Artificial Intelligence-Based Methods for Decision Support to Avoid Collisions at Sea

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Abstract: Ship collisions cause major losses in terms of property, equipment, and human lives. Therefore, more investigations should be focused on this problem, which mainly results from human error during ship control. Indeed, to reduce human error and considerably improve the safe traffic of ships, an intelligent tool based on fuzzy set theory is proposed in this paper that helps navigators make fast and competent decisions in eventual collision situations. Moreover, as a result of selecting the shortest collision avoidance trajectory, our tool minimizes energy consumption. The main aim of this paper was the development of a decision-support system based on an artificial intelligence technique for safe ship trajectory determination in collision situations. The ship’s trajectory optimization is ensured by multistage decision making in collision situations in a fuzzy environment. Furthermore, the navigator’s subjective evaluation in decision making is taken into account in the process model and is included in the modified membership function of constraints. A comparative analysis of two methods, i.e., a method based on neural networks and a method based on the evolutionary algorithm, is presented. The proposed technique is a promising solution for use in real time in onboard decision-support systems. It demonstrated a high accuracy in finding the optimal collision avoidance trajectory, thus ensuring the safety of the crew, property, and equipment, while minimizing energy consumption.

Keywords: fuzzy environment; decision making; artificial intelligence; neural networks; evolutionary algorithm; ship trajectory; collision situations

1. Introduction

Today, artificial intelligence is used in almost all areas, with the optimization of technological processes being at the forefront [1–7]. In the last decade, the development of new information technologies and rapid computing allowed for the creation of suitable opportunities for marine navigation automation and the modernization of decision-support systems that ensure ship movement control along its courses. Thanks to this important development, it is now possible to integrate computer systems for improving the crew’s working conditions and ensuring safety on the ship [8–14]. In this context, many studies have been orientated towards the very interesting topic of ship steering and control. Moreover, certain recent publications have covered the issues of the safety and efficiency of ship steering in various seas areas under different constraints [15–17]. On the other hand, many techniques have been proposed for solving the aforementioned problem of ship steering in specific cases, based on both conventional techniques and more developed ones. Herein, the main aim was to provide assistance to navigators in terms of making the appropriate and accurate maneuvering decisions under certain conditions, using such techniques as those proposed in the references [18–25]. The study presented in this paper was dedicated to the issue of determining the optimal safe trajectory of a ship at sea, where many other ships can be encountered in the vicinity, using selected methods based on...
artificial intelligence techniques, such as fuzzy logic, neural network, genetic algorithms, and particle swarm optimization algorithms. In fact, many papers propose methods for the determination of the safe trajectory of a ship in a collision situation based on fuzzy logic [24–28], while other researchers propose algorithms for solving the same problem based on neural network techniques [26,29,30]. Furthermore, other proposed methods that are used widely in this domain are based on evolutionary algorithms, genetic algorithms, and their modified variants, such as the works presented in [31–33]. Another group of papers proposed the use of particle swarm optimization for finding a ship’s optimal safe trajectory in collision situations, such as the method proposed in [33–35].

Indeed, the research on establishing new effective methods for avoiding ship collisions has become very important as the number of vessels involved in maritime transport has increased. Moreover, the size and speed of these vessels has also increased. On the other hand, since automatic radar plotting aid (ARPA) was integrated in ship controls, the safety of shipping has greatly improved. It is obvious that the information transmitted from the automatic identification systems (AIS) placed on ships provides their locations. These are placed in research manuscripts made up of large datasets that are publicly available on all ships and are used by the anticollision system (ACS), the main task of which is to determine the ship’s trajectory during dangerous situations. The trajectory, which is designated by the ACS, is not only completely safe but is the optimal trajectory so as to avoid major losses on the road, e.g., wasted time and energy consumption. The basic element of the ACS and its software, which were based on modern methods of ship steering, were proposed in various previous studies [36–44].

The process of automatic selection, which allows the best collision avoidance maneuver to be identified corresponding to the optimal safe trajectory of the ship based on the information acquired from the ACS, is a topic of great interest in ship control. In particular, this paper investigates the process of determining a ship’s optimal position and the engaging stages of ship path planning based on the kinematical model. As a result of the navigator’s individual approach to making decisions, and certain concepts that are imprecisely and ambiguously determined, the process of avoiding collisions at sea takes place in a fuzzy environment. Referring to the aforementioned thesis, one can conclude that these terms are subjective and depend, to a large extent, on the circumstances and conditions of navigation.

