

Neuroevolutionary Approach to COLREGs Ship Maneuvers

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ABSTRACT: The paper describes the usage of neuroevolutionary method in collision avoidance of two power-driven vessels approaching each other regarding COLREGs rules. This may be also be seen as the ship handling system that simulates a learning process of a group of artificial helmsmen - autonomous control units, created with artificial neural networks. The helmsman observes an environment by its input signals and according to assigned COLREGs rule, he calculates the values of required parameters of maneuvers (propellers rpm and rudder deflection) in a collision avoidance situation. In neuroevolution such units are treated as individuals in population of artificial neural networks, which through environmental sensing and evolutionary algorithms learn to perform given task safely and efficiently. The main task of this project is to evolve a population of helmsmen which is able to effectively implement chosen rule: crossing or overtaking.

1 INTRODUCTION

General collision avoidance rules between two or more vessels are described in convention known as the COLREGs - the International Regulations for Preventing Collisions at Sea, published by IMO (International Maritime Organization) at London on 20 October 1972. It replaced similar previous regulations of 1960. The Convention contains rules of the road for sea-going vessels, definitions of ships, arrangement of lights and shapes, description of sound and light signals.

It is important to mention that regarding COLREGs there is no absolute "right of way" privilege of a sea-going vessel over any other encountered vessel. It is rather described as "give way" (burdened) vessel and a "stand on" (privileged) vessel, sometimes there may be two "give way" vessels with no "stand on" vessel. A stand on vessel may still be obliged to give way, if there is a risk of

collision. A commander on the bridge shall never assume the other vessel shares his view of which rules apply in particular situation. The decision is not always clear, it may differ depending on weather condition, visibility, experience and many other factors. It may be aided by intelligent decision support system with fuzzy values (Pietrzykowski and Małujda, 2012). There are also solutions for unmanned vessels (Naeem et al., 2012) and finding safe ship trajectories with focus on better handling of COLREGs (Szałpczyński and Szałpczyńska, 2012). Interesting approach to multi-ship collision avoidance under COLREGs regulations has been proposed with usage of Artificial Potential Field method (Wang et al., 2017) to calculate ships safety domain.

2 NEUROEVOLUTION

Neuroevolution is an artificial intelligence method that uses evolutionary algorithms (EA) to generate artificial neural networks (ANN), its parameters, topology and rules. Such combination gives the advantage of flexibility and adaptability, which allows to adjust the computational structures to the dynamically changing conditions encountered during ship maneuvering and are intensively studied and implemented in many different fields of science and research, including robotics (Lee et al., 2013), automation processes (Stanley et al., 2005), multi-agent systems (Nowak et al., 2008) designing and diagnostics (Larkin et al., 2006), and many more.

Neuroevolutionary algorithms are successful methods for optimizing neural networks topologies for dynamic continuous reinforcement learning tasks. Their significant advantage over gradient-based algorithms is the capability to modify network topologies along with connection weights, resulting with broader search space of possible solutions.

The proper maneuvers of ship maneuvering according to COLREGs rules is essential to the safety of people, equipment, cargo and the environment. Increase of computational power of electronic devices allows to implement as complex algorithms as neuroevolution into advanced decision support systems (DSS) also in the field of marine navigation.

Through continuous environment observation and learning process, such DSS shall predict the vessels' rudder angle and propeller revolutions as accurate as possible to ensure safe implementation of chosen rule. It is possible to calculate these output signals when there is a simulation model of the vessel available.

In neuroevolution ANN is treated as an individual in a population of multiple networks. Neuroevolution is able to find a solution of a complex and dynamically changing task with ANN created and modified with EA. The basic topologies of the initial population are randomly determined at the beginning of learning process. Each individual acts as a brain of artificial helmsman and begins the process of finding a solution with the same starting parameters (ships initial position, course, velocity, rudder angle, rpm). The action of each individual is usually assessed with the reinforcement learning algorithms (Stanley et al., 2005) and evolutionary stage of the system shall select individuals best suited to the task during selection stage, which determines the whole population to improve its genetic material over time.

Evaluation of each individual is being processed during whole simulation after some important events took place, as for example:

- moving the vessel out of the area or on forbidden sector, i.e. the safety domain of an encountered vessel,
- making rapid and/or frequently changing maneuvers, i.e. to frequent alteration of rpm,
- leading to improper ships' movement parameters values, i.e. linear and/or angular velocity too low or too high,
- moving the vessel away from goal,
- reaching a goal.

All these event must be arbitrarily rated, resulting in a reward to evaluated individual, thus valuating its fitness important in evolutionary stage of the algorithm and consequently his chance of reproduction and survival to the next generation.

Evolutionary process of the system consists three main steps:

- selection of the best individual or individuals,
- reproduction (with cross-over and mutation sub-processes),
- replacement (offspring replaces worst individuals).

