Research Highlight 1: Using Deep Learning to Forecast the Maritime Vessel Flows, by Research Assistant Professor Cao Zhiguang (Track Leader: Professor LIM Leong Chye, Andrew)

Introduction

Accurate and timely traffic information is of significant importance to both maritime managers and individual vessels, as it not only helps the former to better conduct port planning, alleviate congestion, and improve public security, but also enables the latter to better operate the ship navigation system and plan a route, so as to avoid collisions and reduce the potential cost due to late arrival.

Various conventional solutions have been studied for forecasting maritime traffic flow, and some preliminary successes have been achieved based them. However, most of the methods are shallow and outdated to some extent, given the fact that, deep learning has been unarguably deemed as the state-of-the-art in many areas, such as computer vision, natural language processing, and transportation as well. Therefore, we dig into the deep learning approach and adapt it to forecast the maritime vessel flows.

Preliminaries

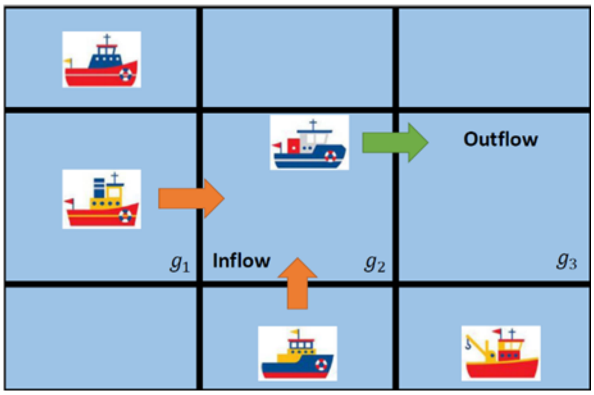

Fig. 1 Illustration for Inflow and Outflow

Our target is to forecast the inflow and outflow of vessels within a given area. To this end, we first divide this area into MXN grids. Thus, the inflow and outflow at a time step can be represented by two matrix, respectively, and the element of which refers to the counts of vessels entering or leaving the corresponding grid during that time step. Formally, given the historical observations $\{X_t \mid t = 0,1,\ldots, n-1\}$, our task is to predict $X_{t+\tau}$, where $\tau \geq 1$ and is an integer. In particular, $X_t = [I_t, O_t]$, where I_t and O_t represent the inflow matrix and outflow matrix at time step t, respectively. Taking Fig. 1 as an example, at time step t, two vessels will enter grid g_2, and one vessel will leave, then $I_t(g_2)=2$, and $O_t(g_2)=1$, respectively.

Methodology

In this research, centering around the deep learning approach, we propose three different solutions to forecast the inflow and outflow of vessels within a given marine region. More specifically, the three solutions are featured by a CNN, a LSTM network, and the integration of a bidirectional LSTM network with a CNN (BDLSTM-CNN), respectively.

1. CNN based Solution

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As depicted in Fig. 2, the CNN based solution has m channels, which correspond to the m historical observations as the inputs. Meanwhile, all the channels share the same weights. In particular, each input contains both the inflow and outflow matrix, and each input channel includes two convolutional layers, two ReLu layers, one batch normalization (BN) layer, and one dropout layer. Among them, the convolutional layers play the most important role, which are used to learn spatial features of different levels.

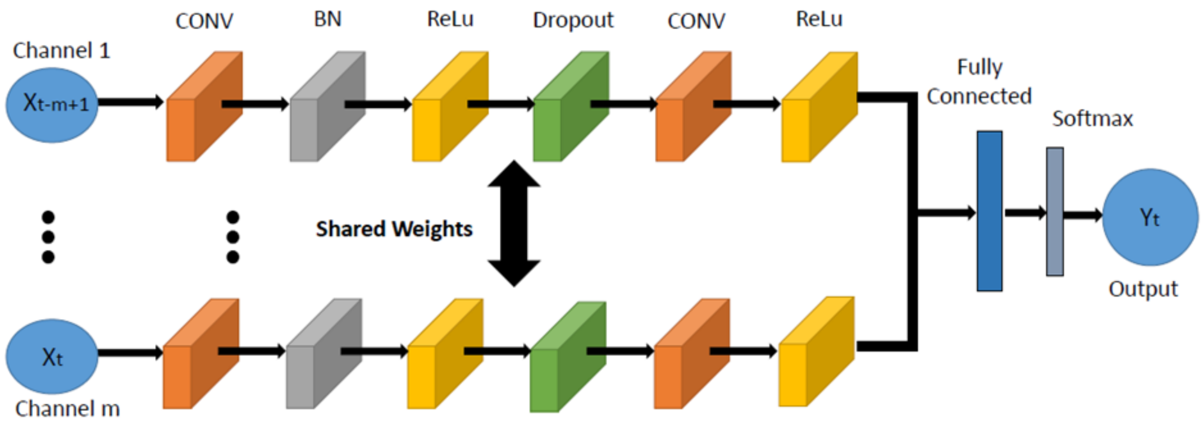

Fig. 2 Illustration for CNN based Solution

2. LSTM based Solution

As depicted in Fig. 3, there are m inputs at the time step t, i.e., X_t, X_{t-1},..., X_{t-m+1}, all of which are fed into the LSTM networks in order. Afterwards, the outputs of the LSTM network are connected to a fully connected network layer and softmax layer, then Y_t is regarded as the final output, which is set as $X_{t+\tau}$.

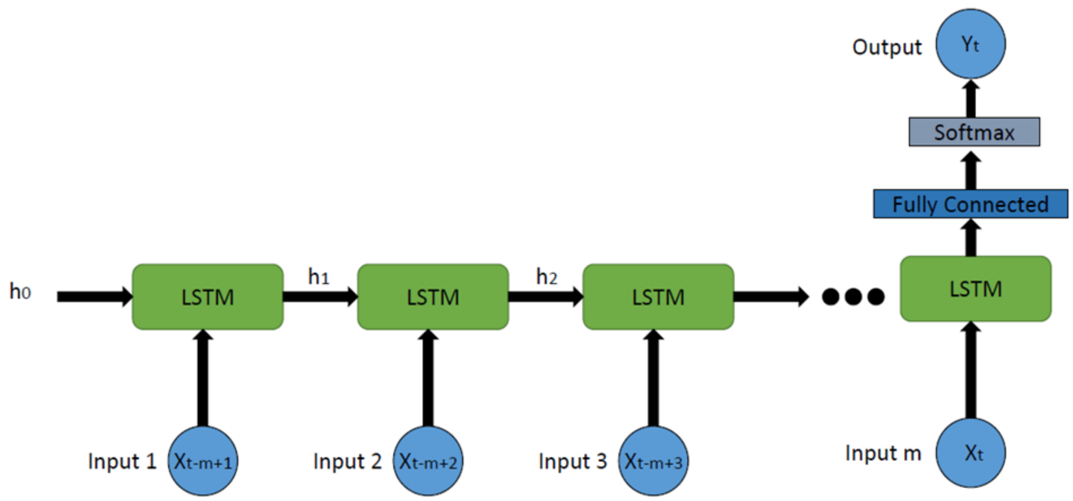

Fig. 3 Illustration for LSTM based Solution

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3. The Hybrid Solution

As depicted in Fig. 4, each input first goes through a convolution layer and a Relu layer, to learn the spatial dependency. Then the output will be fed into the bidirectional LSTM network (i.e., the dotted box in Fig. 4), as the input for both forward sequence and backward sequence. Afterwards, the outputs of the bidirectional LSTM hidden layers are further connected to a sigmoid activation function, which is followed by a fully connected layer and a softmax layer. Lastly, the final output is regarded as the predicted vessel flow.

