set of relations.

5. Behaviour characterisation

Traectory information can be translated into semantic terms with the help of discovered zones and speed and direction labels.

Having discovered in total $k = 1, ..., K$ zones ; and AZn_k^{α} is one zone resulting from the zone learning procedure, we understand then a mobile behaviour as the sequence of transitions between learned zones in its trajectory. Two different transitions can be defined:

• Mobile with $speed - direction - label$ from Zone AZn_k^{α} to Zone $AZn_{k'}^{\alpha}$
• Mobile at Zone AZn_k^{α} with $speed - direction - label$

The complete behaviour is then characterised as the ordered sequence of transitions generated as the mobile moves between zones.

5.1. Addressing PETS2016 behaviours

We employ semantic models to define threat behaviours of the maritime domain. The addressed behaviours stated in Section 4.1 translate then as follows:

Skiff (boat) speeding up: mobile with the semantic label increasing speed.

Skiff (boat) group formation: At least two boats come to a common zone Zn and hold an interaction: mobileA 'stopping' OR 'with decreasing speed' at zone Zn before mobileB 'stopping' OR 'with decreasing speed' at zone Zn.

Skiff (boat) group separation: A boat departs from a group at a common zone Zn towards a different zone Zn': mobileA 'stopping' OR 'Chg direction' OR 'decreasing speed' at Zone Zn overlaps mobileB 'with normal speed' OR 'with increasing speed' from Zone Zn to zone Zn'.

Skiff (boat) suddenly changing direction: mobile with the semantic label change direction.

6. Experimental results

We have addressed the challenge set in PETS2016 [1] regarding the recognition of the following behaviours: 'change direction', 'speeding up', 'group formation', 'group separation'. We have thus processed all sequences marked in the dataset description as containing at least one instance of these behaviours. The total number of sequences processed from the PETS2016 dataset amounts then to nine. The sequences are multisensor recordings comprising visual, thermal and GPS data. We employ the latter as input to our system.

Semantic models are particularly of interest because it allows recognising an attack or a threat despite the different forms the attack may take. The core of the approach consists on working on conveyed semantic from boat kinematics. Semantics are essential to distinguish between a threat and a non-threat.

Consider two cases; for instance scenarios GPS_Sc4_Tk2 and GPS_Sc3b_Tk1. The former represents a real threat and the latter only an abnormality. Both sequences have a very similar development. In sequence GPS_Sc4_Tk2 (depicted in Figure 3), one vessel is at anchorage; a boat approaches and stops interacting with the vessel. Suddenly two stationary skiffs, simulating being fishermen, speed up to attack the main vessel. In the second sequence, GPS_Sc3b_Tk1 (depicted in Figure 4), stationary fishing boats are in the vicinity of the vessel. The boats speed up towards the vessel and finally change direction without reaching the vessel. Key behavioural cues in these sequences are boats speeding-up, changing direction, splitting and meeting.

Our approach succeeds to extract those important boat speeding-up and changing direction points. Figure 2 shows how the speed profile of a given trajectory is analysed with the Haar-based multiresolution approach as described in Section 4.1. A similar procedure is applied on the instantaneous direction at each pont of the trajectory. Important change of speed points and change of direction points are extracted and represented over the original trajectory in the same figure. Qualitatively, the extracted points of interest correctly indicate the speeding up, decreasing of speed as well as change of direction correctly. On the nine processed sequences 23 instances on change direction were obtained from which 19 are considered True Positives and four False Positives (see Table 1). Two of those false positives corresponding to boats being almost stationary (and thus change of direction has no real meaning in this case). However, it must be noted that being at sea, boats are still moving and the recorded direction may be changing even with no significant displacement. Two more false positives are marked for short-lived changes of direction, which do not make for a significant change in the trajectory. Regarding the 'increasing speed' behaviour, six instances were detected on all analysed sequences. All of them correspond to true positives.

