Intelligent guidance in collision avoidance of maritime transportation

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ABSTRACT: This paper focuses on an overview of an autonomous navigation system in maritime transportation that is supplied with intelligent guidance to avoid collision, while respecting the COLREGs rules and regulations and using expert knowledge in navigation for close quarter’s manoeuvres. The proposed collision avoidance process consists of two modules: a fuzzy logic based parallel decision making module and a Bayesian network based sequential action formulation module. Successful simulation results of the intelligent guidance in collision avoidance of maritime transportation that is capable of making multiple collision avoidance decisions and actions in order to avoid complex multi-vessel collision situations are also illustrated in this study.

1 INTRODUCTION

The intelligent guidance in maritime transportation is still underdeveloped when compared with the land and air transportation systems. In conventional maritime transportation, the most important navigation factor is still the human guidance, and wrong judgment and miss-operations by humans have resulted in many casualties and environmental disasters. The reported data shows human errors are still one of the major causes of maritime accidents (Guedes Soares, & Teixeira, 2001) and 75–96% of marine accidents and causalities are caused by some types of human errors (Rothblum et al. 2002, and Antão & Guedes Soares, 2008).

Therefore, the implementation of intelligent and autonomous capabilities and the limitation of human subjective factors in navigation, to increase the safety and security of ocean navigation, are proposed in this study. Similarly, the replacement of human inference by an intelligent decision formulation process resulting in feasible actions for navigation and collision avoidance can reduce the number of maritime accidents and their respective causalities.

To avoid collision situations, all vessels should follow the law of the sea. The current law of the sea was formulated by the International Maritime Organization (IMO) in 1972 by the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs). However, the reported data of the maritime collisions presented by Statheros et al. (2008), show that 56% of major maritime collisions involve violation of the COLREGs rules and regulations. The detailed description of the COLREGs rule and regulations and their interpretation for autonomous ocean navigation with respect to the collision avoidance are presented in Perera et al. (2010a).

This paper focuses on an overview of an intelligent maritime transportation system that includes an autonomous collision avoidance process while respecting the COLREGs rules and regulations and expert knowledge in navigation. The autonomous guidance in collision avoidance described in this work consists mainly of a fuzzy logic based parallel decision making module whose decisions are formulated into sequential actions by a Bayesian network based module. The proposed collision avoidance process capabilities of making multiple parallel collision avoidance decisions regarding several target vessels and those decisions are executed as sequential actions in the vessel navigation to avoid complex collision situations are also presented.

2 RELATED WORK

The decision making process and strategies in interaction situations of avoidance of collision in maritime transportation are presented in Chauvin & Lardjane (2008), Sato & Ishii (1998) proposed combining radar and infrared imaging method to detect the target vessel position conditions as a part of the collision avoidance system. Lisowski et al. (2000) used neural-classifiers to support the navigator in the process
of determining the vessel’s domain. On a similar approach, Pietrzynowski and Urias (2009) proposed the notion of a vessel domain in a collision situation as depending on the parameters like vessel size, course and heading angle of the encountered vessels.

Kwik (1989) presented collision risk calculations for a two-ship collision encounter based on the kinematics and dynamics of marine vessels. Yavin et al. (1995) considered the collision avoidance conditions of a ship moving from one point to another in a narrow zig-zag channel proposing a computational open loop command strategy for the rudder control system. Sutulo et al. (2002) studied the problem of predicting a ship trajectory based on simplified maneuvering models. An alternative approach based on neural networks is also proposed by Moreira and Guedes Soares (2003). Smierzchalski and Michalewicz (2000) modeled safe ship trajectory in navigation using an evolutionary algorithm and considering static and dynamic constraints for the optimization process.

Ito et al. (1999) used genetic algorithms to search for safe trajectories on collision situations in ocean navigation. Similarly, experimental results on the same topic are presented in Zeng et al. (2001). Hong et al. (1999) presented a collision free trajectory in ocean navigation based on a recursive algorithm that is formulated by analytical geometry and convex set theory. Similarly, Cheng et al (2006) have presented trajectory optimization for ship collision avoidance system based on a genetic algorithm.