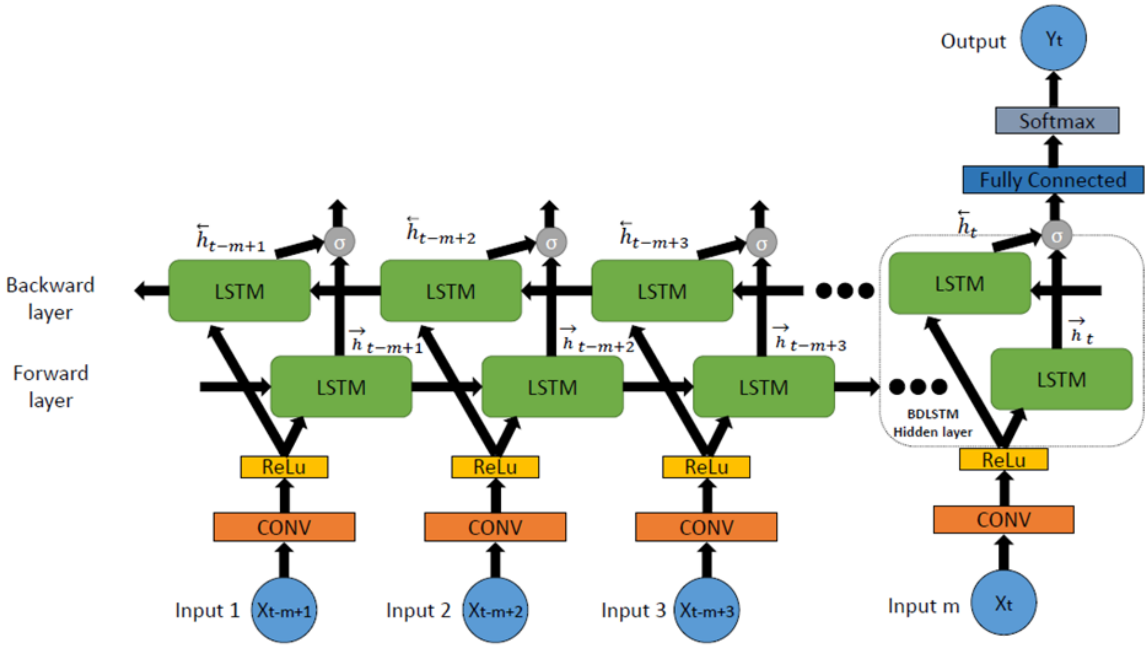

Fig. 4 Illustration for BDLSTM-CNN based Hybrid Solution

Experimentation

We use the AIS (Automatic Identification System) data of maritime vessels for a given area (divided into 7X7 grids) in Singapore Straits, to perform the forecasting task. Particularly, the AIS data we collected for the given area lasts about 31 days, from 01-10-2013 to 31-10-2013. We set the duration for each time step as 5 minutes. Then we have 8525 samples for each grid (with some data missed), which include the amount of vessels entering and leaving the given grid. We divide them into training dataset and testing dataset according to the time order, i.e., from 01-10-2013 to 25-10-2013, and from 26-10-2013 to 31-10-2013, which include 6305 and 2220 samples, respectively. In addition, we implement all the experimentation using pytorch, in a laptop with Intel i7 CPU, 8G RAM, and Nvidia GTX 1060.

1. Comparison within the three deep learning based solutions

We first calculate the mean absolute errors (MAE) over the 49 grids against the training iterations. From Fig. 5(a) and (b) we can see that, as the training iteration increases, the MAE for testing data of the three deep learning based solutions drop quickly. With respects to both $Y_t = X_{t+1}$ and $Y_t = X_{t+2}$, all the solutions seem to converge after about 85 iterations. Pertaining to the two different Y_t settings, the BDLSTM-CNN based hybrid solution always achieves the

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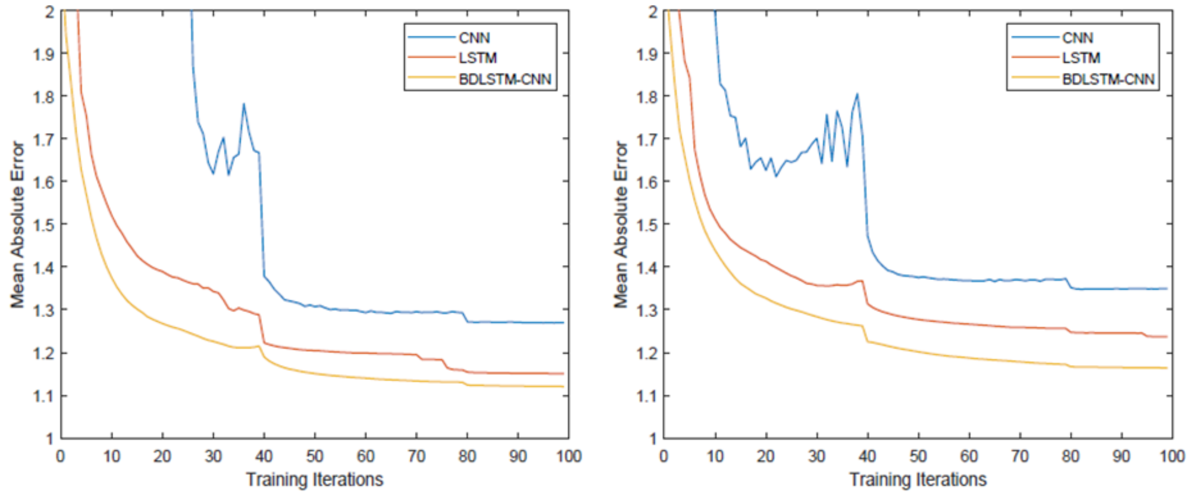
the lowest MAE, which are around 1.11 and 1.14, respectively.

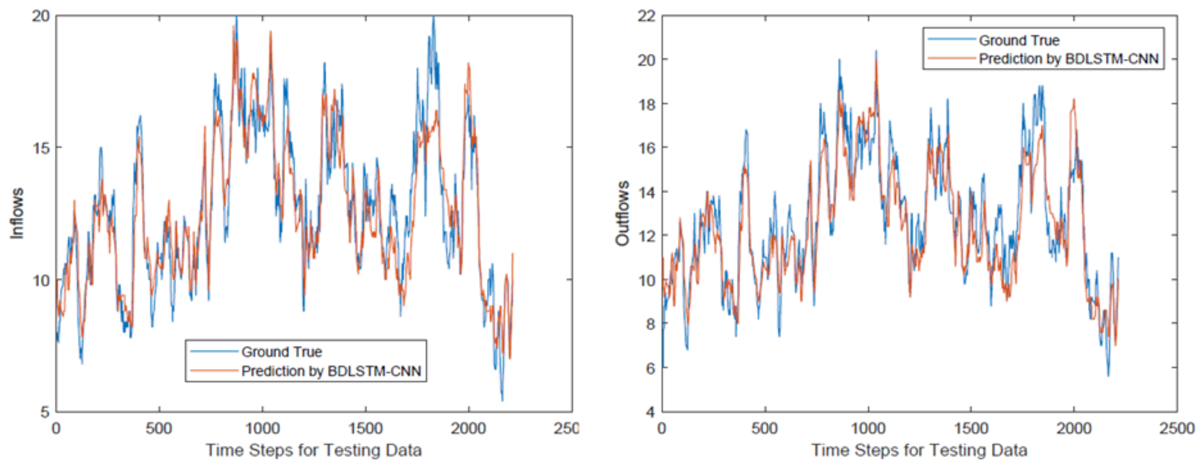


(a) $Y_t = X_{t+1}$ (b) $Y_t = X_{t+2}$

Fig. 5 MAE Comparison for the three deep learning based solutions

2. Breakdown Performance for the Hybrid Solution

Taking the single grid (6,6) as an example, we plot the forecasting curves of the hybrid solution for inflow and outflow, respectively. From Fig. 6 (a), we observe that, the hybrid solution can catch most of the crests and troughs for the inflow curve, no matter how sharp or smooth they are, such as the crest at time step 400 and the trough at time step 1250. An unsatisfactory forecasting is found as well at time step 1800, where a sharp crest is missed. From Fig. 6(b), we observe that the hybrid solution can also successfully follow both sharp and smooth crests and troughs for the outflow curve, such as the crest at time step 1050, and trough at time step 1450. Although the hybrid solution mismatched the ground truth at some points, such as time step 1800, most of the failures are tolerable.