This paper presents a method for approaching safe ship control in collision situations as a multistage decision-making and control process in a fuzzy environment, as shown in Figure 1 [45]. Ship trajectory determination in collision situations requires decisions to be made at every stage of this trajectory. This means that at each stage, it is necessary to select the optimal safe maneuver of the ship, i.e., all decisions taken at each stage of the optimal maneuver make up the safe optimal trajectory of the ship.

![Figure 1. The flowchart of the proposed decision-support system principle.](image-url)
In previous a study, the authors of this paper presented a method for identifying the fuzzy properties of the process under study, i.e., the determination of the safe trajectory of a ship when it encounters one or more targets in the sea in the vicinity: what is known as a collision situation. Indeed, this task cannot be performed without specifying the accurate parameters to as great a degree as possible, which characterize the navigator’s subjective decisions in a specific situation. The research that was conducted by the authors in the previous work among captains and navigational officers based on prepared questionnaires led to the identification and selection of the type of decisions that are used in the multistage decision-making process model [6]. It is obvious that it is not possible to investigate every navigational situation and take into account all the constraints. However, a description of several basic situations allows one to treat any situation as the result of several basic situations based on the principle of superposition. For this reason, it is important to investigate all basic navigational situations. It is worthy of mention that each situation can be distinguished by the course angle, the course difference, the ship speed, the dynamic properties of the ship, and the visibility criteria, which depend on the surrounding weather. It can be said that, while a navigator’s reaction to the parameters is subjective, the role of the navigator, i.e., the human factor, is taken into account, and was incorporated into the equations that represent the process. This is the main contribution of this paper. Indeed, the two methods proposed for solving the presented task were based on the anticollision neural network (ACNN) and anticollision evolutionary algorithm (ACEA).

2. The Process Modeling

For the precise description of a ship’s safe trajectory, the ship’s movement as driven by its rudder in the deep water must be presented. On the other hand, for the dynamic properties of ship evaluation, the parameters of model transfer function, maximum angular speed $\omega_z$, and advance time $t_w$ were investigated by the authors in this paper. Indeed, the maneuver parameters were chosen based on ship dynamic behavior under operating conditions, which depend on the speed, the load, the rudder angle, and the local conditions around the ship.

Typically, ship maritime maneuvers in collision situations comprise two phases:

1. Target tracing, based on the TCPA (time to closest point of approach) and DCPA (distance to closest point of approach), is used to assess the collision situation risk.
2. The anticollision maneuver is executed, following the recommendations of the International Regulations for Preventing Collisions at Sea COLREG, whereby the determination of the ship’s safe trajectory in a fuzzy environment is limited to multi-stage decision making. The fuzzy decision allows for the evaluation of the decision quality, which can be presented by an aggregation of the fuzzy environment and objectives [46].

The anticollision system ensures the interpretation of the radar signals and the generation of precise information concerning the traffic of the objects being traced, both relative and real. Therein, the processing circuit of the signal performs initial and secondary signal processing. In the primary process, the interpretation of the radar signals is performed, i.e., they are synchronized with the rotational movement of the antenna rotation. Moreover, the polar coordinates are identified through this process, including the distance and bearing between the ship and the objects, as shown in Figure 2.
which can be presented by an aggregation of the fuzzy environment 

\[ DCPA(CPA) = \text{the closest point of approach}; D_j = \text{distance between ship and } j\text{-target}; V = \text{ship speed}; V_j = j\text{-th object speed}; \psi = \text{ship course}; \psi_j = j\text{-th object course}; N_j = \text{bearing of the } j\text{-th object}. \]

By omitting the speed drop during the maneuvering course, the kinematic relative movement of the ship as regards its dynamic properties can be approximated using the following equations:

\[ X_j(t) = X_j(t - 1) + (V_j \sin \psi_j - V \sin \psi)t_w + \frac{(V_j \sin \psi_j - V^* \sin \psi^*)}{\omega_z} \cdot t_w \left( \frac{|\psi^* - \psi|}{2} \right) + (V_j \sin \psi_j - V^* \sin \psi^*)t_k \tag{1} \]

\[ Y_j(t) = Y_j(t - 1) + (V_j \cos \psi_j - V \cos \psi)t_w + \frac{(V_j \cos \psi_j - V^* \cos \psi^*)}{\omega_z} \cdot t_w \left( \frac{|\psi^* - \psi|}{2} \right) + (V_j \cos \psi_j - V^* \cos \psi^*)t_k \tag{2} \]

where \( X_j(t - 1), Y_j(t - 1), X_j(t), \) and \( Y_j(t) \) are the corresponding coordinates of the \( j\)-th target in the floating coordinate system associated with the ship under control before and after the maneuver; \( \psi_j \) and \( V_j \) are the corresponding course and speed of the \( j\)-th target, respectively; \( \psi, V, \psi^*, \) and \( V^* \) are the corresponding course and speed of the ship under control before and after the maneuver, respectively; \( t_w \) is the ship overtaking time, and \( \omega_z \) is the maximum angular speed.