Statheros et al. (2008) give an overview of computational intelligence techniques that are used in collision avoidance in ocean navigation. Liu and Liu (2006) used Case-Based Reasoning to illustrate learning of collision avoidance techniques in ocean navigation using previous recorded data of collision situations. Furthermore, an intelligent anti-collision algorithm for different collision conditions is designed and tested on the computer based simulation platform by Yang et al. (2007). Zhuo and Hearn (2008) presented a study of two vessel collision avoidance in ocean navigation using a self-learning neuro-fuzzy network based online and offline training scheme.

A fuzzy logic approach for collision avoidance conditions with the integration of a virtual force field is proposed by Lee et al. (2004). Similarly, automatic collision avoidance facilities for ship system using a fuzzy logic based controller is proposed by Hasegawa (1987). Benjamin et al. (2006) propose behavior based controls formulated with interval programming for collision avoidance of maritime transportation. The collision avoidance behavior is illustrated in accordance with the Coast Guard Collision Regulations. Benjamin and Curcio (2004) present the decision making process of ocean navigation based on an interval programming model for a multi-objective decision making algorithm.

A computational algorithm based on the If-Then logic is defined and tested under simulator conditions by Smeaton and Coenen (1990) regarding different collision situations. Cockcroft and Lameijer (2001) present a detailed description of the COLREGs rules and regulations, implementation, interpretation of judicial authorities of vessel collision and near-miss situations.

3. COLLISION AVOIDANCE SITUATIONS IN OCEAN NAVIGATION

3.1 Two vessel collision situation

A two-vessel collision situation is presented in Figure 1, where the own vessel, which is the one that is equipped with the collision avoidance system, is located in the point \( O(k)(x_o(k), y_o(k)) \), at the \( k \)th time instant. The \( i \)th target vessel, which is the one that needs to be avoided, is located at point \( P_i(k)(x_i(k), y_i(k)) \), with the estimated navigational trajectory of \( P_i(k)B_i(k) \).

The target vessel estimated trajectory \( P_i(k)B_i(k) \) will intercept the own vessel domain with the closest distance of \( R_{DCPA}(k) \), around the points of \( B_i(k) \). The own vessel speed and course conditions are represented by \( V_o(k) \) and \( \psi_o(k) \); the \( i \)th target vessel speed and course conditions are represented by \( V_i(k) \) and \( \psi_i(k) \); the \( i \)th target vessel bearing and relative bearing conditions are represented by \( \theta_i(k) \) and \( \psi_{Ro}(k) \); the relative speed and course conditions of the \( j \)th target vessel are represented by \( V_{Ro}(k) \) and \( \psi_{Ro}(k) \). All angles are measured with respect to the positive Y axis.

The own vessel navigational space is divided into three circular regions with radii \( R_{oa} \), \( R_b \) and \( R_c \). The radius \( R_a \) represents the approximate distance to the target vessel, when
the own vessel is in a "Stand on" situation with the higher priority for navigation should take appropriate actions to avoid collision due to absence of the appropriate actions from the target vessel. The radius $R_{vd}$ represents the vessel domain.

### 3.2 Multi-vessel collision situation

The expansion of a two vessel collision situation into a multi-vessel collision situation is presented in Figure 2. The own vessel is located in the point $O(k)$. The target vessels are located at the points of $P_1(k), P_2(k), \ldots, P_n(k)$ with the navigational trajectories of $S_1(k), S_2(k), \ldots, S_n(k)$ at the kth time instant respectively. The own vessel trajectory $S_0(k)$ will intercept the trajectories $S_1(k), S_2(k), \ldots, S_n(k)$ around the points of $C_1(k), C_2(k), \ldots, C_n(k)$ at the time instants of $T_1(k), T_2(k), \ldots, T_n(k)$ respectively.

