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Semantic model of ship behaviour based on ontology engineering

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Abstract: Given the complex situation of traffic at sea and the large amount of data that grows with the information technology, the ship behaviour cannot be precise recognised or fully expressed based on the raw and noisy data itself. A semantic model of ship behaviour based on ontology engineering is developed in this study. First, an interrelated semantic network is created, which allows the easy annotation, expression, and acquisition of information about ship trajectory. Then, the time-series compression techniques are used to recognise behaviour and event in the semantic model, which, respectively, indicate the states of track points and trajectory segments, and which also can be represented as a time series. Finally, the accuracy and practicality of the model is verified by automated identification system data and geographic data; the result shows that the semantic model solves the conflict between expressiveness of ship behaviour and complexity of the situation, and reduces the amount of data by building semantic representation in higher abstraction levels.

1 Introduction

Accurate recognition of ship behaviour is critical for maritime safety [1]. Marine transportation is a huge, open system, in which busy traffic and complicated rules result in a complex situation regarding the recognition of ship behaviour. Further, with the rapid growth of automated identification system (AIS) data and explosive increase in the number of ships and waterways/routes, massive multi-source data need to be collected and analysed within a short time to get accurate and comprehensive ship behaviour, which is difficult using conventional methods [2].

The conventional data analysis approaches used for ship behaviour usually are statistical analyses in a large scale; for example, Liu Z *et al.* [3] analyse vessel traffic flow according to the characteristics of ship motion. These analyses cannot describe a single ship's behaviour according to its situation. In addition, some studies consider only one aspect of the ship's behaviour, such as position, course, or speed etc. In the meantime, there are some research studies on abnormal ship behaviours, and the method used for it is usually based on statistical models [4]. Their major interest is how to find the anomalous location, speed, or trajectory compared to normal behaviours [5]. However, challenges such as data heterogeneity, situation complexity, and lack of contextual information are often faced. Further, the recognised results sometimes are hard to understand by users due to lack of related information to explain ship behaviours. The increasing flow of data and complex situation result in a demand for new data structures, algorithms, and a novel knowledge organisation model to strengthen the intelligent understanding ability of ship behaviour. In fact, its purpose is to find the true meaning of the raw and noisy data in a complex situation, which is called semantics in the field of information science and artificial intelligence (AI) research [6, 7].

Computers and smart systems find it difficult to process and understand the semantic of data; a series of technologies, such as XML (eXtensible Markup Language), XML schema, RDF (Resource Description Framework), and Semantic Web, have been proposed to solve these machine understanding problems. Semantic Web technologies have experienced a rapid growth in the past few years and offer useful reasoning and representation features for a wide range of applications [8, 9]. To use the semantic model in a computer system, it has to be encoded with a well-defined syntactic structure, which is called ontology [10].

The semantic model found its applications in transportation in recent years [11, 12]; even its application in maritime transportation research is still limited; among them, one of the most significant studies is Semantic Trajectory [13–15]. Semantic Trajectory means enriched trajectories beyond latitude, longitude, and timestamp information using semantic information. Renso *et al.* [14] proposed a similar semantic model to represent human behaviour. Baglioni *et al.* [16] have formulated Web Ontology Language (OWL) Description Logic (DL) axioms to establish the Stop/Move model and highlighted the need for semantic trajectories. The pedestrian movement model was established by Orellana and Renso [17] based on interactions between movement patterns and context. Nogueira *et al.* [9] established a framework for the semantic annotation of trajectories based on episodes. Fileto *et al.* [18] described the Baquara2 framework, which provides a semantic model for abstracting and structuring movement data of movement segments that generalise concepts such as stops, moves, and trajectories.

In maritime transportation, several Semantic Trajectory studies of ship behaviour have been published. Van Hage *et al.* [19] established a simple event model, and used piecewise linear segmentation to recognise simple behaviour events from AIS data. Vouros *et al.* [20] presented a method to mine ship movement data under a maritime situation using datACRON ontology, and enrich ship trajectories using semantic annotation.

Other studies applied semantic models to examine large datasets and reveal true relationships. Arenas *et al.* [21] established a semantic model to analyse historical maritime records and it can identify patterns that might be hidden due to the large size of the dataset. Patroumpas *et al.* [22] presented an online monitoring system of ship activity over streaming positions.

