A Ship Based Intelligent Anti-Collision Decision-Making Support System Utilizing Trial Manoeuvres

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Abstract: To provide a novel intelligent anti-collision decision-making support system it is necessary to facilitate a precise anti-collision information capability. In the reported research an innovative self-learning neurofuzzy network is proposed and applied to learn new information adaptively without forgetting old knowledge. To handle imprecise information a fuzzy set interpretation facility is incorporated into the network design. Additionally neural network architecture is used to train the parameters of the Fuzzy Inference System (FIS). The learning process is based on a hybrid learning algorithm and off-line training data. The training data is obtained from trial manoeuvres. This support system has been developed to help ship operators make a precise anti-collision decision, whilst simultaneously reducing the burden of bridge data processing.

Key Words: intelligent anti-collision, decision-making, trial manoeuvre, self-learning system, neurofuzzy

1 INTRODUCTION

The human error in ship operation is one of the most important factors leading to accidents. The International Maritime Organization cites human error as the casual fact in 80% of ship accidents [1]. Ship owners are constantly increasing the size and speed of new ships，this may reduce the manoeuvrability of the ship and make the waterways more congested. It can reduce the manoeuvring options as a wide-ranging variety of operational data and information must be correlated (manually) and mentally assessed by ship operators. The process can also be viewed as laborious because of the frequency of occurrence and hence can become a serious error-prone process. Navigation is becoming more and more complicated and can be dangerous.

Whilst anti-collision remains an important concern for all ships at sea, the collision avoidance regulations (COLREG 72) do not suggest precise or proper manoeuvres regarding specific situations. Many rules are qualitative and can only be used after quantifying the situation. Finding a safe, anti-collision manoeuvre is traditionally executed by drawing radar plots based on the observed echoes of the moving objects.

Newly built ships are equipped with specialized radar based anti-collision systems and automatic radar plotting aids (ARPA). With the rapid advances in computer technology, accurate positioning and navigation systems, there is a growing interest in applying intelligent methods to ship manoeuvring control. Automation is becoming more and more accepted in ship operations and ship-to-ship communication. e.g. Automatic Identification System (AIS). Such automation may be used in anti-collision measures.

Provision of an intelligent model for collision avoidance action requires careful consideration of the decision making scheme, identifying when to take action, an appreciation of anti-collision behaviour and assessing when to take action. These issues together with the computer simulation and off-line learning processes are presented in the following sections prior to applying the technique developed.

2 ANTI-COLLISION DECISION-MAKING SCHEME

Most of the information used for navigation is supplied independently to navigators by individual sensors in a raw form. Continuous monitoring and analysis of all information regarding all target ships becomes difficult due to human limits of analysis capability and hence mistakes can be made. Decision-making is mainly based on visually observed information. Prediction relying on visual observation is often difficult and so the execution of an anti-collision action is a very complicated task.

Collision avoidance decision-making is the comprehensive utilization of raw data, regulations for preventing collisions, human experience and skills. Human ability is obviously influenced by environmental and psychological factors. When encountering a developing situation, ship operators will be confronted with data from a variety of sources and are then required to make collision avoidance decisions in a tense situation. These conditions can cause information overload, which results from the operators' inability to interpret a large amount of data rapidly.

In parallel with the development of world shipping, modern science and new technology, many researches have designed automatic collision avoidance systems. The core of the anti-collision process is the automatic decision making task. Several anti-collision models have been set

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up. Goodwin suggests a model based upon the theory of 'ship domain' [2]. A ship domain may be thought of as the sea around a ship that the navigator would like to keep free of other ships and fixed objects. Davis et al. enhanced the model by adding the theory of 'arena' [3]. A ship arena is a larger domain based upon the distance from another ship at which a mariner would start to take action in order to avoid a close quarter's situation. Colley et al. proposed the Range to Domain and Range Rate model (RDRR) [4]. Each of these models endeavours to address the navigator's concern with physical separation of ships, and their perception with ship-ship encounters when regions (domain or arena et cetera) become populated with other ships. The concepts have little to do with either the selection or the timing of an avoidance action.