Extracted semantics allow, with activity zones, to recognise meeting and splitting situations. As shown in Section 5.1 the recognition of these behaviours depend on extracting the expected semantic while the tracked object is active in a given zone. For instance, for the first considered sequence (GPS_Sc4_Tk2), the boats splitting (see Figure 3) is correctly recognised because of the extracted 'speed increasing' semantic and both boats depart from a common activity zone to a non-common one. Equally, the attack to the vessel is confirmed as the skiffs meet the boat. The meeting situation recognised as the boats are 'decreasing speed' and come to a common zone. Similarly in sequence GPS_Sc3b_Tk1 (depicted in Figure 4), the split between the boats is correctly recognised (see Table 1). There is however a short-lived meeting situation (mobile 242 meets 240) between a boat and the detected vessel because the 'meeting' takes the 'decreasing speed' semantic, in a common zone, as an indication of willingness or intention to meet. This meeting situation is cancelled out as the system detects the boat leaving from the vessel vicinity.

In the nine sequences, 16 pairwise meeting situations are detected. All of them constitute true positives except the shortlived meeting event detected in sequence GPS_Sc3b_Tk1. Regarding detected mobiles splitting, the system recognised nine splitting situations between pairs of

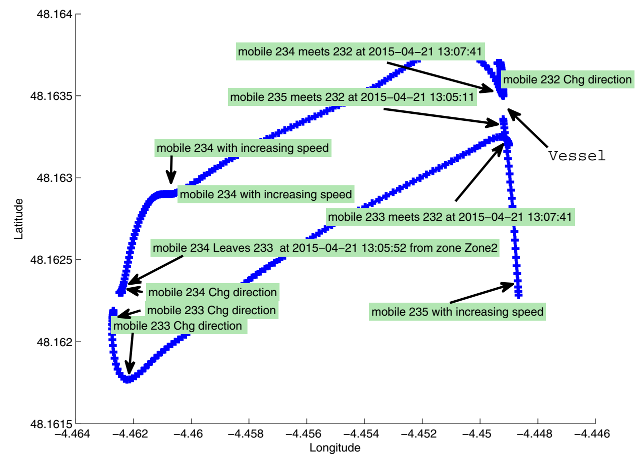

Figure 3. GPS trajectory data for sequence Sc4_Tk2. Important behavioural cues detected by the system are signaled over the trajectory.

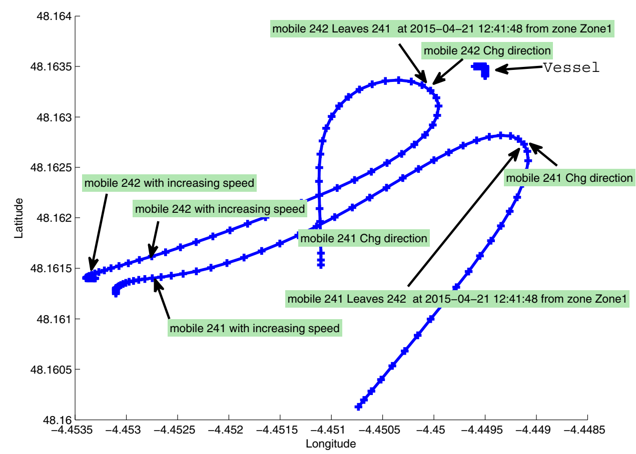

Figure 4. GPS trajectory data for sequence Sc3b_Tk1. Important behavioural cues detected by the system are signaled over the trajectory.

mobiles. All of them are true but two. The false positive would correspond to the 'boats leaving' the vessel in sequence GPS_Sc3b_Tk1 if it is considered that no splitting should be attributed if no actual group formation occured (as the boats did not stop to interact or attack the vessel). Note however marking the event as false positive depends entirely on the interpretation as the two boats 'leaving the vessel' from its anchorage point conveys the right semantic description and it can be an indication of a threat to the vessel diminishing.