Semantic models based on ontology engineering can give ship behaviour a systematic, clear, and precise ontology network of information and relationships in marine transportation, which can also express ship behaviour and related elements clearly. However, despite significant research efforts, compared to land

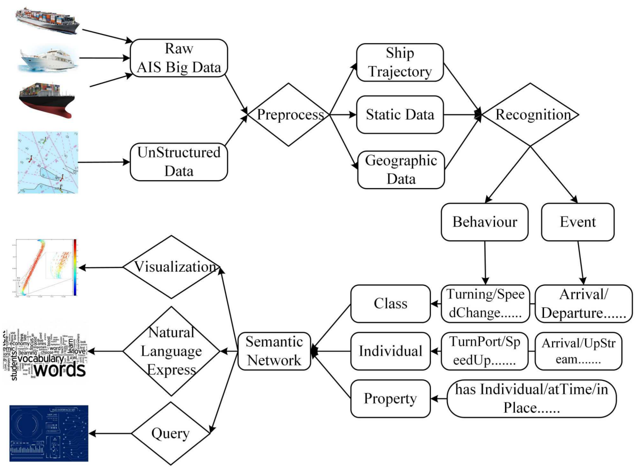

Fig. 1 *Semantic model of ship behaviour*

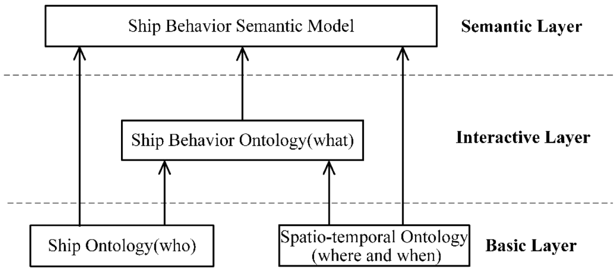

Fig. 2 *Semantic model structure*

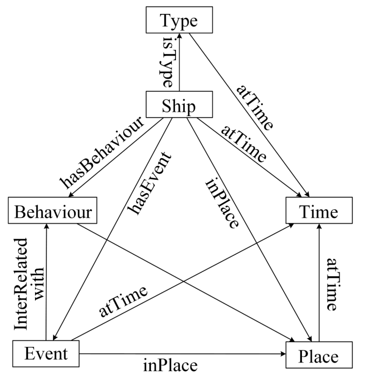

Fig. 3 *Core classes of a semantic model*

transportation, the relevant research is still not enough to meet the needs of users.

Given the limited applications in maritime research and lack of detailed analyses from trajectory to trajectory points, which are necessary to identify and delineate the unique behaviour of a particular ship, authors feel the need to develop a semantic model with multiple levels of ontology networks. As shown in Fig. 1, this study developed a semantic model of ship behaviour and related recognition methods, which allows the easy annotation, expression, and acquisition of information about trajectories from complex situation and big data. Going a step further, the semantic model can express ship behaviours in natural language or query by ontology query language, which is easy to understand by port authorities, coast guard, pilots, tug operators, crewmembers etc.

2 Semantic modelling of ship behaviour

Ship behaviour can be group into macrobehaviour and microbehaviour. Macro-ship behaviour describes the movement of traffic flow on the global scale while microbehaviour depicts the behaviour of individual ships on the local scale. This paper focuses on the microbehaviour of ships using the AIS data. According to Vandecasteele *et al.* [23], there are two main standards for defining ontology. One is called Resource Description Framework Schema and the other is labelled OWL. OWL itself is an extension of RDF; so, OWL and RDF have many similarities, and OWL conforms to RDF's syntax. However, compared to RDF, OWL has a larger vocabulary and stronger ability for expression; so, OWL is selected to construct a semantic model.

As shown in Fig. 2, a semantic model with a three-tier structure has been constructed. Ship behaviour ontology (what) is formed by the interaction between ship ontology (who) and spatio-temporal ontology (where and when), and then they relate to each other to build a semantic model. Finally, according to 'Who do what in where at when' (4 W) the Class, Property and Individual of the semantic model is established. The next section describes each of these separately.

2.1 Class

As shown in Fig. 3, there are six core classes in the semantic model of ship behaviour, which are *Ship* (who), *Behaviour* (what), *Event* (what), *Place* (where), *Time* (when), and *Type*.