Concerns regarding ship safety are partially addressed through improved availability of relevant information and through the provision of Automatic Radar Plotting Aids (ARPA), Electronic Chart Display and Information System (ECDIS) and Automatic Identification System (AIS). With the rapid advances in computer technology, accurate positioning and navigation systems, the intelligent method is receiving more attention in the context of anti-collision system development.

To make a collision avoidance decision requires the own-ship operators to address three important points:

(1) Whether an anti-collision action is necessary.
(2) Pattern of the anti-collision behaviour.
(3) When own-ship should take action.

Here intelligent approaches are applied to collision avoidance decision-making by extending the processing of radar data and AIS data to provide a quantitative measure of collision risk for any traffic situation. If such a risk does exist, then specific manoeuvre advice is generated. The proposed anti-collision scheme is demonstrated in Fig. 1.

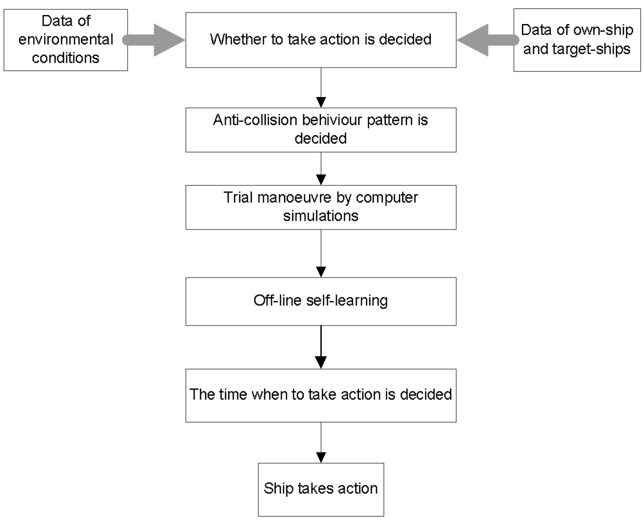

Fig. 1 Demonstration of process to identify anti-collision action scheme

3 WHETHER TO TAKE ACTION

Ship operators normally decide on the need for any actions through their appreciation of the collision regulation, the size of the ships involved and the value of Distance of the Closest Point of Approach (DCPA). When DCPA is less than half the sum of the width of the two encountering ships, the two ships will collide in all encountering situations unless some action is taken. Let the universe U_d be the class that represents the changing field of DCPA, where $\tilde{A}_d$ is the fuzzy set in U_d such that $\mu_{\tilde{A}_d}$ indicates the membership function of $\tilde{A}_d$ and the authors assign it as follows:

$$\mu_{\tilde{A}_{d\alpha}}(DCPA) = \begin{cases} 1 \\ : DCPA \le (w_o + w_t)/2 \\ \exp[-(\dfrac{DCPA - (w_o + w_t)/2}{L_o + L_t})^2] \\ : DCPA > (w_o + w_t)/2 \end{cases} \qquad (1)$$

Thus $\mu_{\tilde{A}_d}$, as defined, provides an assessment of the need (degree of urgency) to take some action to prevent a collision scenario. It is treated as a function of DCPA, w_o, the width of the own-ship, w_t, the width of the target-ship, L_o, the length of the own-ship and L_t, the length of the target-ship. The units of DCPA, ship width and ship length are nautical miles. That is, in restricted waters the ship dimensions influence the decision-making process. For the ships to keep well clear, after collision avoidance action, DCPA should be made as large as possible. On the other hand, optimal economic navigation requires the least deviation from the original selected course. $\mu_{\tilde{A}_d}(DCPA)$ as defined, provides a continuously varying function. However, in reality it is more likely that action will be taken or not depending on whether $\mu_{\tilde{A}_d}$ assumes a value above or below some threshold of concern. This situation is addressed by use of the so-called α-cut concept, that is, action is based on a binary value of $\mu_{\tilde{A}_d}$ defined as:

$$\mu_{\tilde{A}_{d\alpha}}(DCPA) = \begin{cases} 1 : \mu_{\tilde{A}_d}(DCPA) \ge \alpha \\ 0 : \mu_{\tilde{A}_d}(DCPA) < \alpha \end{cases} \qquad (2)$$