The safe control of the ship is described as a decision-making process within a fuzzy environment [47,48]. In this paper, a nonlinear discrete-time state equation is used to present the studied system model as follows [49]:

\[ X(k + 1) = f(X(k), U(k)) \tag{3} \]

where \( X(k+1), X(k) \in X \) are sets of real ship position coordinates at times \( t + 1 \) and \( t \), respectively.

\( U(k) \in U \) is the control set.

The ship will reach final states, which are defined by \( W \subset X \). These are called the turning points and are points at which the process ends. The set of final states must fulfill the following conditions:

\[ \begin{align*}
V &= V^*_{opt} \\
\psi &= \psi^*_{opt} \\
\mu_R &\leq \mu_{safe}
\end{align*} \tag{4} \]
where $\psi^*$ is the ship under control’s optimal course; $V^*$ is the ship under control’s optimal speed; $\mu_R$ is the value of the collision risk membership function.

The fuzzy set decision is defined as the fuzzy set $D \subseteq X \times U$. It is a result of an operation “$*$” of the fuzzy set of the goal $G$ and the fuzzy set of the constraints $C$, as follows:

$$D = G * C,$$

Hence, the membership function is

$$\mu_D(\ldots) = \mu_C(\ldots) * \mu_G(\ldots)$$

### 2.1. The Fuzzy Goal Membership Function

The anticollision maneuver, i.e., the action performed to avoid a collision with another sea traffic participant, should be made in a manner so that the two ships, which are near each other, can pass at a safety distance without collision. The maneuver has to be controlled until the nearby ship passes and leaves. Indeed, different security assessments can be performed by navigators and can be described as a fuzzy goal membership function, which allows a subjective assessment. This can be defined as follows:

$$\mu_G(k, j) = 1 - \frac{1}{\exp(\lambda_D(k,j)DCPA^2)}$$

if $TCPA > 0$,

$$= 1$$

if $TCPA < 0$

### 2.2. The Fuzzy Constraints Membership Function

Each attempt at an anticollision maneuver changes the objective of the navigator’s course. It is obvious that the change of course leads to an increase in the length of the ship’s trajectory, which causes additional fuel and time losses. Therefore, the navigator’s main task is to ensure that the ship moves away from the target at a safe distance with an optimal trajectory that ensures minimal losses. To take this issue into account, the fuzzy constraints membership function is introduced and can be presented as maneuvering restrictions at each stage and is expressed as follows:

$$\mu_C(k) = \frac{1}{\exp(\lambda_C(k)(V\cos\psi(k) - V\cos\psi(k-1) + L)t_k^2)}$$

where $t_k^2$ is the time in minutes to pass between stages 0 and $k$; $L$ is the distance from the original course, which is defined by the following expression:

$$L = |c(k) + tg(V\cos\psi(k) - V\cos\psi(k-1) + \Delta d)|$$

where $c(k)$ is the distance from the original course at that stage; $\Delta d$ is the distance separating two successive stages within the original path.

The limitation value of the fuzzy membership function is greatest when the ship does not change course and when it is on the original course $\mu_C(k) = 1$. With the increase in the difference between the original course and the course of the anticollision maneuver at a given stage $t$ and the distance from the original course, the membership function tends to zero $\mu_C(k) \to 0$.

### 2.3. The Fuzzy Collision Risk Membership Function

Ships involved in a collision situation are evaluated according to the degree of collision risk, which is considered as a collision risk indicator. This indicator is defined in relation to the current approximated situation, as defined by the DCPA(CPA) and TCPA parameters, and to a safe situation as determined by a safe time and safe distance, which are required to avoid the eventual collision maneuver. Many scientists base a ships’ safety maneuver
on the collision risk assessment [50–55]. In this paper, the fuzzy collision risk membership function is proposed as a collision risk assessment tool and is defined as follows:

$$\mu_R(k, j) = \begin{cases} \frac{1}{\exp(\lambda_R D(k, j) + \lambda_D DCPA_j + \lambda_C TCPA_j^2)}, & \text{if TCPA}_j > 0, \\ 0, & \text{if TCPA}_j < 0 \end{cases}$$ (10)

where $\lambda_{RD}$, $\lambda_{RT}$, $\lambda_D$, and $\lambda_C$ are the parameters determining the subjectivity of navigators; $DCPA_j$ is the distance to closest point of approach; $TCPA_j$ is the time to closest point of approach.