Ship refers to the subject of behaviour – the ship, which is generally represented by the ship's unique identifier – MMSI, also a ship name, such as '*JiangCheng4Hao*' (hereinafter referred to as *JC4*) and so on; so, that a ship may have different representations in the semantic model. *Ship* can be associated with other classes through Property such as *hasBehaviour*. In an event, there may be multiple ships involved (such as salvage activities), and there may be no instance related to them (such as missing data in information source); this can be flexibly changed according to the situation.

Behaviour refers to the behaviour of a ship, such as *TurnPort*, *SpeedUp*, *Leave*, and so on. It should be noted that the corresponding *Time* of *Behaviour* is a certain time rather than a period of time, but at the same time, *Behaviour* at a certain time can represent the subsequent period of time's behaviour, which ensures the ship behaviour's continuity in time.

Event refers to an event that consists of *Behaviour* or is caused by *Behaviour*, such as *Berth*, *Departure*, *UpStream* etc. *Event* is sometimes composed of multiple *Behaviour*, such as *ThroughBridgeArea* need to speed down, enter the bridge area, leaving the bridge area etc. *Event* has Property: *BeginTime* and *EndTime*, to indicate that the event occurred within a time period. *Time* can be ambiguous if the start time is unknown or the event is not finished.

Place refers to the place where the *Behaviour* or *Event* occurs, and can be represented either by name, latitude, longitude etc. It may be associated with other ontologies such as Geonames and so on. *Place* can be inaccurate, such as the centre of a sea expressed in latitude and longitude ranges, or relative position of other geographical locations.

Time refers to the time; its expression should be consistent with the W3C standard, such as 2017-06-15T23:13:30+08:00.

Type indicates the type of ship or place, such as *ContainerVessel*, *Ferry*, *HighSpeedVessel*, *Harbor*, *Dock*, *Anchorage*, and so on. The same ship may be different types in different events and at different times, such as a ship is a tug in an event and a towed ship in another event; it may also be a high-speed ship at a time and a low-speed ship at another time. Therefore, *Type* has Property: *hasEvent*. *Ship* and *Place* are associated with *Type* through Property: *isType*.

2.2 Property and individual

Classes are related by property, which includes the Object property and the Data type property. The Object property in this paper includes:

- between *Ship* and other Classes: *atTime* (Class: *Time*), *hasBehaviour* (Class: *Behaviour*), *hasEvent* (Class: *Event*), *inPlace* (Class: *Place*), *isType* (Class: *Type*);
- between *Event* and *Behaviour*: *Interrelatedwith*;
- between *Event* and *Time*: *BeginTime* and *EndTime*;
- between *Time* and other Classes: *atTime*;
- topological property: composed of eight spatial topological relations in the region connection calculus that are possible

between two regions: externally connected, externally equal, partially overlapping, tangential proper part (*TPP*), TPP inverse (*TPPi*), non-TPP (*NTPP*), and non-TPP inverse (*NTPPi*).

Data type property is the data description or data constraint for Class or Individual, such as ship A's *Speed* is 10 kn, *HighSpeedShip*'s *Speed* is at least 15 kn and so on.

Individual is the instance of Class, such as a ferry named *JC4* (MMSI: 413932547) is an Individual of *Ship*, a dock named *ZhongHuaLu* (Hereinafter referred to as *ZHL*) is an Individual of *Place*, and so on.

2.3 Reasoners

The reasoner is used to get the hidden information from an existing semantic network and check whether there is inconsistent ontology. If it has the definition *Ship DC Place* (means that *Ship* and *Place* do not have intersection), and a ferry named *JC4* is defined as *Ship*, then *JC4* is mistakenly defined as *Place*; the reasoner will find *JC4*'s inconsistency. If *NTTP* is defined as transitive, *JC4* NTTP (is mooring at) *ZHL* dock, and *ZHL* dock NTTP (belongs to) *WuHan* port, after reasoning it would find that *JC4 NTTP WuHan* port. In this paper, Hermit is chosen because it is the fastest reasoner.

3 Ship behaviour recognition

The ship trajectory can be regarded as track points under the time series or continual trajectory segments; so, the time-series compression techniques can be used to extract the high-level meaning and represent trajectory attributes as a time series [24]. The purpose of the recognition method is to extract the critical points, which represent the beginning of ship behaviour, based on the trajectory data itself and the context information, e.g. geographic information. Then the semantic model can give the track points or trajectory segment semantic annotation, form natural language expression of the original trajectory, and can be queried by users if necessary.

