Domain and Its Model Based on Neural Networks

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This paper presents a concept on the subjective ship domain. The factors related to the domain are discussed. A method based on the neural networks is used to establish a model of the domain that considers the effects of visibility and manoeuvrability, which can react quickly to various ships within a certain range.

KEY WORDS

1. Marine. 2. Collision avoidance. 3. Modelling.

1. INTRODUCTION. The concept of ship domain is very important in marine traffic engineering and has been widely used in ships' collision avoidance, marine traffic simulation, risk assessment, VTS design, etc. The concept of a ship's domain was first presented in the early sixties by Dr Fujii *et al*., (1971), who established a domain model in a narrow channel. Later, Dr Goodwin (1975) established a domain model in the open sea. In the eighties, Dr Coldwell (1983) established the domain model for end-on and overtaking encounters in restricted waters. Many scholars have worked on improving the models of ship domain (Davis *et al*., 1980 and Colley *et al*., 1984). Most of the models are in geometrical forms and do not have the capacity to express the effects of various factors, such as visibility and manoeuvrability. Some papers have discussed the problems that exist in the present domain models (Colley *et al*., 1984 and Zhao *et al*., 1993), but a more effective model has not been developed to date. In this paper, the concept of subjective domain will be discussed and the main factors affecting the domain will be analysed. Based on this work, a new model will be established using a method of neural networks.

2. THE CONCEPT OF SHIP DOMAIN. Of the present domain models, that of Goodwin's is considered to be the most representative. The definition of the domain made by Goodwin is 'the surrounding effective waters that the navigator of a ship wants to keep clear of other ships or fixed objects'. From the definition, the domain should be a subjective concept rather than an objective one. However, the model presented by Goodwin results from a series of observations of ships; that is to say, the model is an objective one. Certainly, the objective results contain the subjective factors, but they are different as analysed below.

First, the subjective domain is the waters that a navigator really 'wants' to be kept safe, usually used for risk assessment by the navigator, while the objective domain is the facts that a navigator 'has to' accept. Geometrically, so long as the passing distance between two ships does not reduce to zero, a collision will not occur. But that doesn't mean a non-zero distance is a safe distance in the view of the navigator.

Second, for a specific ship in certain waters, its subjective domain is relatively

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steady, while the objective domain is apt to change with the encounter, bearing and relative velocity, etc. Goodwin's model has shown that the navigator's actions are influenced by the COLREGS. Therefore the subjective domain is easily determined, while the objective domain is difficult; even when it is determined, there is difficulty in distinguishing the effect of each factor from the facts.

Third, the subjective domain is suitable for application to problems such as collision avoidance and assessment of collision risk, while the objective domain is more useful in traffic simulation and path design etc.

As well as the differences mentioned above, there are relationships between the two kinds of domains. Briefly, the objective domain is the result of actions taken by both (or one) of the ship's navigators to protect their subjective domains from infringement. So investigation into the subjective domain is not only useful for problems of collision avoidance, but is also helpful in the explanation of the objective domain.

3. HOW NAVIGATORS USE THE DOMAIN. To investigate how navigators use the subjective domain (called domain for short in the following text) in the process of collision avoidance, a well-planned questionnaire is needed. In the following, we analyse the results from such a questionnaire. Before the analysis, it is necessary to define the two variables in Figure 1. One is the closest distance of safe

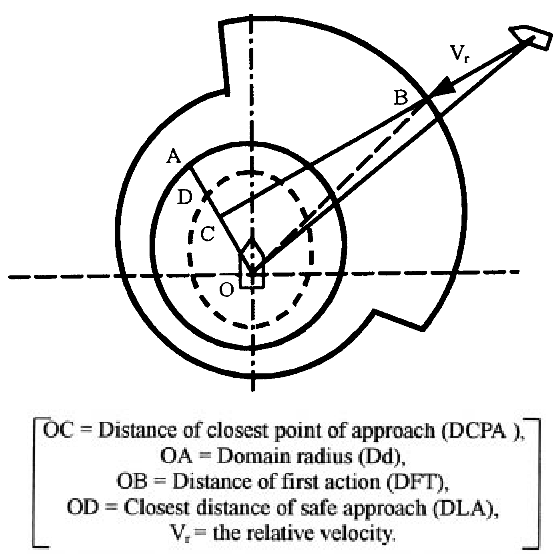

Figure 1. The Ship Domain.

approach – DLA, shown as OD. Another is the distance at which the ship first begins to take action for collision avoidance – DFT, shown as OB. [OC = Distance of closest point of approach (DCPA), OA = Domain radius (Dd), OB = Distance of first action (DFT), OD = Closest distance of safe approach (DLA), V_r = the relative velocity.]