2.4. The Fuzzy Properties of the Ship Control Process

Identifying the fuzzy properties of the process, which represent the determination a ship’s safe trajectory in a collision situation, cannot be achieved without the accurate determination of the parameters, which characterize the navigators’ subjective decisions within a given situation. On the basis of the study carried out among navigators using surveys for this purpose, the categories of decision types used in the multistage decision-making process were determined, which can be summarized as follows:

I. It is not possible to investigate every navigational situation that may occur in the course of a voyage. However, describing several basic situations creates the opportunity to treat any situation as the result of several basic situations (the superposition principle). Therefore, it is of great importance to investigate all eventual basic navigation situations. These situations can be classified according to the exchange angle, the difference in courses, the ship under control’s speed, the target speed, the dynamic characteristics of the ship, and the visibility criteria.

II. Twelve categories were determined from all ship meetings. The surface surrounding the ship is split up into sectors following to the exchange angle. Thanks to this, one can classify all basic ship meetings based on the course and the courses between ships. Because the angles are divided into sectors, the twelve ship meeting categories are determined depending on the side of the ship facing the measured object.

To ensure a precise description of the fuzzy set membership function, the coefficients $\lambda_{RD}$, $\lambda_{RT}$, $\lambda_D$, and $\lambda_C$ were used to precisely characterize the subjective ship safety assessment and the loss of the path, and to determine the fuzzy collision risk membership function. These coefficient values were calculated based on empirical studies carried out among navigators. The simulations presented in this paper take into account the navigator characteristic collision situations, which were based on the information obtained from previous ship traffic studies.

For example, it is important to initially specify the values of the fuzzy collision risk membership function for each situation and the category of the ship with accurate and limited visibility. It is clear that the collision risk membership function can have values from 0 to 1, i.e., $\mu_R(k, j) = 0$ means a total safety situation is ensured, and $\mu_R(k, j) = 1$ means the situation is an extremely dangerous.

3. Algorithms

3.1. Assumptions about EA in Multistage Fuzzy Control—ACEA

In the context of multistage fuzzy control, a unit is known as a sequence of individual control values at successive control stages $U_0, \ldots, U_{N-1}$. In the terminology of evolutionary algorithms, this unit corresponds to the concept of an individual whose adaptation in a fuzzy environment is assessed using the fuzzy decision membership function. On the basis of the value of this decision, potential solutions (control sequences) are selected. The set of these solutions constitutes the population. It should be assumed that the algorithm will operate on a population of a certain size, which is initially generated randomly. Some members of the population, playing the role of parents, are reproduced by crossing and mutating, producing descendants (children), i.e., new solutions. The best of these (the most
adapted) “survive”, that is, they continue to participate in this process. At the end of this process, one can expect to find a very good, perhaps even optimal solution [49,55].

The problem of determining the safe trajectory of a ship, which was formulated above in this paper, is to find the optimal sequence of controls such that

$$
\mu_D(U_0^*, U_1^*, \ldots, U_{n-1}^*|X_0) = \max_{U_0, \ldots, U_{n-1}} \mu_D(U_0, U_1, \ldots, U_{n-1}|U_0)
$$

\[= \max_{U_0, \ldots, U_{n-1}} \left[ \mu_0^D(U_0) \land \mu_1^C(U_1) \land \mu_1^G(X_1) \land \mu_2^C(U_2) \land \ldots \land \mu_n^C(U_n) \right] \] (11)

where at each time \((t-1)\), a fuzzy constraint \(\mu_{t-1}^C(U_{t-1})\) is imposed on the control \(U_{t-1} \in \mathbf{U}\) and a fuzzy goal \(\mu_t^G(X_t)\) is imposed on the state \(X_t\) at time \(t\).