3.1 Recognition of ship turning and speed change behaviour

When the ship continues to turn in the same direction and the number of turning points exceeds the threshold x (x is determined by the state of the ship and traffic environment), *Turning* behaviour will be assigned to the first turning point. Different from the movement of vehicles, in order to offset the impacts of wind, current, and so on, the ship's heading often has an angle with the track course, such as leeway, when the ship is in an environment that has wind; so, turning behaviour is judged by track instead of heading. If AIS data has n trajectory points, then these points can be connected to $n-1$ consecutive and non-overlapping trajectory segments. The turning of trajectory points is judged by the turning of adjacent trajectory segments. Recognition of turning behaviour is based on the vector product:

$$\vec{c} = (x\vec{i}, y\vec{j}, z\vec{k}) = \vec{a} \times \vec{b} \tag{1}$$

In Fig. 4, $\vec{a}$ is the vector representing the front line segment, and $\vec{b}$ is the vector representing the other line segment in adjacent trajectory segments. If z is positive, it means that from $\vec{a}$ to $\vec{b}$ turning is counterclockwise, that is, point A is the turning left point, ship behaviour is *TurnPort*. If z is negative, it means that from $\vec{a}$ to $\vec{b}$ the turning is clockwise, that is, point A is the turning right point, ship behaviour is *TurnStarboard*. If z is 0, then $\vec{a}$ and $\vec{b}$ are collinear, and the ship behaviour is *GoStraight*.

TurnPort and *TurnStarboard* have a clear direction of steering; however, there was a lot of turn points when the ship is going straight because of the influences of wind, current, course correction of ship, and collision avoidance manoeuvre, so that *GoStraight* behaviour is difficult to recognise. In this paper, when the ship doesn't have *TurnPort* or *TurnStarboard* behaviour, it is considered to have *GoStraight* behaviour. There may be a slight trajectory point turn to starboard (called opposite point) in

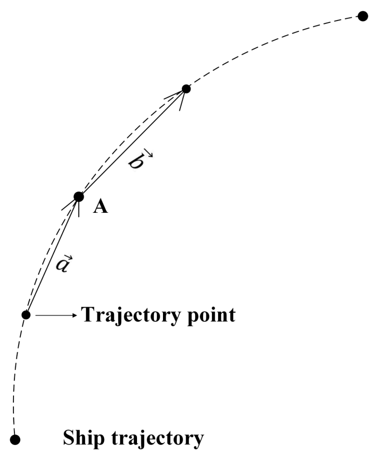

Fig. 4 *Diagram for Turning behaviour's recognition*

TurnPort behaviour, which does not change the direction of the ship's ongoing turning and is not conducive to *Turning* behaviour recognition. The point whose turning direction is different from three points, respectively, before and after it is taken as the opposite point, and it will be treated to have the same direction with its nearby points.

The course over ground (COG) in AIS data can be used for detecting *SharpTurn* behaviour, which means the ship may have an emergency situation with other ships and turns fast to avoid collision. In this paper, *SharpTurn* behaviour is recognised by the turning rate (COG difference/time difference) of adjacent trajectory points and the *SharpTurn* threshold (according to different ship type and different navigation environment). When calculating the heading difference, the recursion of COG data should be noticed, that is, 0° and 360° are the same in space, the angle between 0° and 359° may be smaller than the angle between 0° and 180°. The COG difference is calculated by the below equation:

$$\Delta\theta = \begin{cases} 360 - |\mathrm{cog}_i - \mathrm{cog}_j|, & |\mathrm{cog}_i - \mathrm{cog}_j| > 180 \\ |\mathrm{cog}_i - \mathrm{cog}_j|, & |\mathrm{cog}_i - \mathrm{cog}_j| < 180 \end{cases} \tag{2}$$

The *SpeedChange* behaviour is recognised by the acceleration of each trajectory point. If the acceleration of continuous multiple points is positive, it is judged as *SpeedUp* behaviour; if it is negative, it is judged as *SpeedDown* behaviour; the rest are recognised as *Run*, which means the ship is sailing with a uniform speed. If the number of adjacent acceleration points is greater than the threshold, it will be judged as *EmergentSpeedChange* behaviour. The *SpeedChange* behaviour's recognition method is similar to the *Turning* behaviour's recognition method except that there is no assimilation of the opposite point.