### 3.3 Modules of collision avoidance system

A block diagram for the proposed Collision Avoidance System (CAS) is presented in the Figure 3. The complete CAS consists of four modules: the Vessel Tracking & Trajectory Prediction (VTTP) module, the Collision Risk Assessment (CRA) module, the Parallel Decision Making (PDM) module, and the Sequential Action Formation (SAF) module.

The inputs into the VTTP module are the real-time position of the own vessel $(x_0(k), y_0(k))$, that can be measured or estimated by the GPS integrated Inertial navigational systems, in the Cartesian coordinates, and the real-time position of each target vessel’s $(R_i(k), \theta_i(k))$ that is measured in Polar coordinates. The Range $(R_i(k))$ and Bearing $(\theta_i(k))$ values of the $i$th target vessel can be obtained using Radar or Laser measurement systems by the $k$th time instant as further discussed by Perera and Guedes Soares (2010a).

The VTTP module consists of four units: the Scan Unit, the Data Classification Unit, the Clustered Data Tracking Unit and the Trajectory Prediction Unit. The integrated Radar or Laser measurement system is considered for the Scan Unit where the real-time position data of the target vessels is collected. The target vessel’s data are used in the Data Classification Unit to identify each vessel and the Clustered Data Tracking Unit tracks each target vessel separately using this data. Finally the collected tracking data is used to predict each target vessel’s trajectory in the Trajectory Prediction Unit. Due to the target vessels constant speed and course condition assumptions, this process is simplified in this study. Further details on target vessel tracking under ocean navigation conditions are presented in Perera and Guedes Soares (2010b).

The main objective of the CRA module is to evaluate the collision risk of each target vessel with respect to the own vessel navigation. This is achieved by the Relative Trajectory Formation Unit and the Collision Time and Point Estimation Unit. The inputs into the CRA module are the measured/estimated position data of the own vessel and target vessels. The outputs of the CRA module are Range $(R_i(k))$, Bearing $(\theta_i(k))$, Relative course $(\psi_{io}(k))$ and Relative speed $(V_{io}(k))$ of $i$th target vessel. These outputs will be used as the inputs of the PDM module at the $k$th time instant.

In addition, the Time until the collision situation $T_i(k)$ of the $i$th target vessel will input into the SAF module from the CRA module. The PDM module consists of a fuzzy logic based decision making process...
that generates parallel collision avoidance decisions with respect to each target vessel at \(k\)th time instant.

As the next step, the parallel/ith decision of collision avoidance, \(D_i(k)\), will forward from the PDM module to the SAF module. The main objective of the SAF module is to transform the parallel collision avoidance decisions made by the PDM module into sequential actions, \(A_i(k)\), considering the Time until the collision situation, \(T_i(k)\), that will be executed on the own vessel navigation. These actions are further divided into two categories of Course and Speed control actions that will be implemented on the propeller and rudder control systems of the own vessel.

4 PARALLEL DECISION MAKING MODULE

The main objective of the PDM module is to make the collision avoidance decisions considering the collision risk warnings. An overview of the PDM module is also presented in Figure 3. The module consists of 3 main units: the Fuzzification Unit, the Fuzzy Rules Unit and the Defuzzification Unit.

4.1 Fuzzification unit

The inputs from the CRA module, Range \((R_i(k))\), Bearing \((\theta_i(k))\), Relative course \((\psi_{i,o}(k))\) and Relative speed \((V_{i,o}(k))\) of the ith target vessel at the \(k\)th time instant are fuzzified in this unit with respect to the input Fuzzy Membership Functions (FMFs): the Range FMF \((R_i(k))\), the Speed Ratio FMF \((V_i(k)/V_o(k))\), the Bearing FMF \((\theta_i(k))\), and the Relative Course FMF \((\psi_{i,o}(k))\). Then, the fuzzified results from the Fuzzification unit will be transferred to the Fuzzy Rules Unit for further analysis.

4.2 Fuzzy inference and rules

A Mamdani type IF <Antecedent> THEN <Consequent> rule based system is developed and inference via Min-Max norm is considered in the Fuzzy Rules Unit. The IF-THEN Fuzzy rules are developed in accordance with the Knowledge Base (i.e. the COLREGs rules and regulations). However the expert navigational knowledge is also considered in the Fuzzy rules development process. Overtaking, Head-on and Crossing, the three distinct situations that involve risk of collision are considered for the development of the IF-THEN Fuzzy rules.