Before using this algorithm, the following assumptions must be taken into account:

- The problem is represented by the sequence of controls \(U_0, \ldots, U_{N-1}\) and, due to the relief of the algorithm and the simplification of the analysis of the results, the ship under control’s speed is assumed to be constant, and the control \(U_{t+1}\) at \(t+1\) is defined as the course angle \(\Psi_{t+1}\) with respect to the angle at the previous angle, which can be expressed as follows:

\[S_{t+1} = \psi_{t+1} - \psi_t \in \mathbf{U} \] (12)

- Without changing the coding, the real representation of each uniformly distributed gene is assumed to be \(U_t \in [0, 360]\), which is the most realistic range in the case under consideration;
- The evaluation function of each individual is the membership function of a fuzzy minimum-type decision defined by the following expression:

\[\mu_D(U_0, U_1, \ldots, U_{n-1}|X_0) = \mu_0^D(U_0) \land \mu_1^C(U_1) \land \mu_1^G(X_1) \land \mu_2^C(U_2) \land \ldots \land \mu_n^C(U_n) \] (13)

- Individuals with the highest value of the evaluation function have the largest share in the next parental population, and the “weaker” individuals are rejected in the selection process;
- The selection process is proportional- or rank-based selection;
- The averaging cross is used as it presents the most suitable for floating point encoding;
- The used mutation presents a perturbation of genes in accordance with the Cauchy distribution and a certain probability of occurrence in subsequent generations;
- When creating the next generation, the individuals of the parent population are not all rejected, and a certain number of (the best) are added to the descendant individuals;
- The algorithm computation is stopped when a certain criterion is satisfied. In this paper, this criterion is taken as being when the individuals progress is less than a given threshold. The outline of the simplest evolutionary algorithm that meets the above suppositions can be presented in the form of pseudocode and in the form of block, as shown in Figure 3.
Figure 3. The flowchart of the anticollision evolutionary algorithm (ACEA).
Algorithm 1 Pseudo code

BEGIN
k:=0;
INITIALIZATION P(k)
Determining an initial population P(k), which consist of randomly generated control strings (real numbers in the range [0,360]);
EVALUATION P(k)
For each \( U(t) \) in each sequence in the population P(k), find the achieved \( X(t+1) \) from the equation of state transition \( X(t+1) = f(X(t), U(t)) \), and apply an evaluation \( \mu_D(U_0, U_1, \ldots, U_{n-1} | X_0) \) of each sequence P(k);
WHILE not (no improvement) DO
BEGIN
REPRODUCTION
Creating a temporary population T(k) for genetic operations that consists of control sequences with the highest values of the evaluation function in the population P(k), where the number of duplicated sequences depends on the values that the evaluation function takes for them;
GENETIC OPERATION on T(k)
Performing crossing and mutation on individuals of the temporary population T(k) creating a new descendent population O(i);
EVALUATION O(i)
For each \( U(t) \) in each sequence in the population O(k), find the achieved \( X(t+1) \) from the equation of state transition \( X(t+1) = f(X(t), U(t)) \), and apply an evaluation \( \mu_D(U_0, U_1, \ldots, U_{n-1} | X_0) \) of each sequence O(k);
SUCCESSION P1(k)+O1(k)
Creating a new base population P(k+1) by elite selection, combining the best individuals of the previous population P(k) with the best individuals of the descendant O(k) population;
k:=k+1;
END;
END.

3.2. Assumptions about NN in Multistage Fuzzy Control—ACNN

The solution to the above problem requires the use of special neurons with the considered artificial neural network. These neurons were proposed by Rocha and are known as maximum- and minimum-type neurons [49]. These neurons allow one to build a neural network to solve the problem of optimal multistage control in a fuzzy environment.

The structure of an artificial neural network depends on the number of layers and the rules of the connections between neurons. This determines its size, speed of action, and, above all, the effectiveness of its operations, which are a tool for solving a given problem.

The neural network proposed in [49] was used in this paper to solve the fuzzy programming tasks presented in this work. Its structure is composed of alternating layers based on minimum and maximum neurons. The weights (connections) of the inputs of neurons are not assigned by learning in the usual sense, but they result from the description of the task, i.e., state transitions, constraints, and fuzzy goals. Therefore, in order to ensure that the structure of the neural network works properly, it is necessary to define the connections between the neurons of the minimum \( m^i_k \) and maximum \( M^j_k \) type on the same layer of a well-defined stage and between the maximum neurons of the previous layer (stage – 1) and the minimum neurons on a given layer (stage). The \( W(m^i_k, M^j_k) \) connection function is responsible for connecting two types of neurons from the same stage, which can have two values: 0 which means there is no connection, and 1 which means there is a connection.