3.2 Recognition of ship Enter/Leave behaviour and stay event

The *Enter*/*Leave* behaviour determined by whether the line connected by two trajectory points intersects the area boundaries. The areas include the closed areas (such as dock, anchorage, bridge area, fishing area, and ring road) and the non-closed areas (such as channel, danger line, and boundary line).

As shown in Fig. 5, the AIS trajectory points are $e:(x_1, y_1)$, $f:(x_2, y_2)$ and the ends of the area boundary line are $g:(m_1, n_1)$, $h:(m_2, n_2)$; the equation of the area boundary line is

$$ax + by + c = 0 \tag{3}$$

where:

$$a = n_2 - n_1 \quad b = m_1 - m_2 \quad c = m_2 \times n_1 - m_1 \times n_2$$

Put two end points into the equation and multiply:

$$z = (ax_1 + by_1 + c) \times (ax_2 + by_2 + c) \tag{4}$$

If z is less than zero, the two AIS trajectory points are on the different sides of the area boundary line, that is, the line connected by the two points intersects the boundary line. If the previous trajectory point is in the area, then the ship *Leave* the area; if the next trajectory point is in the area, then the ship *Enter* the area. It should be noted that if both the two points are outside the area, but the trajectory line (not the line segment) intersects one boundary of the area, it is wrong to judge the ship *Enter* the area according to the previous point not being in the area, and this is avoided by taking the point in the area as the basis for judgement.

A ship's *Stay* event mainly includes mooring and anchoring. As the ship state information from AIS is inaccurate, and the speed value may be temporarily zero when the ship is sailing and greater than zero when the ship is being anchored, *Stay* cannot be recognised directly based on state information or speed value. In this paper, *Stay* is recognised based on the intervals between *Enter* and *Leave* behaviour. If the staying duration is greater than a given threshold, it is considered a *Stay* event.

If the area boundary is not a straight line, but a circle, such as a ring line, or irregular curves, such as boundary lines, water depth lines etc., the same method can be used as long as the equation of boundary line is known.

3.3 Recognition of ship Arrival/Departure and UpStream/DownStream event

In port or anchorage, except for the *Stay* event, a ship has *Arrival* and *Departure* events, which cover the time period from *Enter* to *Stay* and the time period from *Stay* to *Leave* separately. When a ship has Arrival or Departure events, combined with whether the ship is a ferry and the area is port in the semantic model, other ships could realise this ship would berth or across the river, and take appropriate measures to avoid emergent situations. The method of recognising *Arrival* is based on the *SpeedChange* behaviour; when a ship is *SpeedDown* and in a port or anchorage area, it has *Arrival* event. When a ship does not have *Arrival* or *Berth* events, the *Departure* event is being recognised.

The current has a great impact on ship manoeuvre in a river; so, there is a big difference between upstream ship's behaviours and downstream ship's behaviours, For example, in the Yangtze river, a downstream ship's trajectory is more straight, and usually navigates along the ‘mainstream’ (middle of the river); the upstream ship's trajectory varies greatly in space, its manoeuvering performance is relatively good and belongs to that of a give-way ship according to the *Regulations for Preventing Collisions at Inland Waters of China*. Therefore, it is necessary to identify upstream/downstream for ship behaviour characteristic cognition. The *UpStream/DownStream* event is based on the fact that the Yangtze River flows from west to east. This paper divides ship trajectory according to the *Stay* recognition method of Section 3.2, and calculates the longitude difference of two ports; if the longitude increases, it is a *DownStream* event, on the other hand, it is an *UpStream* event.

4 Application Examples

Prior to behaviour recognition, the raw AIS data needs to be extracted and cleaned. Data extraction refers to getting required AIS data according to the target area's latitude/longitude and ship's MMSI. Data cleaning refers to remove data in cases where ship's length and width do not meet the actual situation, position is abnormal (not in navigable waters), speed is abnormal (too high or less than zero), course is abnormal (not between 0 and 360°), and ship in the same position at adjacent time when the speed is greater than 0. In order to ensure authenticity and accuracy, the data was not interpolated. Further, the graphic data is from Google Earth.

The AIS data of different types and time of ships is used to verify the proposed method, as shown in Table 1. It can be seen that the number of behaviours/events of the *JiangCheng* ferry series is more than those of other ships because the ferry has more *Turning* behaviours and *Berth*, *Arrival*, *UpStream* events. In contrast, *KuoTai* has less behaviours because it has a longer sailing time in each voyage. Table 2 shows the comparison of the accuracy of different methods, and the proposed method in this paper has better performance.