4.3 Defuzzification

The collision avoidance decisions, \(D_i(k)\), for each target vessel are generated by the Defuzzification Unit. The Fuzzy inference results from the previous unit are defuzzified based on the output Course Change FMF and Speed change FMF to obtain the Course change decisions, \(D_{\delta \psi}(k)\), and Speed change decisions, \(D_{\delta V}(k)\), that will be formulated for collision avoidance actions in the own vessel navigation.

5 SEQUENTIAL ACTION FORMATION MODULE

5.1 Action execution in navigation

The main objective of the SAF module is to transform the parallel collision avoidance decisions that are generated by the PDM module into a sequential action formulation that can be executed in the own vessel. This can be achieved by collecting the PDM module multiple collision avoidance decisions for the \(k\)th time instant, \(D_i(k)\), and evaluating them using the Time until the collision situation, \(T_i(k)\), from the CRA module with respect to each target vessel.

Final results are arranged as a sequential formation of actions, \(A_i(k)\), involving the course and speed action at given time instants \((T_{\delta \psi}(k), T_{\delta V}(k))\). Figures 4 gives examples of the sequential course collision avoidance action function (CCAF) and the speed collision avoidance action function (CCAF). \(D_{\delta \psi}(k), D_{\delta V}(k)\), and \(A_{\delta \psi}(k), A_{\delta V}(k)\) represent the course and speed change decisions and actions at \(k\)th time instant respectively.

The overview of the SAF module is also presented in Figure 4. The SAF module consists of 2 units: the Course and Speed Actions Formation Units. The main objective of these 2 units is to formulate the collision avoidance course and speed control actions.

5.2 Bayesian network

The continuous Bayesian Network module that is formulated to update the parallel collision avoidance decisions into the sequential actions is presented in Figure 5. The Bayesian network consists of four
5.3 Collision risk functions

The Collision Risk Functions (CRF) of the own vessel ($\Delta(k)$) due to the $i$th target vessel in the $k$th time instant are modeled as a Gaussian distribution $\Delta(k) \sim N(\mu_{\Delta}(k), \sigma_{\Delta}^2(k))$, with the mean $\mu_{\Delta}(k)$ that is estimated by the average time until collision, $T_i(k)$, which can be defined as:

$$T_i(k) = \mu_{\Delta}(k) = \frac{|OP_{i}(k)|}{V_i(k)}$$

where $|OP_{i}(k)|$ is the relative range and $V_i(k)$ the relative speed of the $i$th target vessel with respect to the own vessel at the $k$th time instant. Furthermore, the covariance $\sigma_{\Delta}^2(k)$ is considered in this distribution. It is assumed that the CRF, $\Delta_i(k)$, can be obtained from noisy Observation Function of $Z_i(k)$ and can be written as:

$$Z_i(k) = \Delta_i(k) + \omega_{z_i}(k)$$

where $\omega_{z_i}(k) \sim N(0, \sigma_{\omega_{z_i}}^2(k))$, is a Gaussian observation noise with the mean 0 and the constant covariance $\sigma_{\omega_{z_i}}^2$. Hence, the prior distribution of the CRF due to the $i$th target vessel at $k$th time instant can be written as a Gaussian distribution:

$$P(\Delta_i(k)) = \frac{1}{\sqrt{2\pi}\sigma_{\Delta}(k)} \exp\left(-\frac{1}{2} \frac{(\Delta_i(k) - \mu_{\Delta}(k))^2}{\sigma_{\Delta}(k)^2}\right)$$

where $\mu_{\Delta}(k)$ is the mean of the CRF, $\sigma_{\Delta}(k)$ is the standard deviation of the CRF, and $\sigma_{\omega_{z_i}}^2$ is the covariance of the observation noise. The transition model of the CRF is considered as a Gaussian perturbation of the constant covariance $\sigma_{\Delta}^2$ to the current states of the CRF and can be written as:

$$P(\Delta_i(k) | \Delta_i(k-1)) = \frac{1}{\sqrt{2\pi}\sigma_{\Delta}(k)} \exp\left(-\frac{1}{2} \frac{(\Delta_i(k) - \mu_{\Delta}(k))^2}{\sigma_{\Delta}(k)^2}\right)$$