For a give-way ship, an encounter-manoeuvre can be split into the following stages:

(a) appraising the risk of collision;

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(b) determining the time at which to manoeuvre;
(c) determining the magnitude of the manoeuvring;
(d) determining the time at which to alter back to course.

An interesting phenomenon is that navigators take their own ship's domain as the criteria at stages (a) and (b), while they tend to take the target's domain as the criteria at stages (c) and (d), so long as the DCPA is greater than the DLA. Usually, DLA approximates to half of the domain radius or more. The target's domain mentioned here is the subjective domain determined by the experiences of own ship's navigators, which may be a little different from that of the target's navigators. For example, while a small give-way ship is passing a large stand-on ship, the navigator uses the domain of the large ship instead of his own smaller one.

If this phenomenon exists generally, it is not difficult to explain why Goodwin's model seems to be contradictory, while the same model is used for all stages. Dr Zhao has pointed out the contradiction existing in Goodwin's model and concluded that the model is untenable (Zhao *et al.*, 1993). This conclusion is based on the supposition that both ships used their own domains for all stages. If the supposition is not true, Zhao's conclusion may be untenable. As Goodwin's model is a statistical result from a series of facts, it inevitably covers the differences between ships and the differences between the encounters.

A stand-on ship tends to wait for the actions of a give-way ship. Even if her domain has been intruded on a little, she tends to keep the stand-on state, so long as the DCPA is not less than the DLA. Both give-way ship and stand-on ship determine the DFT by their own domains, the DCPA, the TCPA and the COLREGS, which will be discussed in a future paper.

4. THE FACTORS AFFECTING DOMAIN. To obtain the domains used by navigators, a series of consultations were made with veteran navigators. The results show that a ship's domain is mainly affected by the following factors:

(a) the local visibility,
(b) the manoeuvrability of the ships, and
(c) the bearing of the CPA.

The encounter situation has less effect on the subjective domain, but has a great effect on the DFT. In the following, each factor will be discussed separately.

4.1. *Local Visibility*. Fujii held that: 'It looks as if decreasing visibility will increase the range of an effective domain, but that the further deterioration of visibility will not affect the range of a domain.' Consultation with the veteran navigators shows the same results. The variations of the domain radius Dd with the visibility are illustrated in Figure 2. The value of d_1 and d_2 in Figure 2 varies with different ships. The ships with good equipment have a smaller difference between d_1 and d_2 than those with poor equipment.

4.2. *Ship Manoeuvrability*. As the domain we are talking about is a subjective domain around a ship, it is certainly affected by the ship's manoeuverability. A ship's geometrical parameters relating to the manoeuverability are as follows (Inoue, 1981):

(a) the ratio of length to breadth L/B,
(b) the ratio of breadth to draft (mean) B/T,
(c) the block coefficient C_b, and
(d) the rudder area A_r.

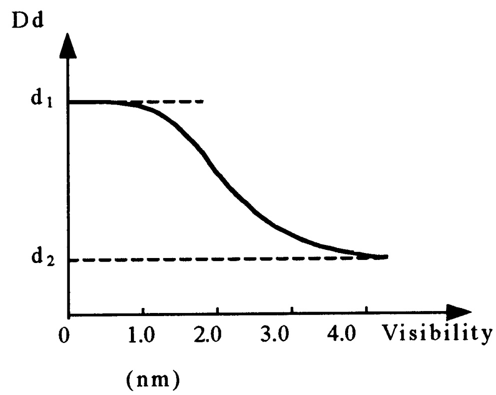

Figure 2. The Effect of Visibility.

The parameter A_r is not considered in the following domain model because compared with the hull hydrodynamics, the forces created by the rudder are relatively less important. This can be demonstrated from the expressions of the manoeuverability criteria K and T (Chen, 1981). How a domain depends on those parameters is unknown but, as described in section 4, the relationships between them can be found by neural networks.

4.3. *The Bearing of the CPA*. As shown in Figure 1, while a ship is approaching from the starboard side of own ship, her CPA is on the port side. Dd is the distance from point O to A, which is the 'radius' of the domain. Theoretically, the domain should be a circle with own ship at the centre. However, since the domain is influenced by the navigator's psychological factor, the forward section is larger than the after-space. Goodwin's objective model showed that the navigator's actions were influenced by the COLREGS. Indeed, the navigator's actions are influenced, but not his sense of safety. That is to say, the COLREGS simply have an effect on DFT, instead of Dd (Figure 1). Therefore, the subjective domain is symmetric about the longitudinal axis of a ship.