The recognition results are mapped to the semantic network through OWL API. At present, the ontology API mainly has Jena, Protégé OWL API, and OWL API. Jena and Protégé OWL API are based on triples, OWL API is based on the axiom and follows the OWL2 standard directly. OWL API's advantages are as follows: (a) the OWL2 language is in the axiomatic specifications; (b) dealing with OWL ontology at the level of axiom is more efficient and less error than the triples; and (c) many operations, such as reading or comparing ontology fragments, are only effective at the level of the axiom. So, the OWL API is used to establish and modify the semantic network.

Table 3 shows some of the *Enter/Leave* behaviours of *JiangCheng1Hao* (hereinafter referred to as *JC1*). It can be seen that *JC1 Enter WuHanGuan* (hereinafter referred to as *WHG*) dock and *ZHL* dock alternately, and it is in line with actual ferry behaviour. Further, the *Stay* event's recognition method was used to recognise whether the *JIANGCHENG* ferry series (*JC1-5*) moored at the *WHG* dock, and Table 4 shows a partial result.

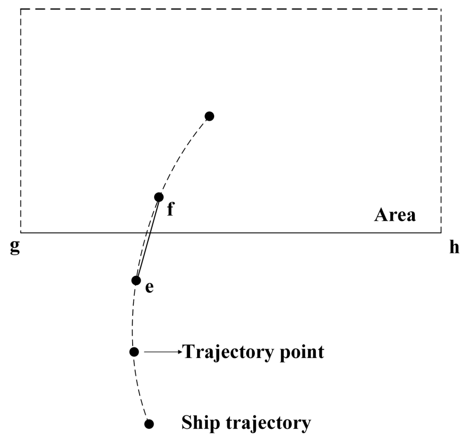

Fig. 5 *Diagram for Enter/Leave behaviour's recognition*

Table 1 Dataset and the recognition results

Ship name	Type	MMSI	Date	The amount of data	Number of behaviours	Number of events
JiangCheng1-5	ferry	413932544–413932548	1/1/2014–31/1/2014	165,913	25,434	5050
YuXinHuo13618	bulk	413932544	1/6/2016–30/6/2016	32,466	5065	106
KuoTai	container	371625000	1/12/2017–31/12/2017	43,267	4734	57

Table 2 Comparison of accuracy of different methods

Method	Behaviour/event							
	Turning, %	SharpTurn, %	SpeedChange, %	Emergent speed change, %	Enter/ Leave, %	Stay, %	Arrival/ Departure, %	UpStream/ DownStream, %
PLS [19]	95.32	94.63	96.13	95.35	a	97.13	97.13	a
datACRON [20]	96.36	a	97.64	a	a	95.74	a	a
Our method	99.21	99.45	99.43	99.12	99.98	98.78	98.67	98.77

[a]Represents the behaviour/event that cannot be recognised by the corresponding method.

Table 3 Recognition results of enter behaviour

Ship	Time	Speed, kn	Place
JC1	06:44:15 + 08:00	4.8	WHG
JC1	07:04:31 + 08:00	2.6	ZHL
JC1	07:21:14 + 08:00	9	WHG
JC1	07:42:31 + 08:00	2.6	ZHL
JC1	07:59:45 + 08:00	8.2	WHG
JC1	08:22:03 + 08:00	3.3	ZHL
JC1	08:41:36 + 08:00	7.2	WHG

Table 4 Recognition results of stay event

Ship	Begin time	End time	Place
JC1	17:45:21 + 08:00	17:51:32 + 08:00	WHG
JC1	18:22:51 + 08:00	18:28:01 + 08:00	WHG
JC1	19:05:25 + 08:00	19:10:36 + 08:00	WHG
JC1	19:45:57 + 08:00	19:59:48 + 08:00	WHG
JC2	20:03:05 + 08:00	20:11:29 + 08:00	WHG
JC2	20:43:28 + 08:00	20:50:40 + 08:00	WHG
JC2	21:22:00 + 08:00	21:31:41 + 08:00	WHG
JC2	22:12:08 + 08:00	22:30:39 + 08:00	WHG