(a) Inflow for grid (6,6) (b) Outflow for grid (6,6)

Fig. 6 Vessel Flow Curve of Ground Truth and Prediction by the Hybrid Solution

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Experimentation

3. Comparison with the conventional approach

We continue to compare the deep learning based solutions with the conventional method, i.e., Support Vector Regression (SVR) based on the whole region (49 grids), the results of which are recorded in Table. 1. We can see that, the error rates of the SVR method are around 51% for both measurements of MAE and RMSE (root mean square error), almost twice as much as the three deep learning based solutions. The inferiority comes from the fact that, the SVR method does not have a sophisticated scheme to learn the underlying spatial dependency, or the long-term temporal dependency. In contrast, CNN has a convolution layer, and LSTM or BDLSTM has a memory and gate to handle the two situations, respectively. On the other hand, the BDLSTM-CNN based hybrid solution always achieves the lowest error rates of 20% to 22.5%, which implies a forecasting accuracy of 77.5% to 80%. Considering that we only use five historical data to predict a new one, and both inflow and outflow of vessels change dramatically, the performance achieved by the hybrid solution is sufficiently satisfactory.

Table 1. Comparison with the conventional approach

	SVR	CNN	LSTM	BDLSTM-CNN
$Y_t = X_{t+1}$, NMAE	50.1	24.5	22.5	22.0
$Y_t = X_{t+2}$, NMAE	50.5	26.0	24.0	22.5
$Y_t = X_{t+1}$, NRMSE	51.2	24.0	21.0	20.0
$Y_t = X_{t+2}$, NRMSE	51.4	26.0	23.5	21.0

Research Highlight 2: Collision Risk Identification of the Autonomous Ships Based On the Synergy Ship Domain, by Academic Visitor Zhou Xiangyu (Track Leader: Professor MENG Qiang)

Introduction

The world has entered the period of "Industrial 4.0", and the Chinese government issued the "made in China 2025" in May 2015, and has made a key explanation of the high-tech ships and the intelligent manufacturing of ships. IMO's Maritime Safety Committee (MSC) considered document MSC 98/20/2, proposing to undertake a regulatory scoping exercise to determine how the safe, secure and environmentally sound operation of Maritime Autonomous Surface Ships (MASS) might be introduced in IMO instruments, and agreed to include in the 2018-2019 biennial agenda of the MSC and the provisional agenda for MSC 99, an output on "Regulatory scoping exercise for the use of Maritime Autonomous Surface Ships (MASS)", with a target completion date of 2020; and encouraged Member States and international organizations to submit substantive proposals and comments on this agenda item to MSC 99. In 2018, for the MSC 99 and in order to aid the work on the regulatory scoping exercise for the use of Maritime Autonomous Surface Ships (MASS), Denmark hereby offers an analysis of regulatory barriers to the use of autonomous ships, and proposes four autonomy levels is M, R, RU and A to analyze the feasibility of autonomous ships from multiple perspectives.

The development of the autonomous ships will effectively solve the main problems which current maritime field faces in energy saving, human cost and ship safety. With the rapid development of mass data and artificial intelligence, autonomous ships have become an inevitable trend in the field of ship manufacturing and shipping. At the end of twentieth Century, a large number of unmanned projects came into being. The prototypes of unmanned merchant vessels are expected to come into service within the coming years. The supporting argument pertains to the increase in navigational safety, which is expected to be achieved by reducing the frequency of human-related accidents on board ships and by removing the crews. The results obtained reveal that the occurrence of navigational accidents (e.g. collision, grounding) can be expected to decrease with the development of unmanned vessels based on what-if analysis to a hundred maritime accident reports.

In order to realize autonomous navigation of the autonomous ships, the intelligent identification of collision risk is one of the most important segments in the unmanned navigation system. According to the summary of the previous quantitative research results, the collision risk of vessels is divided into five stages. The first stage uses ships' encounter rate and the frequency of specific waters in historical collision accidents to evaluate the collision risk index in specific waters which is based on the traffic flow theory that belongs to the category of macro collision risk. The second stage evaluates the collision risk index based on the ship domain which was firstly proposed by Goodwin and Fujii and the arena proposed by Davis. And this stage begins to enter the category of the micro collision risk. In the third stage, some researchers considered the impact of DCPA (Distance to Closet Point of Approach) and TCPA (Time to Closet Point of Approach) separately for collision risk index. The fourth stage is the comprehensive consideration of the impact of TCPA and DCPA on the collision risk, and the weight method is used to calculate the collision risk index. With the rapid development of artificial intelligence technology, some researchers begin to use various intelligent algorithms or intelligent systems to identify the risk of collision in the fifth stage, such as expert system, fuzzy reasoning and artificial neural network. With the vessels' development of large-scale, high-speed, intensive and increasing complexity of water environment, only using the above-mentioned research methods to study the collision risk is far from enough to meet the requirements of the development of autonomous ships. Therefore, in this paper, we propose a novel ship domain based on synergetic theory (SSD). And we also establish a framework for dynamic identification of real time collision risk of unmanned ships. At last, the computer simulations on three encounter situations are presented. The simulation results demonstrate the validation and superiority of the proposed SSD and provide a good reference for the autonomous ships to identify real-time collision risk.

Research Highlight 2: Collision Risk Identification of the Autonomous Ships Based On the Synergy Ship Domain, by Academic Visitor Zhou Xiangyu (Track Leader: Professor MENG Qiang)

THEORY OF COLLISION RISK

The study of collision risk is one of the most important aspects of ship navigation system. The study is also the progressive realization of ship automation, the rise of the intelligent vessels and is particularly critical to determine accurately collision risk in the process of ship sailing. Today, as for the research of ship collision, there is a huge gap between China and other countries. It is mainly embodied in the fact that there is no collision risk real-time warning model or early warning system suitable for intelligent vessels or highly automated vessels. The judgment of traditional collision avoidance decision is mainly based on DCPA and TCPA, DCPA can determine whether if there is any collision risk between vessels, and the extent of danger can be roughly determined by TCPA. In the study of intelligent vessels collision avoidance system and the reliability of different information sources in different waters is different, the collision risk model should be dynamically described and matched in different reliabilities. Obviously, it is an important part to ensure the collision avoidance decision, which identify real-time dynamic collision risk based on the ship domain.

- The Four Stages in Collision Avoidance Procedure

On the vessels' normal sailing procedure, at first, the collision risk needs to be evaluated with the target ship before determining whether to take a collision avoidance action or change current sailing condition. An accurate and clear judgment of the collision risk between ships is an important basis and foundation for further actions. According to the COLREGS, the collision avoidance procedure can be divided into four stages (see Figure 1), which are free navigation stage, risk of collision stage, close-quarters situation stage and immediate danger stage.