For the purpose of this task the neuroevolutionary method, the modified NEAT algorithm, with direct encoding of neural network topology has been implemented.

NEAT (NeuroEvolution of Augmenting Topologies) (Stanley and Risto, 2002) adjust the topology of ANN's with EA gradually, allows to obtain a set of individuals that are best fitted to given task.

Input and output signals of ANN's have been determined at the beginning of designing phase of the system. Properly designed set of signals considered in the model is crucial for efficiency of the system as much as for its fidelity and accuracy in comparison to the real navigational situation.

Input signals in the system, with three degrees of freedom of the vessel movement, are as follows:

- ships' course over ground,
- ships' angular velocity,
- ships' speed over ground,
- ships' position,
- ships' distance and angle to goal, obstacles and to the encountered vessel,
- main propeller revolutions (current and preset),
- rudders' deflection (current and preset).

In future research other signals from environment may be taken into account, i.e. wind, current, waves, cargo, trim and roll, if delivered in a ship model.

Output signals of ANNs generates the values for steering the vessel:

- rpm of main propeller,
- rudders' deflection.

All of the input and output signals are normalized and encoded as real values between 0 and 1.

Each node in ANN represents a neuron that produces a real value between 0 and 1 as a result of normalized weighted sum of its inputs. Normalization of weighted sum is performed with sigmoid function.

The simulation results are shown below for simulation model of three-degrees-of-freedom VLCC crude oil tanker "Esso Norway" with the single-propeller and single-rudder (Figure 1).



Figure 1. VLCC oil tanker „Esso Norway” (1969-1986)

Main parameters of the simulated vessel has been placed in table 1.

Table 1. Main parameters of “Esso Norway”

Parameter	Value
Length overall	323,8 m
Length between perpendiculars	304,8 m
Beam	47,3 m
Max. draft	18,46 m
Deadweight tonnage	193048 t
Max. revolutions of propeller	80 rpm
Max. rudder deflection	$\pm 20^\circ$

In this simulation it has been assumed that “Esso Norway” will encounter second vessel of similar size and heading forward on steady course. Her safety domain has been established as simplified rectangle shape 3 length ahead of her bow and one length behind the stern (Figure 2). Width of this domain is 2 length of the vessel.

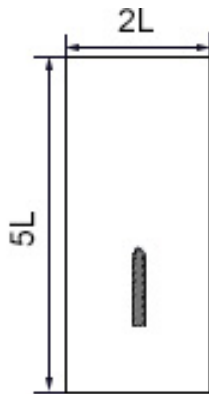


Figure 2. Simplified safety domain of the encountered vessel

3 SIMULATION OF COLREGS MANEUVERS

3.1 Rule 13 – Overtaking

Rule 13 states that:

“a) Notwithstanding anything contained in the Rules of Part B, Sections I and II, any vessel overtaking any other shall keep out of the way of the vessel being overtaken.

(b) A vessel shall be deemed to be overtaking when coming up with a another vessel from a direction more than 22.5 degrees abaft her beam, that is, in such a position with reference to the vessel she is overtaking, that at night she would be able to see only the sternlight of that vessel but neither of her sidelights.

(c) When a vessel is in any doubt as to whether she is overtaking another, she shall assume that this is the case and act accordingly.

(d) Any subsequent alteration of the bearing between the two vessels shall not make the overtaking vessel a crossing vessel within the meaning of these Rules or relieve her of the duty of keeping clear of the overtaken vessel until she is finally past and clear.”

Overtaking situation is presented on figure 3.

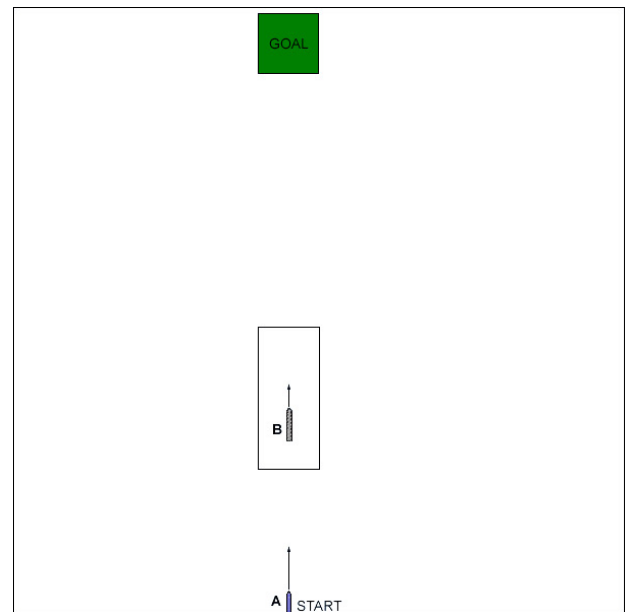


Figure 3. Initial situation of overtaking maneuvers

Vessel A is heading north faster (5 m/s) than vessel B (3 m/s), thus overtaking maneuver occurs. In this case it is strongly recommended that vessel A shall overtake B on her port side.