It could be argued that in GPS_Sc4_Tk3 there is a false negative for a splitting situation between the two skiffs when reaching the vessel. While the two skiffs actually go to different sides of the vessel, they still remain, together

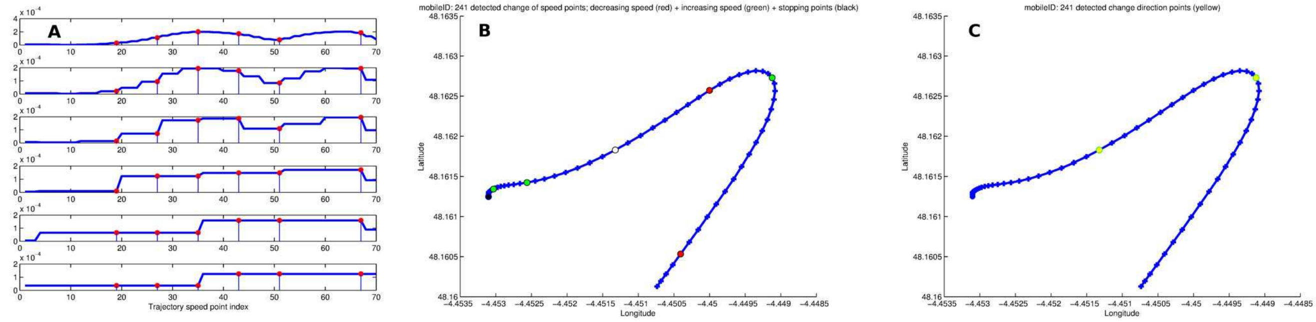

Figure 2. Extraction of points of interest for one trajectory in sequence GPS_Sc3b_Tk1. Panel A) Multiresolution decomposition of the trajectory speed profile with a Haar wavelet. Vertical lines at all scales indicate the significant change of speed points. Panel B) Change of speed points (circular markers) overlaid on the original trajectory. Note that the white marker indicates a 'plateau speed' (a change in speed but not as important to label it as 'increasing' or 'decreasing' speed). Panel C) Change of direction points (yellow circular markers) are superimposed to the original trajectory.

with the vessel, forming a unique activity zone where the two skiff boats and the vessel are contained and interacting. In this case no split is actually detected by the system. Interpreting an split situation in this case probably depends on the granularity at which the activity is observed. The complete set of our results is presented in Table 1.

7. Conclusions

We have addressed in this paper the PETS 2016 challenge on the IPATCH dataset recognising behaviours of interest that can account for a maritime threat to a vessel. Namely, we target detection of the following behaviours set in the challenge: 'change direction', 'speeding up', 'meeting (group formation)', 'splitting (group separation)'. The proposed approach is based on trajectory analysis and automatic learning of activity zones, but the behaviour recognition is made in the semantic domain. Indeed, the proposed approach works by setting a semantic model for each targeted behaviour. This is similar to setting a naturally spoken description of the event as the methodology works by translating trajectory information from the detected mobile objects in the scene into semantics. Automatic learning of activity zones help us to infer important behaviours of the observed mobile objects in the scene, specifically meeting and splitting situations. Our results obtained in the PETS 2016 IPATCH dataset are encouraging. From nine processed sequences 55 behavioural events are detected from which the majority of detections is correct and we only obtain a few false positives (6). Our future work will consist in automatically learning more behavioural cues in order to diminish the number of false positives and address a wider spectrum of general behaviours.