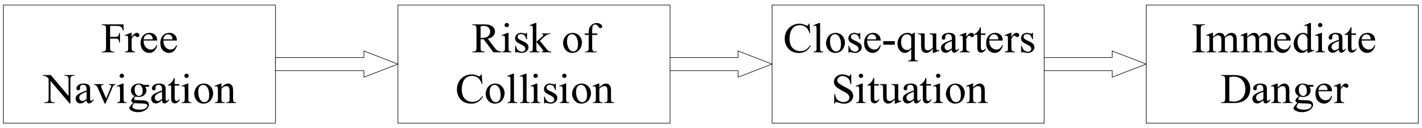

Figure 1. The Four Stages in Collision Avoidance Procedure

- Division of Encounter Situation

At the same time, the current encounter situation should be divided when the stage in collision avoidance procedure is cleared. The judgement of encounter situation is an important basis for determining the applicable rules in COLREGS and identify the responsibility for avoidance and action to be taken. According to the COLREGS this paper divide encounter situation into three types (see Figure 2), is head-on, crossing and overtaking.

There are three types of situations consisting of head-on (A), crossing (B, C, F) and overtaking (D, E). In practice, if a ship comes from the area of A, B and C, it is regarded as target ship and the own ship is considered as given-way ship, thus, the own ship is responsible to take necessary manoeuver to avoid a collision. If the target ship comes from D, E and F area, the own ship should keep its state until the results in a Close-quarters Situation are acquired.

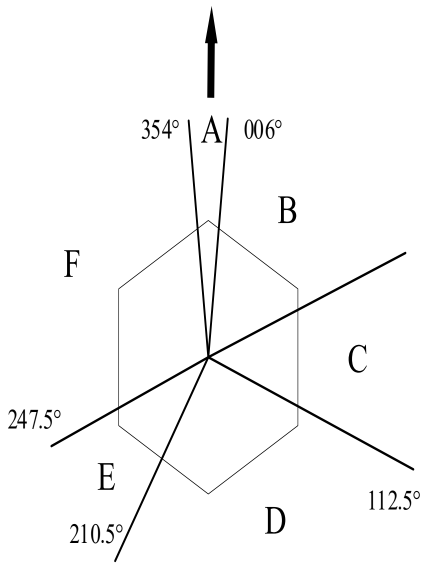

Figure 2. Division Diagram for Ship Encounter Situations

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THEORY OF COLLISION RISK

- Safety Passing Distance

The definition of safety passing distance is "Action taken to avoid collision with another vessel shall be such as to result in passing at a safe distance." in COLREGS. Because of the importance of safety passing distance to real-time collision risk identification, this paper is going to discuss about the safety passing distance based on dynamic ship domain, and identifying collision risk between vessels.

DYNAMIC SYNERGY SHIP DOMAIN BASED ON SHIP MANOEUVERABILITY

The definition of ship domains implies that ship domains are qualitative and quantitative models incorporated with both objective and subjective characteristics. However, most previous ship domain models pursue qualitative investigations; in addition, the subjective ship domains that navigators preserve are usually distinct, with objective models that corresponding vessels should hold. In this paper, a novel dynamic ship domain based on ship maneouverability model is used to identify the changes of collision risk. The model based on a large amount of AIS data, considers elements affecting domain boundary, such as ship's speed, dimension and maneuvering ability which establish safety passing domain and early warning domain. Thus, the target ship domain is superimposed with the own ship domain, and applies psychological functions to make it fuzzy. In this way, a novel dynamic ship domain based on ship maneuverability is established.

The boundary of ship domain is determined by n points in different directions around the ship. The distance from the point in any direction to the ship is defined as d_{si}, the size of ship domain can be defined as $D_s \le d_{si} (i = 1, 2, \cdots, n)$. The actual size of domain varies dynamically is based on ship's speed, size and maneuvering ability and it can be defined as followed:

$$D_s = \{ f(d_{si}), d_{si} \} (i = 1, 2, \cdots, n) \tag{1}$$

where f is fuzzy function, and ship domain is d_{si} when $f(d_{si}) \in [0,1]$.

According to the personification of unmanned ship collision risk identification, this paper applies reference proposed method of determining CRI, and CRI function can be calculated as follows:

$$CRI = f(d_{si}) = \begin{cases} 1 & d_{si} < d_{\min} \\ \left(\dfrac{d_{\max} - d_{si}}{d_{\max} - d_{\min}} \right)^{3.03} & d_{\min} \le d_{si} \le d_{\max} \\ 0 & d_{si} > d_{\max} \end{cases} \tag{2}$$

where $d_{\min}$ is safety passing domain, showing the minimum safe distance that is maintained around the own ship with the target ship. In this area, the own ship refused other ships to invade, but if other ships invade the area, it will be considered that $CRI = 1$. Besides, $d_{\max}$ is the domain boundary of $CRI = 0$ or approach $CRI = 0$ around the own ship.

- Safety Passing Ship Domain

The domain model is applicable to open water and restricted water and the safety passing domain needed between the

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give-way vessel and the stand-on vessel is calculated based on the ship's handling performance, when the give-way vessel completes the avoidance task and the stand-on vessel does not take the avoidance action. Besides, the model considers the give-way vessel's manoeuver characteristics, when it takes avoidance action, it needs a certain advance to complete the action of avoidance (see Figure 3). Therefore, the safety passing distance includes the advance in the process of avoidance and the size of ship.

The domain model can be described as follows:

$$d_{\min} = \left\{ (x,y) \left| \left(\frac{x}{\frac{L}{2} + A_d} \right)^2 + \left(\frac{y}{\frac{B}{2} + A_d} \right)^2 \le 1 \right. \right\} \tag{3}$$

where L is the own ship length, B is the own ship breadth, A_d is advance, which can be calculated as follows:

$$A_d = \left(10^{0.35911\lg V_{own} + 0.0952} \right) \cdot L \tag{4}$$

where V_{own} is the own ship speed represented in knots. It should be noted that the ship safety passing domain model reasonably takes into account the ship maneuvering capability identified by the advance A_d .

In this paper, Yu Kun vessel as an example to verify the rationality of the domain model by using 4829 AIS information record points. The parameters of the vessel and the safety passing domain are showed in Table 1 and Figure 4.

Table1. Yu Kun Ship Parameters

Ship Length	Ship Breadth	Sea Speed	Advance (Sea Speed)
116.00 m	18.00 m	16.7 kn	396.95 m