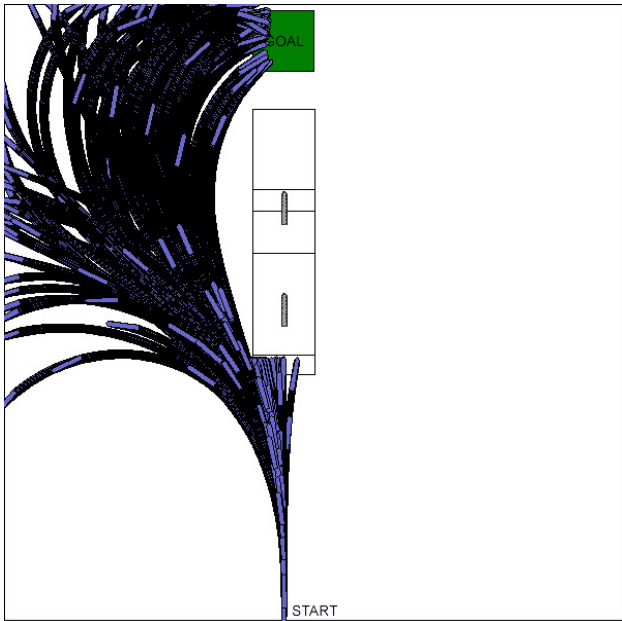


Figure 4. An example of recorded routes of a whole population

As one can see on figure 4 there is a broad spectrum of routes taken on the port side of overtaken vessel B. Many of them end with failure upon entering other vessels' safety domain, or moving out of the area. Some routes end within the goal with improper course over ground, but fitness values of these individuals are better than those leaving the area and their chance of survival to the next generation is greatly higher. It is of course not sufficient to reproduce as intense as the best individuals but is not totally excluded and has a chance to improve its fitness in subsequent episodes of simulation process.

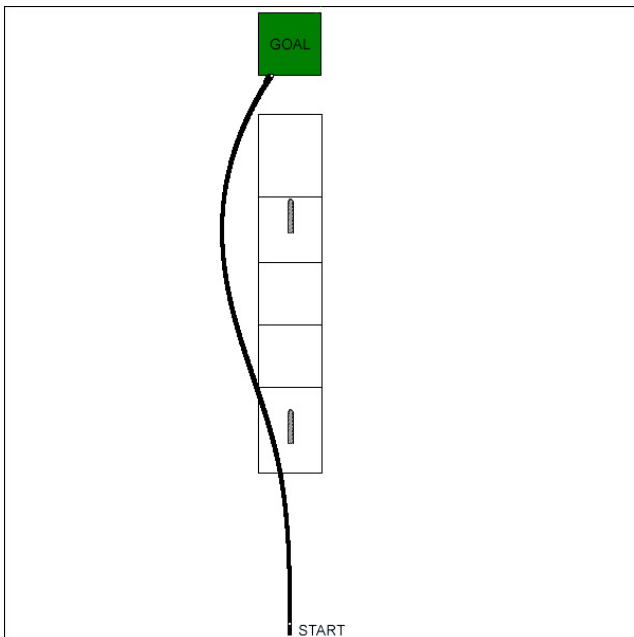


Figure 5. Final route of the best individual

The results of simulation is the route of the best individual, chosen after specified duration of simulation. His actions taken and maneuvering parameters values has been presented in figures 6-10.

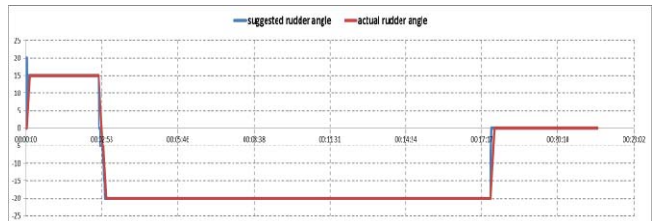


Figure 6. Suggested and actual rudder angle

The system calculated 3 rudder angle changes, resulting changes in angular velocity as well.