When $\mu_{\tilde{A}_{d\alpha}}(DCPA) = 1$, the ship operators will need to take action to avoid collision.

The selection of the threshold α will depend upon the nature of the restricted water, such as wind level and current speed. However, α will be assigned a value from the open interval (0,1).

4 ANTI-COLLISION BEHAVIOUR PATTERN

To make a decision on when to take action depends on what kind of anti-collision behaviour pattern the own-ship will take. The decision must comply with COLREG 72 for the actual encounter situation. The encounter situation is also covered by COLREG 72 and is divided into three main types and each type has some subdivisions. Each main type of encounter situations is now considered in turn.

(1) Head-on

The own-ship and target-ship are approaching each other on a reciprocal or near-reciprocal course. Both ships should alter their courses to starboard so that each shall pass on the port side of the other.

(2) Crossing

The own-ship and target-ship are crossing each others intended path and so involve the risk of collision. The own-ship is the stand-on ship and keeps its course and speed when the target-ship is crossing from port to starboard of the own-ship. If the target-ship fails to take action, the own-ship alters course substantially to starboard and turns 360 degrees. The own-ship is the give-way ship when the target-ship is crossing from starboard to port of the own-ship. If there is sufficient sea room, the own-ship can alter course substantially to starboard and cross from the astern of the target. If the circumstance of the case does not admit course change, then own-ship must reduce speed.

(3) Overtaking

A ship shall be deemed to be overtaking when another ship approaches from a direction more than 22.5 degrees abaft her beam.

If a target-ship overtaking an own-ship, the own-ship is the stand-on ship and keeps its course and speed.

If an own-ship overtaking a target-ship, the own-ship is the give-way ship. If own-ship is on the starboard quarter of target-ship, the own-ship alters course to starboard. If own-ship is on the port quarter of the target-ship, then own-ship alters course to port.

In an implicit way the different scenarios indicate which ship may initiate a change in course and the conditions under which the other ship may take action. This leads us to consider next when an action should commence.

5 ASSESSING WHEN TO TAKE ACTION

For a target-ship, Part (a) of Rule 8 in COLREG 72 states that: "Any action taken to avoid collision shall, if the circumstance of the case admits, be positive, made in ample time and with due regard to the observance of good seamanship."

The last part of this statement implies an understanding of the correct response to the prevailing conditions. If a ship needs to take action as it approaches a target-ship, then the ship should act as soon as possible. However, the environmental conditions are continuously changing and hence there usually exists a reluctance to act too early. The actual time at which action is taken represents a compromise between these two conflicting influences.

Before taking action each ship involved should correctly identify whether it is the give-way ship or the stand-on ship. Only when the give-way ship does not take action in good time, may the stand-on ship take action to avoid collision. It is the value of the 'Time to the Closest Point of Approach (TCPA)' that influences when the selected manoeuvre should be conducted.

In order to determine when the first manoeuvre of anti-collision shall be taken, Davis et al. used a large version of the domain as his arena [3, 5]. It was suggested that the action should be a function of the time taken to the Closest Point of Approach (CPA) of the own-ship. Colley et al. developed the idea to be the time taken for the target-ship to reach the domain boundary according to the RDRR model [4]. The arena and domain boundary have formerly been employed to define distance.