The neuron connection for neuron \( M^j_{k-1} \) with \( m^i_k \) is performed according to the value of the \( q_R(m^i_k) \) receptor and the value of the \( q_T(M^j_k) \) transmitter. These make it possible to obtain the state \( X_{N-1} \) using the state equation by running the neuron driver \( q_C(m^i_k) \). This driver has the task of distributing the value of the \( q_C(m^i_k) \) driver to all maximum-type neurons in the \( k-1 \) layer.
vated, as will those that have the same $q_R(M^l_{k-1})$ receptor value. It is similar to a computer network, i.e., one sends a destination address to the network and, as a result, the computer responds with the same address as the destination address. That is to say that the connection $W(M^l_{k-1}, m^l_k)$ is established between the neuron $m^l_k$ and $M^l_{k-1}$ in a similar way to a computer network.

In this manner, the presented connections offer the possibility to build an algorithm using the structure of an artificial neural network, which allows the dynamic programming problem and its solution within suitable fuzzy environment, known as the fuzzy neural anticollision (FNAC) algorithm, to be emulated precisely.

The neural network topology that allows the ship’s safe trajectory to be determined is a typical network. It comprises six stages: The first stage contains two layers of nine (09) min neurons and one max neuron. The second stage includes thirty-two (32) min neurons and nine (09) max neurons. The third stage is composed of thirty-eight (38) min neurons and twenty-five (25) max neurons. The fourth stage contains an equal number of each, i.e., nine (09) min neurons and nine (09) max neurons. The last stage is limited to only one max neuron. It is worth noting that the neurons weight can be obtained from the function state transitions, the fuzzy constraints membership function, and the fuzzy goals membership function. Furthermore, the main aim of the output step is to determine the connections of the maximum neuron series, the outputs of which have the highest fuzzy decision value $\mu_{D_{\text{max}}}$. 

In the first step, a neural network is created in a similar way to the dynamic programming steps process, which is performed from the final state to the initial state.

Consequently, the step sequence starts with the first step $(k = 0)$, which represents the last state in respect to $X_0$, and moved through to the last step $k$ (equal to the last value starting from $k = 0$), which represents the initial state with respect to $X_0$. This means that the first layer of the neuron is set at the maximum, i.e., $k = 0$, and it increases by 1 in each step. From this step and in each step after, the minimum neuron layer is firstly initialized and then the maximum neurons layer is initialized, as is shown in Figure 2.

The connection step, as its name indicates, can be performed in this phase. The first phase acts to ensure the combination between the minimum and maximum neurons in the same stage $k$. The second phase ensures the combination of the minimum neurons in stage $k$ and the maximum neurons in stage $k-1$. The main goal of the output step is to find a series of maximum neuron connections in which their outputs maintain the highest value, $\mu_{D_{\text{max}}}$.

This is what occurred in the control, which allowed us to obtain a value $\mu_{D_j}(U_0^j, \ldots, U_{N-1}^j|X_0)$ in which the minimum neuron connections were ensured. Hence, these values can be found starting from the initial state $X_0$ and moving to the final state $X_N$.

The final state and the initial state are singular and are directly related to the ship’s maneuvers. Indeed, in a neural network, some structures can have this feature, i.e., the final and initial states are both singular. Therefore, under such cases, the connection may change according to the state selected in the initial stage. Using MATLAB software, the fuzzy neural anticollision (FNAC) was programed and used to precisely identify the safest trajectory in an eventual collision scenario. The algorithm proposed in this paper is presented in the form of a flowchart in Figure 4.
4. Results

For the validation of the collision avoidance methods proposed in this paper and to check its effectiveness in finding the optimal safe trajectory, three simulations tests of real, critical navigational situations were performed in MATLAB, taking into account the convention of the International Regulations for Preventing Collisions at Sea COLREG. The main aim of these simulations was to validate the proposed approach in terms of identifying the optimal safe ship trajectory in collision situations.
4.1. Case One: One Moving Target in Head-On Situation

In this case, the ship under control had a course aligned with a target moving in the opposite direction, which is defined as the head-on situation. The initial coordinates of the ship under control and the target ship considered in the simulation are presented in Table 1. Figure 6 shows the result of the simulation based on the proposed approach for the determination of the safe ship trajectory in this head-on scenario, which is considered to be a very dangerous situation. The risk of collision in this case was close to 1 and the DCPA = 0 Mm. As can be seen clearly in Figure 4 in both cases (ACNN and ACEA), an anticollision maneuver was identified that allowed the target to avoid the collision by passing on the left side of the initial course. The choice of this avoidance measure was mainly based on the navigator’s subjective parameters taking into account the COLREG regulations. On the other hand, when both ships were at the same altitude, the course...
was leveled and, after evaluation of the distance from the target, the ship under control returned to the primary course.