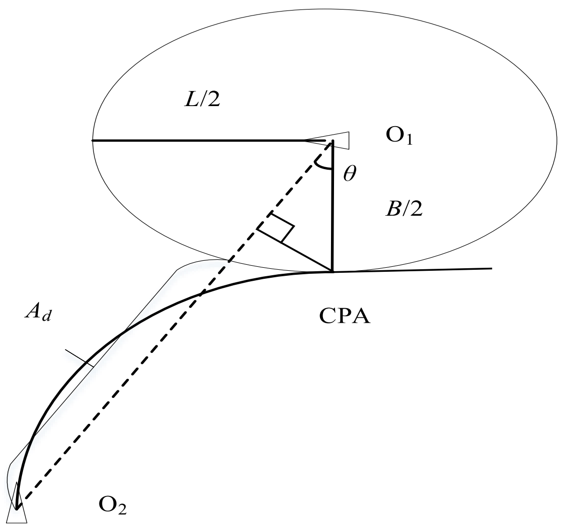

Figure 3. The Ship Safety Passing Domain Considering Advance

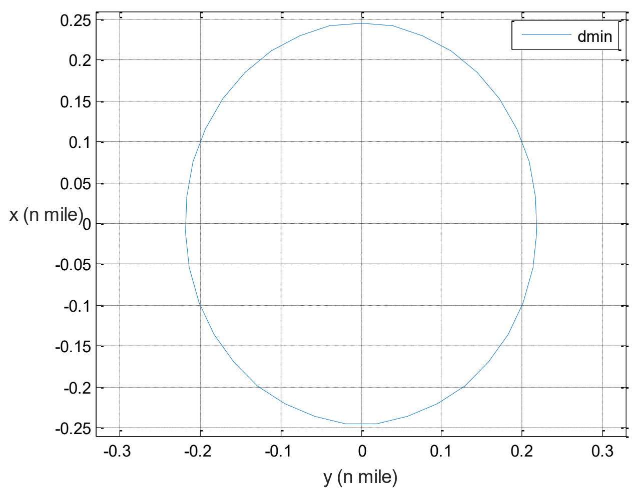

Figure 4. Ship Safety Passing Domain of Yu Kun

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DYNAMIC SYNERGY SHIP DOMAIN BASED ON SHIP MANOEUVERABILITY

- Early Warning Ship Domain

In this paper, the ship early warning domain refer to a quaternion ship domain (QSD), which can be applied in the process of collision risk assessment and collision avoidance at sea, particularly in shipboard navigational decision support systems. Because that $d_{\min}$ is the minimum domain for vessels which cannot be invaded absolutely. Therefore, on the basis of QSD, the domain boundary of $d_{\max}$ can be described as follows:

$$d_{\max} = \left\{ (x,y) \middle| g(x,y;Q) \le 1, Q = \left\{ R_{fore}, R_{aft}, R_{starb}, R_{port} \right\} \right\} \tag{5}$$

$$g(x,y;Q) = \left(\frac{2x}{(1+\operatorname{sgn} x)R_{fore} + (1-\operatorname{sgn} x)R_{aft} + L + 2A_d} \right)^2 + \left(\frac{2y}{(1+\operatorname{sgn} y)R_{starb} + (1-\operatorname{sgn} y)R_{port} + L + 2A_d} \right)^2 \tag{6}$$

where g is the function defining the boundary of the $d_{\max}$.

Estimation formulae for parameters of the blocking area are referred to estimate longitudinal and lateral radii in Q which can be given by:

$$\begin{cases} R_{fore} = \left(1 + 1.34\sqrt{k_{AD}{}^2 + (\frac{k_{DT}}{2})^2} \right) \cdot L \\ R_{aft} = \left(1 + 0.67\sqrt{k_{AD}{}^2 + (\frac{k_{DT}}{2})^2} \right) \cdot L \\ R_{starb} = (0.2 + k_{DT}) \cdot L \\ R_{port} = (0.2 + 0.75k_{DT}) \cdot L \end{cases} \tag{7}$$

where L is the own ship length, k_{AD} and k_{DT} represent gains of the advance A_d and the tactical diameter D_T respectively, the advance A_d can be calculated from (4), the tactical diameter D_T can be calculated as follows:

$$\begin{cases} k_{AD} = \dfrac{A_d}{L} = 10^{0.3591 \lg V_{own} + 0.0952} \\ k_{DT} = \dfrac{D_T}{L} = 10^{0.5441 \lg V_{own} - 0.0795} \end{cases} \tag{8}$$

According to ship maneuverability standards of IMO, the advance A_d and the tactical diameter D_T should satisfy

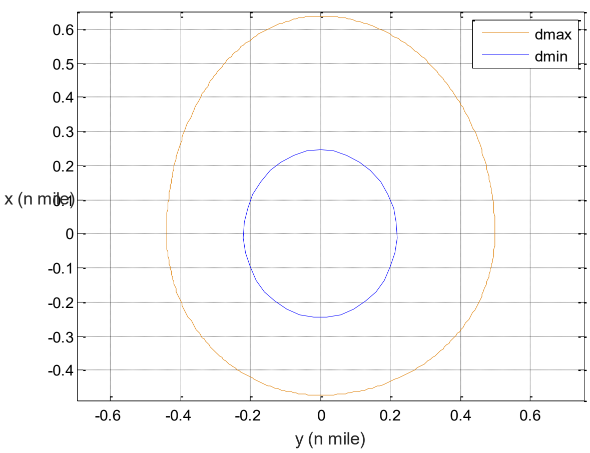

Figure 5. Ship Safety Passing Domain of Yu Kun

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DYNAMIC SYNERGY SHIP DOMAIN BASED ON SHIP MANOEUVERABILITY

the following relationships with ship length L.

$$\begin{cases} A_d \le 4.5L \\ D_T \le 5L \end{cases} \tag{9}$$

Similarly, the early warning domain still use Yu Kun parameters as an example, which is showed in Figure 5.

- Synergy Ship Domain

At present, there is no clear consideration of the interaction and coaction between the two ships in the conventional ship domains. Basically, most of the conventional ship domains are based on the point of view of the own ship, that is, only considering the characteristics of the own ship and neglecting to the target ship. However, because of the limitation of the construction method and shape of the conventional ship domains, which would lead to two vessels receipt different collision risk in encounter situations. According to the conception synergetic theory, in any encounter situation, the same collision risk should be receipted between vessels. Therefore, to circumvent these problems, a novel synergy ship domain is proposed in this paper.

Based on the above analysis of ship domains, we can find out that no matter which encounter angle between two vessels is, there is the collision risk when the ship domains are tangent or intersecting. It indicates $CRI \neq 0$. We suppose that the ship domains of own ship and target ship are tangent, when they formed head-on, crossing and overtaking encounter situations with each other. According to the geometry of the ellipse, the semi-major axis is longest between center and any point on the ellipse. Therefore, the distance between the two ships' center d_c can be described as follows:

$$d_c \le d_{\max} + R'_{fore} + d'_{\min} \tag{10}$$

where R'_{fore} is the target ship's longitudinal radii, and $d'_{\min}$ is safety passing distance of the target ship. The relationship is showed in Figure 6.

In order to the same collision risk can be receipted between vessels, a novel synergy ship domain (SSD) is proposed in this paper. Unlike previous ship domains defined by circles, ellipses and polygons, the proposed SSD is identified by the own ship domain and the target ship domain, where considering the advance and the tactical diameter of two vessels in different speed. Consequently, the SSD is an area defined by a closed curve joining these elements and the inner zone, which can be described as follows:

$$SSD = \left\{ (x,y) \middle| h(x,y;S) \le 1, S = \left(d_{\max} + R'_{fore}, d_{\min} \right) \right\} \tag{11}$$

where h is the function defining the boundary of the SSD, R'_{fore} is longitudinal radius of the target ship domain between $d_{\max}$ and $d_{\min}$. Therefore, h and R'_{fore} can be described as follows:

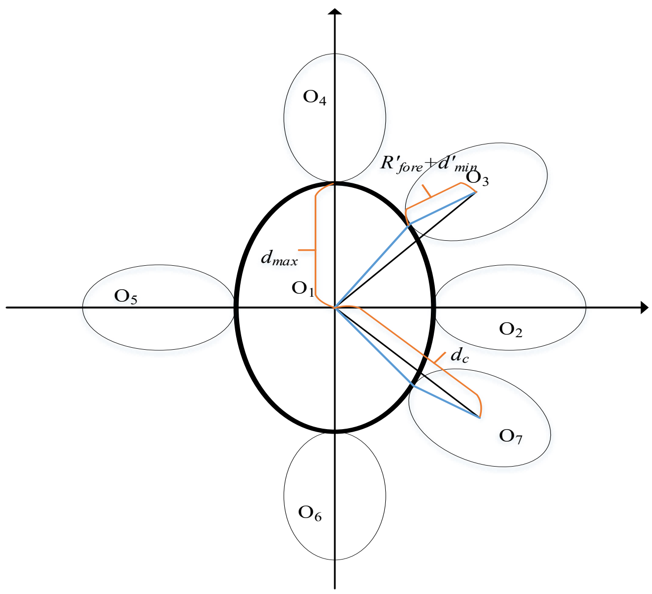

Figure 6. The Distance Between the Two Ship's Center

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$$R'_{fore} = \left(1 + 1.34\sqrt{k'^{2}_{AD} + \left(\frac{k'_{DT}}{2}\right)^{2}}\right) \cdot L' \tag{12}$$

$$h(x,y;S) = \left(\frac{2x}{(1+\operatorname{sgn} x)R_{fore} + (1-\operatorname{sgn} x)R_{aft} + 2R'_{fore} + L + 2A_d}\right)^2 + \left(\frac{2y}{(1+\operatorname{sgn} y)R_{starb} + (1-\operatorname{sgn} y)R_{port} + 2R'_{fore} + L + 2A_d}\right)^2 \tag{13}$$

where L' is the target ship length, k'_{AD} and k'_{DT} can be calculated by (8).