Here, the collision avoidance model will be defined in terms of time. Firstly the ship operators should decide on the Safety Distance to Approach (SDA) according to the environmental situation. Then trial manoeuvres by computer simulation will be implemented to collect data. Finally, the Time to Take Action (TTA) will be obtained by off-line self-learning intelligent approach. TTA here means the value of TCPA at the moment the own-ship should take action

6 TRIAL MANOEUVRE BY COMPUTER SIMULATIONS

The Automatic Radar Plotting Aids (ARPA) provides efficient navigational support with regard to speed and accuracy of calculation. ARPA facilitates the navigator's work considerably with its ability to process data and display the navigational situation on the radar screen, thus allowing the navigator to make reasonable decisions about which manoeuvre to adopt. However, on the basis of this information, the final decision on how to act to avoid the collision must still be made by an individual navigator. The most significant feature of ARPA is the so-called trial manoeuvre facility, in which the vector representing the own-ship motion may be modified continuously, with all target-ship vectors being adjusted and displayed accordingly. Thus a proposed manoeuvre by own-ship may be rapidly assessed in terms of its effectiveness relative to all nearby target-ships. Thus in theory to identify the efficient action one may simulate all possible anti-collision actions by trial manoeuvres using ARPA. However, this is a large task and may take more time than the time available before the own-ship should take action.

In this paper, it is assumed that AIS is to be installed on board. To collect the required training data set, a trial manoeuvre is investigated by means of a live off-line computer simulation in non-real-time style. This means the simulation is applied at the time when own-ship encounters a target-ship. The heading, speed and bearing of target-ship and hence the relative speed, DCPA and own-ship manoeuvrability are fixed at that moment. After a new course is set, the Passing Distance (PD) is determined for different randomly assigned TTA values.

The MMG model is used as the ship manoeuvring mathematical model for trial manoeuvre. The ship manoeuvring mathematical model group in Japan built the nonlinear ship mathematical model. For the anti-collision problems only the horizontal ship motions of surge, sway and yaw to the rudder at a constant cruising speed is considered. The detail of the model is described in the work of Jia [6].

Having outlined how manoeuvring data is made available to assist with the decision making the off-line learning procedure can be described.

7 OFF-LINE SELF-LEARNING SCHEME

Within the context of the research reported 'self-learning' means the construction of a Fuzzy Inference System (FIS) to achieve a desired nonlinear mapping between a number of relevant input-output pairs related to the target-ship. The quality of the mapping is dependent upon the number of pairs and the data that is regulating the mapping is sufficiently large and representative data set. Once the FIS parameters have been adjusted to improve performance, the system can perform a prescribed task without resorting subsequently to human experts. Here the only input factor is SDA.

The data that is generated to train the network is obtained through the trial manoeuvre of a virtual own-ship using the indicated computer simulations. Through each manoeuvre, a set of data (SDA, TTA) is collected. After 100 such simulations there are 100 inputs of the SDA with 100 corresponding values of output TTA, determined on the basis that SDA has been equated PD. The self-learning off-line training scheme deployed in this research is shown in Fig. 2.

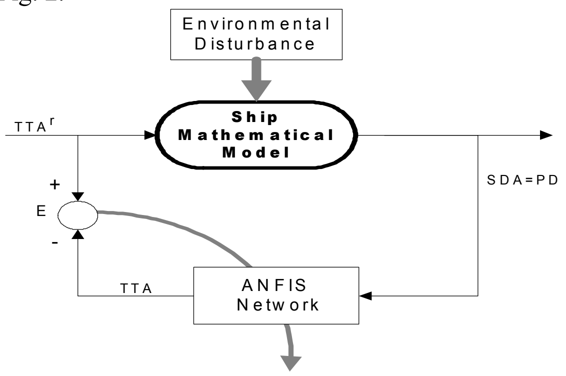

Fig. 2 Self-learning off-line training scheme

Fuzzy logic provides a feasible control method in the sense that it can readily capture the approximate and qualitative aspects of human knowledge and reasoning. However, the performance of fuzzy logic relies on two important factors:

(i) The quality of the knowledge acquisition techniques used.
(ii) The availability of domain experts.