**Table 1.** Ship coordinates and targets coordinates (one target).

| Ship Coordinates | Position [X, Y] | Course \( \psi \) [°] | Speed \( V \) [kn] | Visibility |
|------------------|----------------|----------------|----------------|-------------|
| 0.0, 0.0         | 0              | 12             | good           |

| Targets Coordinates | Target | \( N_j \) [°] | \( D_j \) [nm] | \( \psi_j \) [°] | \( V_j \) [kn] |
|---------------------|--------|---------------|---------------|---------------|--------------|
| 1                   | 0.0    | 7.0           | 180.0         | 10.0          |

**Figure 6.** Safe ship trajectory when passing with one moving target in a head-on situation. (a) ACNN, (b) ACEA.

On the basis of the results presented in Tables 2 and 3, the following can be deduced:

- The computation time of the ACNN approach was 1.2s, which was significantly lower than that of the ACEA approach;
- The obtained total maneuvering path under the ACNN approach was 7.808 Mm, which was longer than that of the ACEA. Moreover, the path offsets were higher for the ACNN approach.

**Table 2.** Data on the trajectories of the ship—ACNN algorithm.

| KERRYPNX | Course \( \psi \) [°] | Speed \( V \) [kn] | DCPA [nm] | TCPA [nm] | Calculation Time [s] |
|----------|----------------|----------------|-----------|-----------|----------------------|
| 1        | 14             | 10.3           | 7.8       | 16.08     | 12                   |
| 2        | 14             | 10.3           | 7.8       | 11.48     | -                    |
| 3        | 14             | 10.3           | 7.8       | 6.88      | -                    |
| 4        | 0              | 10             | 5.8       | 2.60      | -                    |
| 5        | 0              | 10             | 5.7       | -2.00     | -                    |
| 6        | 0              | 10             | 5.7       | -6.60     | -                    |
| 7        | 0              | 10             | 5.7       | -11.20    | -                    |
Table 3. Data on the trajectories of the ship—ACEA algorithm.

| Stage | Course $\psi$ [$^\circ$] | Speed $V$ [kn] | DCPA [nm] | TCPA [nm] | Calculation Time [s] |
|-------|--------------------------|----------------|-----------|-----------|---------------------|
| 1     | 25.9                     | 10             | 0.846     | 18.00     | 5.1                |
| 2     | 16.2                     | 10             | 0.848     | 14.01     | -                  |
| 3     | 12.1                     | 10             | 0.72      | 10.06     | -                  |
| 4     | 9.7                      | 10             | 0.68      | 6.10      | -                  |
| 5     | 6.9                      | 10             | 0.66      | 2.16      | -                  |
| 6     | 1.1                      | 10             | 0.7       | -1.71     | -                  |
| 7     | 0                        | 10             | 0.804     | -5.58     | -                  |

4.2. Case Two: One Moving Target in Crossing Situation

In this case, the ship under control passed along a course that crossed the course of a moving target. The initial coordinates of the ship under control and the moving target are presented in Table 4. The main objective was to find the optimal trajectory for the ship under control that allowed the collision with the moving target to be avoided. The obtained simulation results for the determination of the optimal safe trajectory using both control approaches (ACNN and ACEA) are shown in Figure 7.

Table 4. Ship coordinates and targets coordinates (one target).

| Ship Coordinates | Targets Coordinates |
|------------------|---------------------|
| Position [X,Y] | Course $\psi$ [$^\circ$] | Speed $V$ [kn] | Visibility |
| 0.0; 0.0         | 0                   | 12              | Good       |
| Target          | $N_j$ [$^\circ$] | $D_j$ [nm] | $\psi_j$ [$^\circ$] | $V_j$ [kn] |
| 1               | 45.0               | 7.0            | 270.0      | 10.0       |

Figure 7. Safe ship trajectory when passing with one moving target in a crossing situation. (a) ACNN; (b) ACEA.