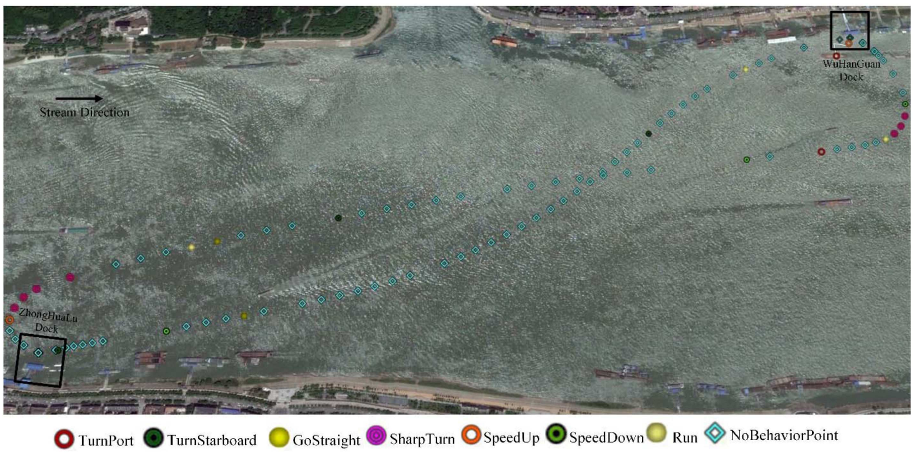

Fig. 6 *Behaviour recognition results of JC4*

The ferry *JC4*'s first voyage (from *WHG* dock to *ZHL* dock, and then return to *WHG* dock, 1 January 2014) is annotated by the semantic model, as shown in Fig. 6; it can be seen that *JC4*'s *Turning* behaviour conforms to its trajectory and the ship has a *SharpTurn* behaviour when it has a big steering angle. The ship has a *SpeedDown* behaviour before it *Enter* a dock and has a *SpeedUp* behaviour after it *Leave* a dock, and when it cross a river it usually has a *Run* behaviour.

The events are shown in Fig. 7; the *Arrival/Departure* event is recognised accurately, and from *WHG* dock to *ZHL* dock is the *UpStream* event and on the contrary is the *DownStream* event.

Further, the *Turning* behaviour's recognition result of the bulk ship *YuXinHuo13618*, which navigates through most segments of the Yangtze River, match with the direction of track and channel boundary, and this is consistent with reality.

The semantic network in Fig. 8 shows the behaviours of *JC4* when it is around the *ZHL* dock. This model has a natural ability for expression; part of the voyage can be expressed as follows with simple semantic organisation:

- JC4 (Ferry) SpeedDown at 2014-01-01T06:42:14+08:00;
- JC4 (Ferry) end UpStream and begin Arrival in ZHL (Dock) at 2014-01-01T06:43:04+08:00;
- JC4 (Ferry) end Arrival and begin Berth in ZHL (Dock) at 2014-01-01T06:44:40+08:00;
- JC4 (Ferry) end Berth and begin Departure in ZHL (Dock) at 2014-01-01T06:51:58+08:00;
- JC4 (Ferry) end Departure, begin DownStream, TurnStarboard in ZHL (Dock) at 2014-01-01T06:52:21+08:00;
- JC4 (Ferry) SpeedUp at 2014-01-01T06:52:45+08:00;