These two factors substantially restrict the application domains of fuzzy logic. Here this means that whilst the FIS consists of interpretable linguistic rules, the FIS cannot learn and therefore learning algorithms, based on neural networks, are used to create the FIS from the available generated data. The learning algorithms can identify fuzzy sets parameters and fuzzy rules and exploit any available prior knowledge.

The intelligent method used is known as an Adaptive Neuro-Fuzzy Inference System or ANFIS for short. Fundamentally, ANFIS is about taking a fuzzy inference system (FIS) and tuning it with a back-propagation algorithm using the available input-output data. This allows the fuzzy systems to learn. The ANFIS can construct an input-output mapping based on both human knowledge and stipulated input-output data pairs. The selected ANFIS network uses a hybrid-learning algorithm to identify the parameters of the Sugeno-type FIS [7]. A combination of the least-squares method and the back-propagation gradient descent method is used in the training the parameters of the fuzzy inference system membership function required to emulate a given training data set [8]. As already stated the selected training data set consists of a finite number of pairs consisting of SDA and TTA values. The self-learning system is demonstrated in Fig. 3.

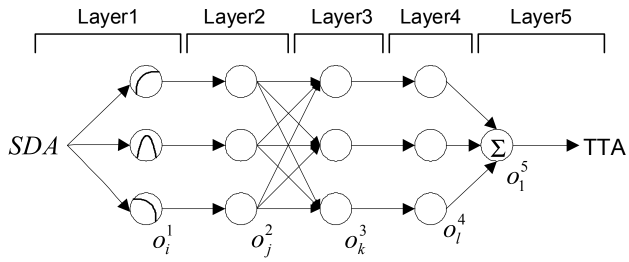

Fig. 3 The proposed ANFIS network

The Neurofuzzy network has 5 layers. The subscripts i, j, k and l define the number of neural units in each layer.

The first layer uses the input parameter *SDA* to form the three outputs defined by:

$$O_i^1 = \mu_{A_i}(x) : i = 1,2 \,\&\, 3. \tag{3}$$

Here x denotes the input to i^{th} node. The actual value of x is also expressed in terms of the linguistic label (small, big, etc.) associated with this node function. O_i^1 is essentially the membership function of A_i when x assumes the input value A_i. The membership functions are defined to have the bell-shaped form:

$$\mu_{A_i}(x) = \frac{1}{1 + (\frac{x - c_i}{a_i})^{2b_i}} \tag{4}$$

where a_i, b_i and c_i are the neural network parameters that are updated in the adaptation process.

The second layer computes the values of the membership functions of the input variables. Normally the outputs of the nodes in this layer are a result of the multiplication of inputs from the first layer nodes, but since there is only one input (*SDA*),

$$O_j^2 = w_j = \mu_{A_j}(SDA) : j = 1,2 \,\&\, 3, \tag{5}$$

In this case the values of the node outputs is said to represent the strength of the rule.

The third layer of the fuzzy controller network corresponds to the rule base. A node k in the third layer combines all the conditions in the if-part of rule k and computes the rule strength w_k, the degree to which the k^{th} rule at the k^{th} node is satisfied using

$$O_k^3 = \overline{w_k} = \frac{w_k}{\sum_{j=1}^{3} w_j} : k = 1,2 \,\&\, 3, \tag{6}$$

The fourth layer corresponds to the rule consequent part. It produces the defuzzified Sugeno-type output to each previous l^{th} output

$$O_l^4 = \overline{w_l} f_l = \overline{w_l} s_l SDA + t_l : 1,2 \,\&\, 3, \tag{7}$$

where s_l, t_l are consequent parameters which are updated on the forward pass.