4.3. Case Three: Three Moving Targets in Different Situations

In this case, the ship under control passed along a course that crossed the courses of three moving targets. The initial coordinates of the ship under control and the three moving targets are presented in Table 5. In this case, the main goal was to find the best course that
ensured collision avoidance with the three moving targets at the same time, which means that the direction of the ship under control was adapted according to the position of each target individually. The obtained simulation results for the determination of the optimal safe trajectory of the ship under control using both control approaches (ACNN and ACEA) are shown in Figure 8a,b.

Table 5. Ship coordinates and targets coordinates (three targets).

| Ship Coordinates   | Targets Coordinates |
|--------------------|---------------------|
| **Position [X,Y]** | **Target**          |
| 0.0; 0.0           | 1                   |
| 12                 | N_j [°]             |
| 90.0               | D_j [nm]            |
| 10.0               | ψ_j [°]             |
| 10.0               | V_j [kn]            |
| Good               |                     |
|                    |                     |
|                    | 2                   |
|                    | 3                   |
|                    |                     |

Figure 8. Safe ship trajectory when passing with three moving targets in restricted visibility. (a) ACNN; (b) ACEA.

5. Conclusions

In this study, a model that reflects the real process of a ship’s safe navigation in collision situations was developed. It takes into account several parameters, such as the navigation field, the visibility conditions, the maneuverability of the ship, the movement of objects in the eventual collision, and the navigator’s maneuvers in accordance with the COLREG regulations. Furthermore, two techniques were proposed to ensure ship collision avoidance that allow one to identify the optimal trajectory with the lowest fuel consumption. The first is based on the anticollision neural network (ACNN) and the second is based on the anticollision evolutionary algorithm (ACEA). To ensure the accuracy of the proposed model, the subjective nature of a nautical navigation maneuver was taken into account, in which the collision risk membership function was used as a criterion for estimating the risk of collision in a given situation. It was found that the computation time for finding the safe ship trajectory in a collision situation in real time, which is also
dependent on the number of targets involved in a given situation, is lower when using the ACNN technique as compared to the ACEA technique. However, the safe trajectory obtained with the ACEA was shorter as compared to that of the ACNN, which means lower energy losses were achieved using this technique in collision avoidance. On the basis of the results obtained from the simulation tests, it can be concluded that the model proposed in this paper, based on both the ACNN and ACEA techniques, is an efficient solution that can help decision-support systems on ships identify the optimal trajectory of collision avoidance in collision situations with multiple objects.

Indeed, this paper concerns the application of these methods in the field of safe ship control. However, it does not cover all the issues related to this area of research. In future work, cooperation between the objects being encountered can be taken into account in order to improve the decision making. In addition, increasing the amount of real sea conditions that are taken into account will improve these methods and enable them to obtain more accurate results. Finally, it can be concluded that the techniques proposed in this paper are a promising tool that can be implemented in anticollision systems, such as ARPA, to support navigator decision making in collision situations. Furthermore, the proposed techniques can be further incorporated into robot and moving object applications to determine the safest path between moving objects while taking into account the aspects of cooperation between the encountered objects.

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Nomenclature

C fuzzy set of constraints,
c(k) distance from the original course at that stage,
D fuzzy set of decision,
Db safe approach distance,
DCPA distance to the nearest point of approach,
Dj(c(k)) distance to the j-th object,
G fuzzy set of goal,
L distance from the original course,
mkj minimum neuron,
Mjk maximum neuron,
Nj bearing of the j-th object,
O(k) descendent population,
P(k) initial population,
qC a driver,
qR receptor,
qT transmitter,
T(k) temporary population,
TCPA time remaining to approach,
\[ U \] control set,
\[ U \] control,
\[ t_k \] time passed from stage 0 to stage \( k \),
\[ V \] ship under control’s actual speed,
\[ V_j \] the \( j \)-th object’s actual speed,
\[ V^* \] ship under control’s optimal speed,
\[ W \] set of final states,
\[ X \] Y ship position co-ordinates,
\[ X \] ship position co-ordinates set,
\[ \Delta d \] distance between successive stages of the original course.
\[ \lambda_{RD}, \lambda_{RT}, \lambda_D, \lambda_C \] the parameters determining the subjectivity of navigators,
\[ \mu_C \] fuzzy constraints membership function,
\[ \mu_D \] fuzzy decision membership function,
\[ \mu_G \] fuzzy goal membership function,
\[ \mu_R \] membership function of collision risk,
\[ \psi^* \] course of the ship before and after maneuver,
\[ \psi^*_j \] course of the \( j \)-th object,
\[ \psi^*_{opt} \] optimal course of the ship,
\[ \omega_z \] maximum angular velocity of the vessel turning.

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