5. THE DOMAIN MODEL BASED ON A NEURAL NETWORK.

Neural networks are trainable, dynamic systems that can estimate input-output functions. Unlike statistical estimators, they estimate a function without a mathematical model of how outputs depend on inputs. Since they behave as model-free estimators, neural networks have been applied to a wide variety of problems.

5.1. *The BP Neural Network*. The BP neural network (BPNN) is a neural system with a back-propagation algorithm that can learn input-output functions from a series of samples. A three-layer BPNN consists of an input layer LA, a hidden layer LB and an output layer LC (Figure 3). The process of learning can be described as follows. The input information is first processed by the elements of the hidden layer, and is then propagated to the output layer. If no desired output values are gained, the error between the computed and desired output values is back-propagated. A cost function, which is the squared error, is minimised by making weight connection adjustments.

The elements of the input layer are usually linear elements, the effect function of which is f(u) = u. Supposing $(x_0, x_1, \ldots, x_{n-1})^T$ has n inputs, and the number of

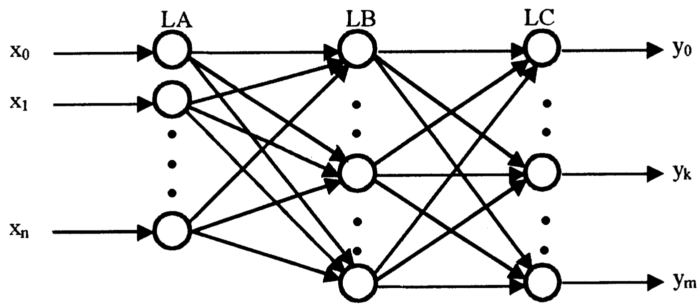

Figure 3. A Three-layer BPNN.

elements in hidden and output layers are n_1 and m respectively. The weights and thresholds values between the layers are noted as $[w_{ij}]$, $[\theta_{ij}]$ and $[w'_{jk}]$, $[\theta'_{jk}]$ respectively. The effect functions of the hidden layer and the output layer are Sigmoid functions:

$$f(u) = 1/(1+e^{-u}).$$

Then the propagation of inputs is expressed by following formulae:

$$\text{outputs of LA:}\quad X_i = (x_0, x_1, \ldots, x_{n-1})^{\mathrm{T}},$$
$$\text{outputs of LB:}\quad X'_j = (x'_0, x'_1, \ldots, x'_{n_1-1})^{\mathrm{T}},$$

where:

$$x'_j = f\left(\sum_{i=0}^{n} w_{ij}\, x_i\right), w_{nj} = \theta_j, x_n = -1$$

$$\text{outputs of LC:}\quad Y_k = (y_0, y_1, \ldots, , y_{m-1}),$$

where:

$$y_k = f\left(\sum_{j=0}^{n_1} w'_{jk}\, x_j\right), w'_{n_1 k} = \theta'_k, x'_{n_1} = -1$$

To P learning samples, inputs are X_i^1, $X_i^2, \ldots, X_i^P$, the desired outputs are T^1, $T^2, \ldots,$ T^P, the computed outputs are Y_k^1, $Y_k^2, \ldots, Y_k^P$. The general error of P samples is noted as E_P:

$$E_P = \frac{1}{2}\sum_{P_1=1}^{P}\sum_{k=0}^{m-1}(t_k^{P_1} - y_k^{P_1}) = E_P(W, T^{P_1}, X^{P_1}),$$

where: W is the array of weights. E_P can be minimised by adjusting weights using a multi-layer gradient descent error-correction encoding algorithm. The back-propagation of error can be formulated as follows:

$$w'_{jk}(n_0+1) = w'_{jk}(n_0) + \eta_2 \sum_{P_1=1}^{P} \delta_{jk}^{P_1}\, x_j'^{P_1}$$

$$\delta_{jk}^{P_1} = (t_k^{P_1} - y_k^{P_1})\, y_k^{P_1})(1 - y_k^{P_1})$$

$$w_{ij}(n_0+1) = w_{ij}(n_0) + \eta_1 \sum_{P_1=1}^{P} \delta_{ij}^{P_1}\, x_i^{P_1}$$

$$\delta_{ij}^{P_1} = \sum_{k=0}^{m-1} \delta_{jk}^{P_1}\, w'_{jk}\, x_j'^{P_1}(1 - x_j'^{P_1}),$$

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where: n_0 is the number of computing times, and η_1 and η_2 are positive constants controlling the learning rate.