Acknowledgement

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Sequence	MobileID	Event	Event timestamp	Visual validation
Sc2_Tk2	217	Chg direction	21/04/2015 07:42:00	FP
Sc2_Tk2	218	Chg direction	21/04/2015 07:42:00	TP
Sc2_Tk2	219	Chg direction	21/04/2015 07:42:00	TP
Sc2a_Tk1	214	Chg direction	21/04/2015 11:08:00	TP
Sc2a_Tk1	215	Chg direction	21/04/2015 11:08:00	TP
Sc2b_Tk3	222	Chg direction	21/04/2015 14:48:00	TP
Sc2b_Tk3	222	Chg direction	21/04/2015 14:49:00	TP
Sc2b_Tk3	222	Chg direction	21/04/2015 14:49:00	TP
Sc2b_Tk3	222	Chg direction	21/04/2015 14:49:00	TP
Sc2b_Tk3	221	Chg direction	21/04/2015 14:51:00	FP
Sc2b_Tk3	221	Chg direction	21/04/2015 14:52:00	TP
Sc2b_Tk3	221	Chg direction	21/04/2015 14:52:00	TP
Sc2b_Tk3	221	Chg direction	21/04/2015 14:52:00	TP
Sc2b_Tk3	222	Chg direction	21/04/2015 14:52:00	TP
Sc2b_Tk3	222	Chg direction	21/04/2015 14:52:00	TP
Sc2b_Tk3	221	Chg direction	21/04/2015 14:52:00	TP
Sc3_Tk1	227	speed up	21/04/2015 12:01:00	TP
Sc3_Tk1	228	speed up	21/04/2015 12:01:00	TP
Sc3_Tk3	230	speed up	21/04/2015 12:18:00	TP
Sc3_Tk3	231	speed up	21/04/2015 12:18:00	TP
Sc3a_Tk2	224	Chg direction	21/04/2015 12:29:00	TP
Sc3a_Tk2	225	Chg direction	21/04/2015 12:29:00	TP
Sc3b_Tk1	242	mobile 242 meets 241	21/04/2015 12:41:12	TP
Sc3b_Tk1	241	mobile 241 meets 242	21/04/2015 12:41:12	TP
Sc3b_Tk1	242	speed up	21/04/2015 12:41:16	TP
Sc3b_Tk1	241	speed up	21/04/2015 12:41:24	TP
Sc3b_Tk1	242	mobile 242 Leaves 241	21/04/2015 12:41:24	TP
Sc3b_Tk1	241	mobile 241 Leaves 242	21/04/2015 12:41:24	TP
Sc3b_Tk1	241	Chg direction	21/04/2015 12:41:48	TP
Sc3b_Tk1	242	Chg direction	21/04/2015 12:41:48	TP
Sc3b_Tk1	242	mobile 242 meets 240	21/04/2015 12:41:40	FP (242 is with decreasing speed)
Sc3b_Tk1	241	mobile 241 Leaves 242	21/04/2015 12:41:48	TP
Sc3b_Tk1	242	mobile 242 Leaves 240	21/04/2015 12:41:48	FP (If we consider there was no meeting)
Sc3b_Tk1	241	mobile 241 Leaves 240	21/04/2015 12:41:48	FP (If we consider there was no meeting)
Sc3b_Tk1	240	mobile 240 Chg direction	21/04/2015 12:41:56	FP (static boat)
Sc3b_Tk1	240	mobile 240 Chg direction	21/04/2015 12:42:04	FP (static boat)
Sc4_Tk2	234	mobile 234 meets 233	21/04/2015 13:05:52	TP
Sc4_Tk2	233	mobile 233 meets 234	21/04/2015 13:05:52	TP
Sc4_Tk2	234	mobile 234 Leaves 233	21/04/2015 13:05:52	TP
Sc4_Tk2	235	mobile 235 meets 232	21/04/2015 13:05:11	TP
Sc4_Tk2	234	mobile 234 Leaves 233	21/04/2015 13:05:52	TP
Sc4_Tk2	232	mobile 232 meets 234	21/04/2015 13:07:41	TP
Sc4_Tk2	234	mobile 234 meets 232	21/04/2015 13:07:41	TP
Sc4_Tk2	232	mobile 232 meets 233	21/04/2015 13:07:41	TP
Sc4_Tk2	233	mobile 233 meets 232	21/04/2015 13:07:41	TP
Sc4_Tk3	238	mobile 238 meets 236	21/04/2015 13:14:57	TP
Sc4_Tk3	237	Separation(mobile 237 leaves 239)		FN
Sc4_Tk3	239	Separation(mobile 239 leaves 237)		FN
Sc4_Tk3	237	mobile 237 meets 236	21/04/2015 13:18:41	TP
Sc4_Tk3	236	mobile 236 meets 237	21/04/2015 13:18:41	TP
Sc4_Tk3	236	mobile 236 meets 239	21/04/2015 13:18:41	TP
Sc4_Tk3	239	mobile 239 meets 236	21/04/2015 13:18:41	TP

Table 1. Recognised behaviours in the PETS 2016 IPATCH dataset.

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