The fifth and final layer is the single output layer that calculates the total output as

$$O_1^5 = \sum_l \overline{w_l f} = \frac{\sum_l w_l f}{\sum_l w_l}. \tag{8}$$

Having outlined the required data sets and the different tools deployed in the innovative collision avoidance algorithm the technique is demonstrated.

8 APPLICATION OF ANTI-COLLISION SUPPORTING SYSTEM

To demonstrate the intelligent anti-collision decision-making supporting system, a general cargo ship with a length of 126.0 m and a width of 20.8 m is used as the own-ship. The speed of the own-ship is 11.8 knots.
The target-ship has a length of 196m, a width of 30m and is travelling at a speed of 7.7 knots. Its course has a setting of 250° with a bearing of 028° with respect to the own-ship as illustrated in Fig. 4. In this environment α is defined as 0.5 and SDA is set at 1.0 miles.
The development of the situation and the calculation procedure associated with the own-ship taking action are as follows:

(1) According to COLREG 72 the own-ship is the give-way ship and the target ship is the stand-on ship. Hence in this case the own-ship is required to take collision avoidance action when necessary. Assume the data about the target-ship is available to the own-ship through implementation of AIS.

(2) In accordance with the positions, speeds and courses of the own-ship and the target-ship, DCPA is calculated as 0.1 nm. In accordance with Equation (1) & (2), $\mu_{\tilde{A}_{d\alpha}}(DCPA) = 1$, so action must be taken in accordance with the model.

(3) Generate a random set of TTA values designated TTA^r Values of PD are obtained by trial manoeuvre. Assign SDA equal to PD. After 100 simulations for the different TTA^r values, Table1 shows the TTA values calculated by ANFIS approach for different angle between original course and new course in crossing situation.

Table1. The relationship between TTA and course changing angle in crossing situation

Angle between original course and new course	20°	30°	40°	50°	60°
TTA (minute)	15.42	12.18	9.47	8.85	8.58

To assess whether such a TTA value is reasonable, simulate the own-ship approaching target-ship with the action of altering course to starboard 30° at this TTA (12.18 minutes). The ship track and the result of the described action are shown in Fig. 5. It should be noted that this TTA almost satisfies SDA = PD.

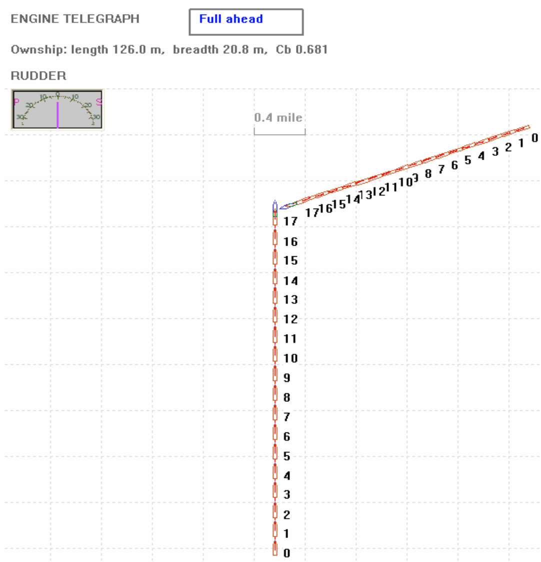

Fig. 4 The ships track when no decision had been made in crossing situation

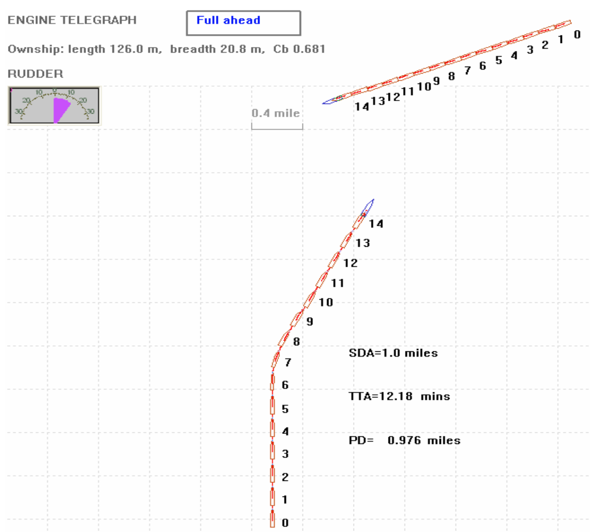

Fig. 5 The test of TTA in crossing situation with altering course to starboard 30°