One of the limitations of a common BPNN is its extremely long training time. Furthermore, it is not guaranteed to find the global error minimum during training, only the local error minimum (Simpson, 1990). To improve the BPNN, the following methods are used during training:

(a) adjusting learning rates to improve the training time;
(b) adding a term of momentum to reduce oscillations;
(c) adding a factor γ to avoid local minimum,

which means that the effect function is formulated as follows when |u| is too large:

$$f(u) = 1/(1+e^{-u/\gamma}),$$

where: $\gamma > 1$. The details are not described here.

5.2. *Network Architectures.* In Section 3, the factors concerning the domain were discussed. These factors are input variables of the three-layer BPNN. To reduce the training time, all input and output variables are processed to be non-dimensional variables, which are in the range [0,1]. So we use B/L instead of L/B, T/B instead of B/T. Besides, the BPNN only learned from the samples with bearing ranges from 0° to 180° because of the domain's symmetry. The network architecture is as follows:

$$(x_0, x_1, x_2, x_3, x_4)^{\mathrm{T}} = (D/D_{\max}, B/L, T/B, C_b, \Phi/180°)^{\mathrm{T}}$$
$$(y_0) = (Dd/30L),$$

where D is the visible distance, $D_{\max}$ is valued to be 5 nm. The number of elements in hidden layer is determined to be 4 according to experience formulation (Zhang, 1992).

5.3. *The Results of Learning.* The BPNN has learned from 60 samples of ships that own a block coefficient value between 0·45 to 0·6 and are in open seas. The factor γ is assessed to be 2 while $|u| \geqslant 2{\cdot}7$. The weight arrays obtained from training are as follows:

$$w_{ij} = \begin{bmatrix} -13{\cdot}1144 & -29{\cdot}8105 & -6{\cdot}3031 & 0{\cdot}7341 \\ 15{\cdot}3340 & 5{\cdot}5597 & 0{\cdot}7590 & -6{\cdot}7113 \\ -11{\cdot}6485 & 2{\cdot}7129 & -0{\cdot}5249 & 6{\cdot}6641 \\ -58{\cdot}9336 & -4{\cdot}8159 & -1{\cdot}3709 & 30{\cdot}4000 \\ -7{\cdot}9328 & 0{\cdot}1178 & -15{\cdot}2356 & -5{\cdot}2774 \\ -36{\cdot}5766 & -18{\cdot}0743 & 2{\cdot}2259 & 16{\cdot}3015 \end{bmatrix}$$
$$w'_{jk} = [0{\cdot}4531 \quad 0{\cdot}5285 \quad 4{\cdot}7019 \quad 1{\cdot}5130 \quad 1{\cdot}0184]^T$$

The model is used to obtain domains for four ships. The geometrical characteristics of ships are as the follows:

Ship A: L = 82m, B = 12·5m, T = 4·2m, C_b = 0·49.
Ship B: L = 112m, B = 16·5m, T = 5·5m, C_b = 0·56
Ship C: L = 134m, B = 15·0m, T = 4·5m, C_b = 0·52
Ship D: L = 154m, B = 21m, T = 7·8m, C_b = 0·58

The results are shown in Table 1.

5. CONCLUSION. The paper has presented a concept of subjective ship domains. The relationship and difference between the subjective domain and the

Table 1. The Domain of Ships (nm).

Visibility (nm)	φ (°) 0	45	90	135	180
Ship A					
4	0·77	0·77	0·64	0·49	0·40
2	0·97	0·91	0·77	0·61	0·53
1	1·08	0·93	0·77	0·62	0·54
Ship B					
4	0·93	0·67	0·55	0·57	0·53
2	1·28	0·90	0·76	0·78	0·73
1	1·38	1·03	0·81	0·78	0·75
Ship C					
4	1·11	0·80	0·65	0·68	0·64
2	1·53	1·07	0·91	0·92	0·87
1	1·64	1·23	0·96	0·94	0·90
Ship D					
4	1·47	1·47	1·28	0·99	0·78
2	1·83	1·74	1·52	1·22	1·03
1	1·94	1·77	1·52	1·22	1·04

objective domain have been discussed. The analysis shows that the two kinds of domain have different usage. Unlike the objective one, the subjective domain is relatively steady for a certain ship. If a complicated objective domain can be decomposed into a few simple subjective domains, it will be easier to analyse the behaviour of navigators during collision avoidance.

A domain model based on neural networks has been derived that can express the effect of visibility and a ship's manoeuverability, and react quickly to a variety of situations. Because of the limited number of learning samples used, the model can only be applied to the ships that have a block coefficient value between 0·45 to 0·6. If learning takes place from enough samples, the model can also be applied to other ships.

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