5.4 Collision avoidance action function

The own vessel Collision Avoidance Action Function (CAAF) is modeled as a Gaussian distribution $\Omega_i(k) \sim N(\mu_{\Omega_i}(k), \sigma_{\Omega_i}^2(k))$ with the mean $\mu_{\Omega_i}(k)$ and the covariance $\sigma_{\Omega_i}^2(k)$. The CAAF with respect to the CRF can be written as:

$$\Delta_i(k) = \Omega_i(k) + \Gamma_i$$

where $\Gamma_i \sim N(0, \sigma_{\Gamma}^2)$, is the time delay function that is approximated by a Gaussian distribution with a constant mean, $\mu_{\Gamma}$, and covariance, $\sigma_{\Gamma}^2$. The conditional CRF with respect to the CAAF as a Gaussian distribution can be written as:

$$P(\Delta_i(k) | \Omega_i(k)) = \frac{1}{\sqrt{2\pi}\sigma_{\Omega_i}(k)} \exp\left(-\frac{1}{2} \frac{(\Delta_i(k) - \mu_{\Omega_i}(k))^2}{\sigma_{\Omega_i}(k)^2}\right)$$

where $\mu_{\Omega_i}(k)$ is the mean of the CAAF, $\sigma_{\Omega_i}(k)$ is the standard deviation of the CAAF, and $\sigma_{\Omega_i}^2$ is the variance of the CAAF. The prior distribution of the CAAF due to the $i$th target vessel at $k$th time instant can be written as a Gaussian distribution:

$$P(\Omega_i(k)) = \frac{1}{\sqrt{2\pi}\sigma_{\Omega_i}(k)} \exp\left(-\frac{1}{2} \frac{(\Omega_i(k) - \mu_{\Omega_i}(k))^2}{\sigma_{\Omega_i}(k)^2}\right)$$

where $\mu_{\Omega_i}(k)$ is the mean of the CAAF, $\sigma_{\Omega_i}(k)$ is the standard deviation of the CAAF, and $\sigma_{\Omega_i}^2$ is the variance of the CAAF. The transition model of the CAAF considered as Gaussian perturbation of constant covariance $\sigma_{\Omega_i}^2$ to the current states of the CAAF and can be written as:

$$P(\Omega_i(k) | \Omega_{i}(k-1)) = \frac{1}{\sqrt{2\pi}\sigma_{\Omega_i}(k)} \exp\left(-\frac{1}{2} \frac{(\Omega_i(k) - \mu_{\Omega_i}(k))^2}{\sigma_{\Omega_i}(k)^2}\right)$$
where $\beta_i$ is the normalization constant. Considering the Bayesian Rule, the CAAF update from the CRF can be written as:

$$P(Q_i(k)|A_i(k))$$

$$= \frac{1}{2} \left( \frac{(Q_i(k)+1)}{(Q_i(k)+1)^2 + \sigma_i^2} \right)^{\frac{1}{2}}$$

$$= \beta_i \beta_i \beta_i e^{-\frac{1}{2} \left( \frac{(Q_i(k)+1)}{(Q_i(k)+1)^2 + \sigma_i^2} \right)^{\frac{1}{2}}}$$