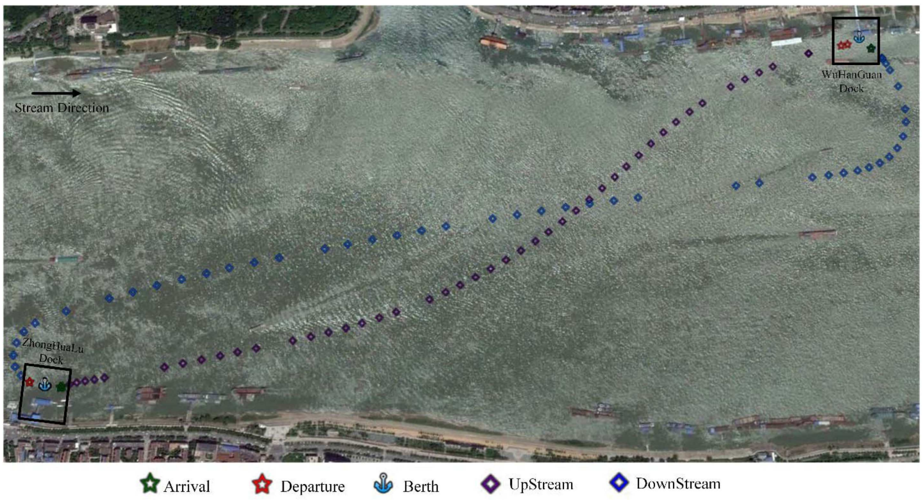

Fig. 7 *Event recognition results of JC4*

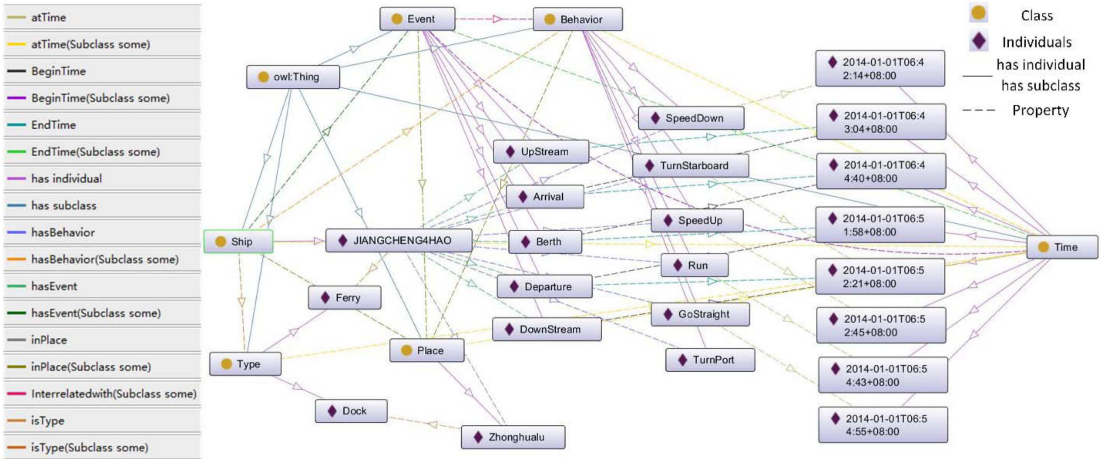

Fig. 8 *Semantic network of JC4's first voyage*

- JC4 (Ferry) Run at 2014-01-01T06:54:43+08:00;
- JC4 (Ferry) GoStraight at 2014-01-01T06:54:55+08:00.

If the VTS operator or pilot wants to get specific information of ship behaviour, SPARQL (SPARQL Protocol and RDF Query Language) [25] can be used to query the semantic network. For example, if the *Turning* behaviour of *KUOTAI* is needed, it can be obtained by this query:

Prefix ShipBehaviour:
<http://www.semanticweb.org/ontology/ShipBehaviour.owl/>
SELECT ?x
WHERE {
ShipBehaviour: KUOTAI ShipBehaviour: hasTurning ?x}

The clause and solution sequence modifiers in SPARQL can be used to get more accurate information and information which hidden in the semantic network, and FILTER, LIMIT, ASK, COUNT, ORDER BY, DISTINCT, and LIMIT are commonly used. For example, the number of ships in dock can be obtained by the following query:

Prefix ShipBehaviour:
<http://www.semanticweb.org/ontology/ShipBehaviour.owl/>
SELECT ?Ship (COUNT(?Ship) ASNumberofShips)
WHERE {
?Ship ShipBehaviour: inPlace ShipBehaviour: Dock.}

5 Conclusion

A valid semantic model of ship behaviour is a powerful tool to facilitate maritime data processing and promote maritime intelligence. Accurate recognition and description of elements and their dynamic relationships in a maritime transportation system will provide a solid platform for users to understand the causality of ship behaviour from massive data and reduce ship collision risk.

This paper analyses ship behaviours from trajectory to sub-trajectory, and finally trajectory points in a semantic model based on ontology engineering. The semantic model can extract accurate ship behaviours that are behind raw and noisy data and express them clearly with an ontology network. Based on the semantic model, ship behaviours can visualised by trajectory annotation, expressed by natural language, queried by SPARQL conveniently. So, the proposed semantic model can help users recognise ship's behaviours from the complex situation quickly.

Further extensions and improvements are planned: (a) navigation rules will be added to identify ship behaviour that violates rules by semantic reasoning; (b) the impact of the natural environment (such as wind, wave, current etc.) will be studied; and (c) the semantic model of maritime traffic situation will be established.

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