In another application the own-ship is a container with a length of 224.5 m and a width of 32.2 m. The speed of the own-ship is 19.6 knots. The target-ship is the same one as above. Its course has a setting of 003° with a bearing of 358° with respect to the own-ship. α is defined as 0.4 and SDA is set as 1.2 miles. Table2 shows the TTA values calculated by ANFIS approach for different angle between original course and new course in overtaking situation.

Table2. The relationship between TTA and course changing angle in overtaking situation

Angle between original course and new course	10°	20°	30°	40°	50°
TTA (minute)	21.35	12.86	10.22	8.89	8.65

The ship track and the result are shown in Fig. 6 when the action of altering course to starboard 20° at the responding TTA (12.86 minutes).

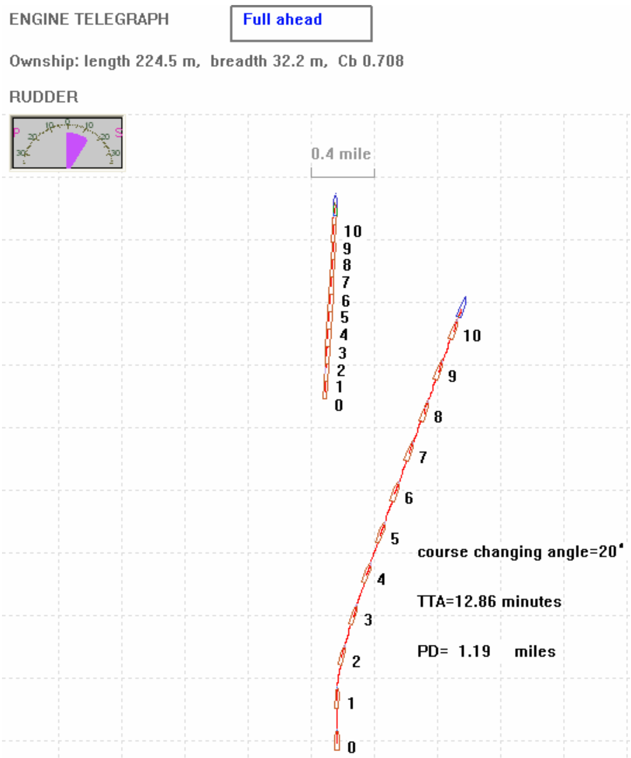

Fig. 6 The ship track in overtaking situation with altering course to starboard 20°

9 CONCLUSIONS

This paper has introduced a self-learning off-line training scheme to obtain TTA values. This is an important parameter in the developed intelligent anti-collision supporting system. The system has used the ANFIS learning algorithm and the three-stage calculation model to facilitate automatic collision avoidance using fuzzy theory and expert navigation experience. The ships selected for the demonstration are assumed to have installed both AIS, ECDIS so as to obtain data and information on the target-ships. Fuzzy logic is applied to identify whether the ship should take action to avoid collision. Recognizing that the ship anti-collision process represents a complicated situation, ship manoeuvrability and ship sizes are considered in the model.

From the simulation results, the ANFIS algorithm with the self-learning training obtains a rather precise TTA. The model appears to be suitable for ship encounters.

Need to mention that in this paper one has only considered the immediate action to take to avoid potential collision. One has not considered the full sequence of anti-collision action. In the future research, multi-ship, uncoordinated ship will be studied.

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