In conclusion, SSD model indicates that when the boundary of the own ship SSD is tangent to the boundary of the target ship safety passing domain $d_{\min}$, $CRI = 1$ .The improved CRI function can be calculated as follows:

$$CRI_{SSD} = f(d_{si}) = \begin{cases} 1 & d_{si} < d_{\min} \\ \left(\dfrac{d_{SSD} - d_{si}}{d_{SSD} - d_{\min}}\right)^{3.03} & d_{\min} \le d_{si} \le d_{SSD} \\ 0 & d_{si} > d_{SSD} \end{cases} \tag{14}$$

REAL-TIME COLLISION RISK IDENTIFI-CATION OF THE AUTONOMOUS SHIPS

According to characteristics of autonomous ships, the collision risk needs be real-time monitored, the whole identification and monitoring process is divided into six stages, and defining the four different thresholds of collision risk index, which is showed in Figure 7.

(1) Using a variety of smart sensors for accessing to information of all kinds of ships and obstacles in the current waters of the own ship, however, according to the credibility of different acquisition devices in different regions is different, we need to endow the weights to information from different collecting devices, and realize real-time updating of weight information. After integration, the dynamic collision avoidance information will be provided in real-time and modified global time domain.

(2) Set up different identification ranges for open waters, restricted waters and port waters, identify the state of vessel motion in this area, and calculate the own ship domain considering the target ship factor.

(3) The target ship comes into the early warning domain of the own ship, that is, the distance from the own ship is , and . At this time, the target ship entering the collision risk stage described in 2.1, which will be marked into the key monitoring list of the own ship, and real-time judgement of the encounter situation and avoidance responsibility between the target ship and the own ship. The give-way vessel will take collision avoidance action.

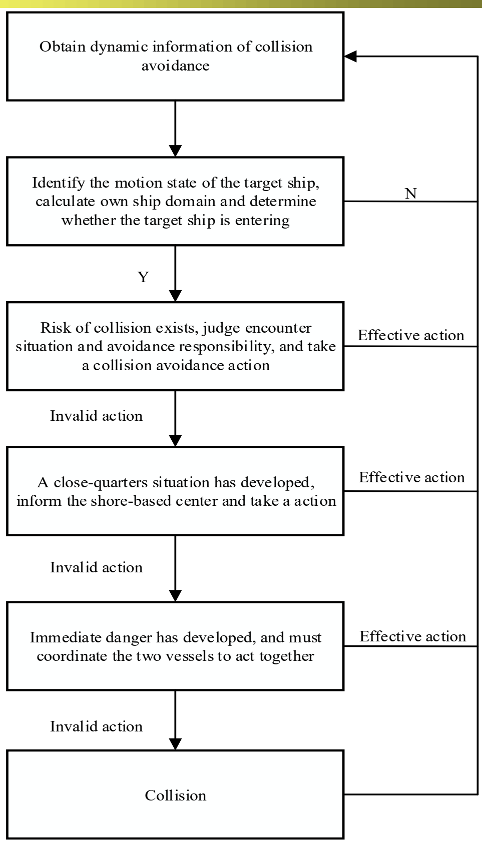

Figure 7 The Process of Collision Risk Identification of the Autonomous Ships

Research Highlight 2: Collision Risk Identification of the Autonomous Ships Based On the Synergy Ship Domain, by Academic Visitor Zhou Xiangyu (Track Leader: Professor MENG Qiang)

REAL-TIME COLLISION RISK IDENTIFI-CATION OF THE AUTONOMOUS SHIPS

(4) The two vessels did not take proper and effective action to avoid collision, the distance of vessels continues to decrease, a close-quarters situation of CRI, and different thresholds can be set in the light of different areas.

(5) The above collision avoidance action is not effective or without taking collision avoidance action, and the distance between ships is continuously reduced. When $CRI = CRI_b$, the immediate danger has developed, at this time, collision cannot be avoided by the action of the give-way vessel alone, or in other words, the two vessels take collision avoidance action together has not resulted in passing at a safe distance. The two ships should immediately issue a red alert, and seek the support of shore-based center to complete two vessels coordinated collision avoidance action to avoid collision. CRI_b is a threshold for immediate danger of CRI, and different thresholds can be set in the light of different areas.

(6) The target ship entered the safety passing ship domain of the own ship, that is, the distance from the own ship is $d_{\min}$,in other words, the safety passing ship domain of the two vessels have been tangential or overlapping. At this time, $CRI = 1$, and collision cannot be avoided by the no matter what any action of the two vessels.

SIMULATION STUDIES

In this section, several encounter situations of the own and target ships in collision risk are made to demonstrate the validity and superiority of the presented SSD. Encounter scenarios between vessels include three types of situations, i.e. head-on, crossing and overtaking and all the above mentioned situations will be considered in this paper in order that the validity of the SSD can be well tested. For comparative studies with other ship domains, numerical simulations are presented in the uniform simulation circumstance whereby the principal dimensions of the own and target ships are listed in Table 2 and initial conditions of ships in encounter situations are listed in Table 3, respectively.

Table 2. Ship Parameters

	Ship Length	Ship Breadth
the Own Ship (Yu Peng)	116.00 m	18.00 m
The Target Ship (Yu Kun)	200.00 m	28.00 m

Table 3. Initial Conditions of Ships in Encounter Situations

	the Own Ship (Yu Peng)		The Target Ship (Yu Kun)	
Scenarios	Speed (knot)	Course (°)	Speed (knot)	Course (°)
Head-on	15	000	12	180
Crossing	15	000	12	220
Overtaking	18	000	12	0

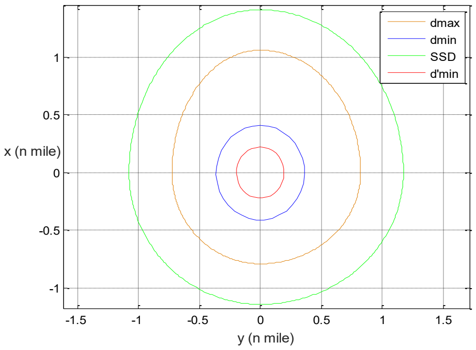

Figure 8 Relative Location Relationships of Ship Domains in Head-On Situation

- Head-on Situation

In this situation, the target ship comes towards the own ship from the front. According to the two ships' sizes, speeds and courses, the safety passing ship domain of own ship is $d_{\min}$, the early warning ship domain of own ship is $d_{\max}$, the synergy ship domain is SSD, and the safety passing ship domain of target ship is $d'_{\min}$. Their relative location relationships are shown in Figure8. From the results, we can see that SSD

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SIMULATION STUDIES

model provides more appropriate and more reasonable ship domain.