5.5 Implementation of collision avoidance actions

The implementation of the accumulated CAAF, $A_i(k)$ is divided into two sections of Course Control ($A_{δψ_i}(k)$) and Speed Control ($A_{δV_i}(k)$) CAAFs as presented in Figures 4. The CAAFs are generated from the collision avoidance decisions of $D_i(k)$, from the course control decisions ($D_{δψ_i}(k)$) and the speed control decisions ($D_{δV_i}(k)$) as described previously. Hence, the accumulated CAAFs of Course Control ($A_{δψ_i}(k)$) and Speed Control ($A_{δV_i}(k)$) actions can be written as:

$$A_{δψ_i}(k) = \sum_{i=1}^{n} A_{δψ_i}(k) = \sum_{i=1}^{n} D_{δψ_i}(k) P(Q_{δψ_i}(k)|A_{δψ_i}(k))$$

$$A_{δV_i}(k) = \sum_{i=1}^{n} A_{δV_i}(k) = \sum_{i=1}^{n} D_{δV_i}(k) P(Q_{δV_i}(k)|A_{δV_i}(k))$$

These accumulated CAAFs are implemented in the computational simulations of collision avoidance. The further details on the Bayesian network based sequential action formulation module including mathematical derivation of the CRF and CAAF are presented Perera et al. (2010c).

6 COMPUTATIONAL SIMULATIONS

The computational simulations for the multi-vessel collision situation are presented in Figures 6 to 16. As presented in Figures 6, the own vessel starts navigation from the origin (0 (m), 0 (m)) and the first, second and third target vessels start from positions (4238 (m), 10238 (m)), (8790 (m), 10000 (m)), and (−10714 (m), 12400 (m)) respectively. All startup and final positions of the own and the target vessels are presented by vessel shape icons at the $k$th time instant in the Figures.

It is assumed that the target vessels are moving in constant speed and course and don’t honor any navigational rules and regulations of the sea. The CRF assessment is formulated by a Gaussian distribution and presented in the $x = −12000$ (m) axis as the first peaks in a time instant. Furthermore, the respective accumulated CAAFs of course and speed, with respect to the collision situation are presented in the same Figure in the axis of $x = −9000$ (m) and $x = −6000$ (m). The accumulated CAAFs, the course to starboard and speed reduction to avoid the first target vessel are also presented in the same Figure.

In Figure 7, the collision avoidance system has observed the second possible collision situations and the accumulated CRF is presented in the $x = −12000$ (m) axis as the second peaks in a different time instant. Furthermore, the respective accumulated CAAFs of course and speed, with respect to each collision situation are presented in the same Figure in the axis of $x = −9000$ (m) and $x = −6000$ (m). The accumulated CAAFs, the course to starboard and speed reduction, to avoid the second target vessel are also presented in the same Figure.

Figure 8 presents the sub-completion of the first action segment of the CAAFs, consisting in speed reduction and continuation of course change to starboard side by the own vessel. However, due the first action segment of the CAAFs, the partially reduced collision actions (i.e. the speed reduction for second collision situation no longer required) between the own
vessel and the second target vessel could also observed in Figures 8 and 9.

The completion of the first action segment of the CAAFs in Figure 10 and the own vessel is about to safe-pass the first target vessel in Figure 11 are presented. One should note that, due the first action segment of the own vessel, the collisions situation with the second target vessel was eliminated.

The own vessel is about to safe-pass the first target vessel trajectory in Figure 12 and about to safe-pass the second target vessel trajectory in Figure 13 are presented.

Furthermore, the collision avoidance system observing the third possible collision situation with the respective accumulated CAAFs, the course to port and speed reduction to avoid the third target vessel are also presented in Figure 13.

Figure 14 presents the sub-completion of the third action segment of the CAAFs, consisting in speed
reduction and continuation of course change to port by the own vessel.

Figure 15 presents the completion of execution of the CAAF s in order to avoid the third target vessel. Finally the completion of all the CAAFs with zero CRF and safe passing of the third target vessel trajectory are presented in Figures 16.

7 CONCLUSIONS

This paper introduces a decisions formulation and action execution process of collision avoidance in maritime transportation. As presented in the computational results, the autonomous Fuzzy-Bayesian based decision-action formulation process could be used to avoid complex navigational conditions. The successful results obtained in this study show the system capabilities of collision avoidance involving multiple vessels under various collision conditions in ocean navigation while still respecting the COLREGs rules and regulations.

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