- Crossing Situation

On this situation, the target ship is positioned before the beam of the own ship at the beginning and crosses the own ship trajectory. Simulation results, shown in Figure 9, are similar to those of head-on situation.

- Overtaking Situation

In this situation, the own ship overtakes the target ship from the stern. Simulation results are shown in Figure 10. Note that the SSD are reasonable for this scenario. According to the $COLREG_S$, the target ship does not need to take actions unless critical situations appear. Therefore, the SSD is appropriate and moderate for this situation.

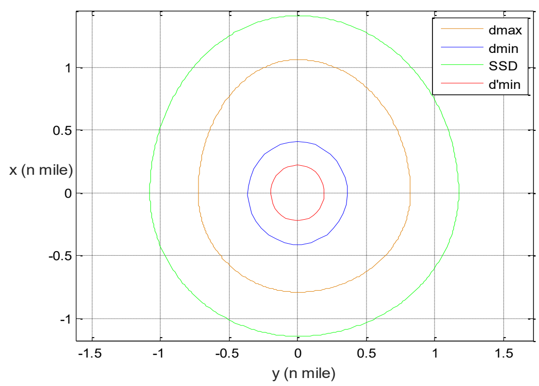

Figure 9 Relative Location Relationships of Ship Domains in Crossing Situation

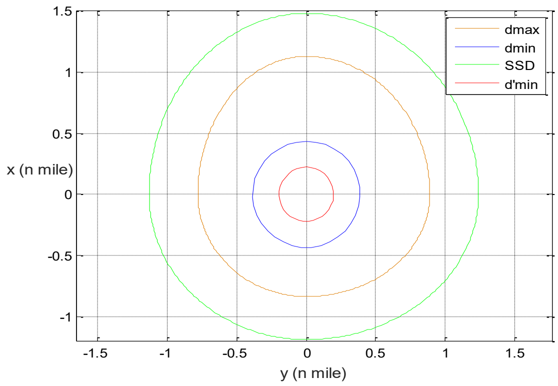

Figure 10 Relative Location Relationships of Ship Domains in Overtaking Situation

CONCLUSIONS

In this paper, a novel synergy ship domain (SSD) has been proposed to make up a universal and reasonable ship domain model for the practical application in the process of collision risk assessment and collision avoidance at sea, etc. Unlike previous ship domains defined by circles, ellipses and polygons, the proposed SSD is identified by the own ship domain and the target ship domain, where considering the advance and the tactical diameter of two vessels in different speed. Besides, it combines the safety passing ship domain and early warning ship domain to identify real-time collision risk. A frame of intelligent monitoring and identification of collision risk has been constructed, and provides better support for the autonomous ships. According to the credibility of different acquisition devices in different regions is different, the paper suggests endowing the weights to information from different collecting devices to improve the accuracy and completeness of the collision information. On this basis, recognition scope and collision risk alert threshold should be adjusted according to the different characteristics of the waters, and the ship control power needs to be handed in shore-based support center as occasion requires. The dynamic monitoring and recognition of the real-time collision risk will lay the foundation for the avoidance decision of the unmanned ship in next stage. Finally, the simulation experiment of the three encounter situations to verify the validity and rationality of the model, which to some extent overcome the conventional ship domain model neglects the mutual interaction between the vessels and there are defects in same encounter situation vessels with different collision risk.

However, there are still some problems to be dealt with in this framework of ship domains for collision risk and avoidance. Future work need establish a three-dimensional ship domain, and take into account the navigation risk in the bridge area and grounding at the same time. And according to the variety of vessels density to modify dynamically ship domain in different areas, so as to better adapt to the traffic environment and ensure the safety of ship navigation.

Published Technical Papers (with Abstracts)

1. **Zhou Xiangyu, Huang Jinjing, Wang Fengwu, Wu Zhaolin, and Liu Zhengjiang (2019), A Study of Application Barriers of COLREGs in Autonomous Ships. Journal of Navigation (under review).**

Abstract:

The autonomous ship is gaining importance in shaping the future of shipping. To better eliminate barriers in the application of autonomous ships, a novel perspective fro navigation practice was adopted for the first time in this paper. The research objects are a remotely-controlled ship with no crew members on board and a fully autonomous ship. The analysis examines the potential conflicts and barriers in COLREGs and minimal safe manning issue in seaworthiness for autonomous ships. In COLREGs, Part A–General and Part B–Steering and Sailing Rules were discussed in detail. This paper analyses in detail the influence of "good seamanship", "proper look-out" and "vessels not under command" with autonomous ships that were flagged out during the interview with ship crews. The results indicate that, in general, there are no obvious conflicts and potential barriers between autonomous ships and COLREGs. However, some provisions need to be revised and amended to eliminate the uncertainty and misunderstanding of interpretation. Alternatively, a special annex for autonomous ships should be considered to be added in COLREGs.

2. **Chai Kah Hin, Lee Xin Ni, and Gaudin Antoine (2019). A systems perspective to market-based mechanisms (MBM) comparison for international shipping. 10.2139/ssrn.3347448.**

Abstract:

There is a long history of debate on which Market-based Mechanism (MBM) should international shipping adopt to reduce carbon dioxide (CO2) emissions. However, literature presents differing preferences for a suitable MBM for international shipping. Broadly, there are those who support a carbon tax, those who support an ETS, and those who remain on the fence. Hence, this study aims to find out: which MBM is suitable to reduce CO2 emissions for international shipping?

The paper begins with an overview of the current state of the MBMs around the world. Thereafter, we build a conceptual model based on a systems perspective to understand the relationship between CO2 reduction, Research & Development (R&D), adoption of existing technology and financial resources. For the purpose of comparative analysis, definitions of the two MBMs, bunker levy and ETS, and their possible sub-types are presented. To determine which MBM is more suitable, we follow a multi-criteria decision-making approach where the criteria are derived from our systems perspective conceptual model and from literature. To reduce ambiguity, criteria with multiple meanings are further divided into unequivocal criteria and operationalised with a specific mechanism.

We find that a bunker levy, regardless of its levy collection approach, is more suitable since it is more effective in encouraging the adoption of technology with high Technology Readiness (TRL), in R&D investment into low TRL technologies (both of which are favourable with greater carbon price stability) and in generating funds. Furthermore, an ETS is harder to operationalise as the large number of ships trading internationally could require a significant number of man-hours to set up, operate and review the system, and high variability in each ship's fuel consumption makes it difficult to allocate credits to ships accurately. An ETS with full auctioning of credits would render ETS comparable with bunker levy in the amount of funds generated and recognition of prior fuel-saving investments. In view of the need for the sector to conduct R&D, we propose that bunker levy is more suitable than ETS for international shipping.

This paper makes three important contributions to literature:

Published Technical Papers (with Abstracts)

1. Conceptually, we adopt a systems perspective, which allows us to draw insights from economics, technology and innovation management literature.
2. Methodologically, we use a multi-criteria decision-making approach where we
   a. Operationalise the MBMs, i.e. bunker levy into 3 sub-types, and ETS into 2 sub-types
   b. Identify the 8 criteria which are then further converted to 10 to ensure clear and unambiguous interpretation of the criteria
3. Our underlying view is that the MBM needs to fit the context in which it will be deployed.

Given the right context, both types of MBMs could be good. In the current context of international shipping – characterised by large number of ships, high variability of each ship's fuel consumption and the importance of R&D for innovation of low TRL low-carbon technologies, bunker levy seems to be more suitable.

3. Wen Song, Donghun Kang, Jie Zhang, Zhiguang Cao, and Hui Xi (2019), A Sampling Approach for Proactive Project Scheduling under Generalized Time-dependent Workability Uncertainty. Journal of Artificial Intelligence Research, Vol. 64.

Abstract:

In real-world project scheduling applications, activity durations are often uncertain. Proactive scheduling can effectively cope with the duration uncertainties, by generating robust baseline solutions according to a priori stochastic knowledge. However, most of the existing proactive approaches assume that the duration uncertainty of an activity is not related to its scheduled start time, which may not hold in many real-world scenarios. In this paper, we relax this assumption by allowing the duration uncertainty to be time-dependent, which is caused by the uncertainty of whether the activity can be executed on each time slot. We propose a stochastic optimization model to find an optimal Partial-order Schedule (POS) that minimizes the expected makespan. This model can cover both the time-dependent uncertainty studied in this paper and the traditional time independent duration uncertainty. To circumvent the underlying complexity in evaluating a given solution, we approximate the stochastic optimization model based on Sample Average Approximation (SAA). Finally, we design two efficient branch-and-bound algorithms to solve the NP-hard SAA problem. Empirical evaluation confirms that our approach can generate high-quality proactive solutions for a variety of uncertainty distributions.

4. Zhiguang Cao, Haozhi Lin, Xiangyu Zhou, Yajuan Xie, Wen Song, and Xuexi Zhang (2019), Using Deep Learning to Forecast the Maritime Vessel Flows. Applied Soft Computing (under review).

Abstract:

Forecasting vessel flows is important to the development of intelligent transportation systems in maritime, as real-time and accurate traffic information has favorable potential in helping maritime authority to alleviate congestion, mitigate emission of GHG (greenhouse gases) and enhance the public safety, as well as assisting individual vessel user to plan better routes and reduce additional cost due to delay. In this paper, we propose three deep learning based solutions to forecast the inflow and outflow of vessels within a given region, including a convolutional neural network (CNN), a long short-term memory (LSTM) network, and the integration of a bidirectional LSTM network with a CNN (BDLSTM-CNN). To apply those solutions, we first divide the given maritime region into MXN grids, then we forecast the inflow and outflow for all the grids. Experimental results based on the real AIS (Automatic Identification System) data of marine vessels in Singapore demonstrate that, the three deep learning based solutions significantly outperform the conventional method in terms of mean absolute error and root mean absolute error and root mean square error, with the performance of the BDLSTM-CNN based hybrid solution being the best.

5. **Zhiguang Cao, Hongliang Guo, Wen Song, Le Zhang, Zhenghua Chen, Wei Chen, and Xuexi Zhang (2019), Using Reinforcement Learning to Minimize the Probability of Delay Occurrence in Transportation. IEEE Transactions on Vehicular Technology (under review).**

Abstract:

Reducing traffic delay is of crucial importance for the development of sustainable transportation systems, which is a challenging task in the studies of stochastic shortest path (SSP) problem. Existing methods based on the probability tail model to solve the SSP problem, seek for the path that minimizes the probability of delay occurrence, which is equal to maximizing the probability of reaching the destination before a deadline (i.e., arriving on time). However, they suffer from low accuracy or high computational cost. Therefore, we design a novel and practical Q-learning approach where the converged Q-values have the practical meaning as the actual probabilities of arriving on time so as to improve the accuracy of finding the real optimal path. By further adopting dynamic neural networks to learn the value function, our approach can scale well to large road networks with arbitrary deadlines. Moreover, our approach is flexible to implement in a time dependent manner, which further improves the performance of returned path. Experimental results on some road networks with real mobility data, such as Beijing, Munich and Singapore, demonstrate the significant advantages of the proposed approach over other methods.

6. **Zhiguang Cao, Hongliang Guo, Wen Song, Kaizhou Gao, Liujiang Kang, Xuexi Zhang, and Yajuan Xie (2019), Reducing the Chance of Transportation Network Breakdown: A Semi-Centralized Pricing Approach. IEEE Transactions on Intelligent Transportation Systems (under review).**

Abstract:

Improving the performance of transportation network is a crucial task in traffic management. In this paper, we start with a cooperative routing problem, which aims to minimize the chance of road network breakdown. To address this problem, we propose a subgradient method, which can be naturally implemented as a semi-centralized pricing approach. Particularly, each road link adopts the pricing scheme to calculate and adjust the local toll regularly, while the vehicles update their routes to minimize the toll costs by exploiting the global toll information. To prevent the potential oscillation brought by the subgradient method, we introduce a heavy-ball method to further improve the performance of the pricing approach. We then test both the basic and improved pricing approaches in a real road network, and simultaneously compare them with two benchmarks. The experimental results demonstrate that, our approaches significantly outperform others, by comprehensively evaluating them in terms of several metrics including average travel time and travel distance, winners and losers, potential congestion occurrence, last arrival time and toll costs.

CMS Research Seminars

1. **System Characteristics and Prevent Technology of Significant Shipping Accidents and A Preliminary Discuss About Potential Hazard for Autonomous Ships, by Academic Visitor Zhou Xiangyu (Track leader: Professor Meng Qiang)**

Seminar Abstract:

Significant shipping accidents is a major challenge for maritime industry and society. These accidents can cause a large number of casualties and property losses, and their serious consequences are likely to cause social problems. Therefore, it is necessary to conduct a statistic and characteristic analysis for significant shipping accidents. At the same time, according to the results of the accident characteristics analysis, combined with the current maritime search and rescue organizations, power and working mechanism, discuss the method of enhancing of ability for emergency response. The summary and results of two significant shipping accidents indicate that we need to explore the experience and learn lessons from these maritime disasters. And learning how to face them.

After the discussion of significant shipping accidents, the seminar will make a preliminary discussion about potential hazard for autonomous ships. Firstly, the development status and existing problems of the autonomous ship are briefly introduced. And a new hazard analysis tool Systems Theory Process Analysis (STPA) has emerged as an approach for improving the safety of modern complex systems for autonomous ships would be discussed. At last, model checking was proposed to combine with STPA, which in order to overcome the limitations of STPA. The novel proposed method will be used to identify the collision hazard for autonomous ships.

2. **Bus and driver scheduling with mealtime windows for a single bi-directional bus route, by researcher Dr. Kang Liujiang (Track leader: Professor Meng Qiang)**

Seminar Abstract:

This study deals with the bus & driver scheduling problems with mealtime windows for a single public transport bus route. Firstly, we develop three explicit Integer Linear Programming (ILP) models to formulate: the bus driver scheduling, bus & driver scheduling, and bus & driver scheduling with mealtime windows, respectively. These ILP models enable bus operators to solve their bus & driver scheduling problems by directly invoking an available optimization solver such as IBM ILOG CPLEX. Moreover, we develop a valid approach to improve the three models' efficiency as well as a self-adaptive search method to determine the upper and lower bounds of driver group and bus fleet sizes. Finally, we test our models and approaches on a real round-trip bus route. The results indicate that compared with the only use of CPLEX to solve the above three models, the valid approach can address large-scale instances in a reasonable CPU time.

3. **Reinforcement learning for heterogeneous fleet VRP, by Academic Visitor Mr. Ruize Gao (Track leader: Assistant Research Professor Cao Zhiguang)**

Seminar Abstract:

A deep reinforcement learning model is proposed to solve the heterogeneous fleet vehicle route problem (HVRP) by planning route different types of vehicles in depot. In this model, a masking mechanism is employed to ensure that results are all feasible solutions, and parameterized stochastic policy and actor-critic algorithm are utilized to optimize four parameter matrixes. In the test, our trained model can plan the route for 60 customers and 3 types of vehicles (hvrp60) within only 11s, and has achieved excellent results. After subsequent improvements, the model is expected to solve the more generalized HVRP with more customers, more vehicles with different speed and capacity.