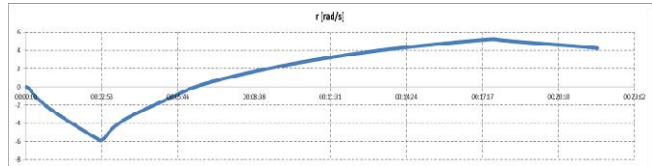


Figure 7. Angular velocity

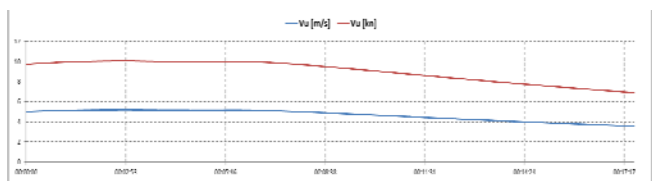


Figure 8. Linear velocity in m/s and in knots

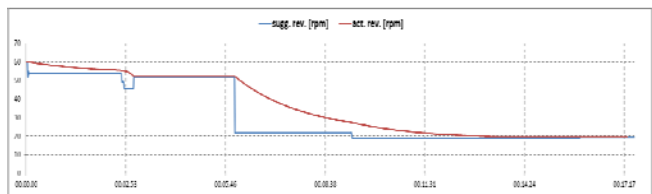


Figure 9. Suggested and actual revolutions [rpm]

Propeller revolutions changes suggested by the system seem to be too low, causing in linear speed decrease below 4 m/s [7 kn]. It may be solved in further simulation by the adjustment of a reward value related to ships' velocity or time of travel.

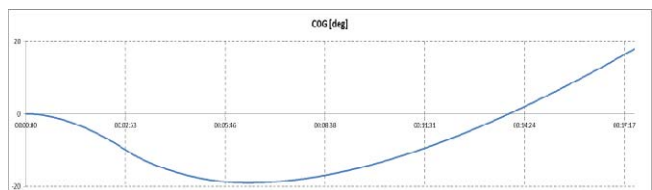


Figure 10. Course over ground

3.2 Rule 15 – Crossing Situation

Crossing maneuvers are described in rule 15:

“When two power-driven vessels are crossing so as to involve risk of collision, the vessel which has the other on her own starboard side shall keep out of the way and shall, if the circumstances of the case admit, avoid crossing ahead of the other vessel.”

An example of simulation process of crossing situation is presented on figure 11. Give-way vessel

starts with course 110° on the port side of the encountered vessel which is heading north.

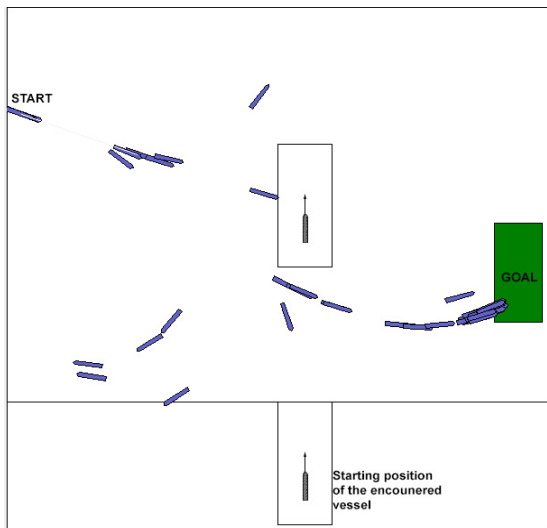


Figure 11. An example of simultaneous positions of each individual in population of helmsmen during simulation

During simulation each artificial helmsman tries to safely navigate through area to a goal, and according to rule 15, he tries to avoid crossing ahead of the other vessel during maneuvers.

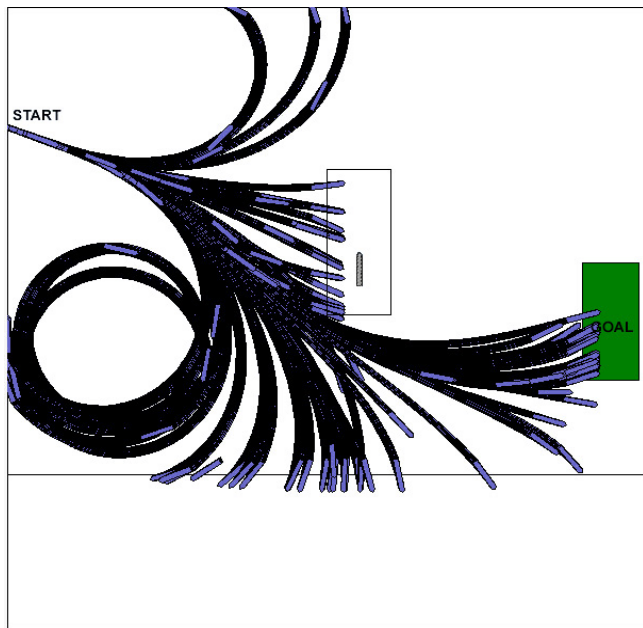


Figure 12. An example of recorded routes of a whole population

There are some individuals that prefer relatively safe circulation than risky maneuvering near forbidden domain of the encountered vessel. Their fitness is slightly better than ones leaving the area, but they are still too weak to compete with better units during selection.

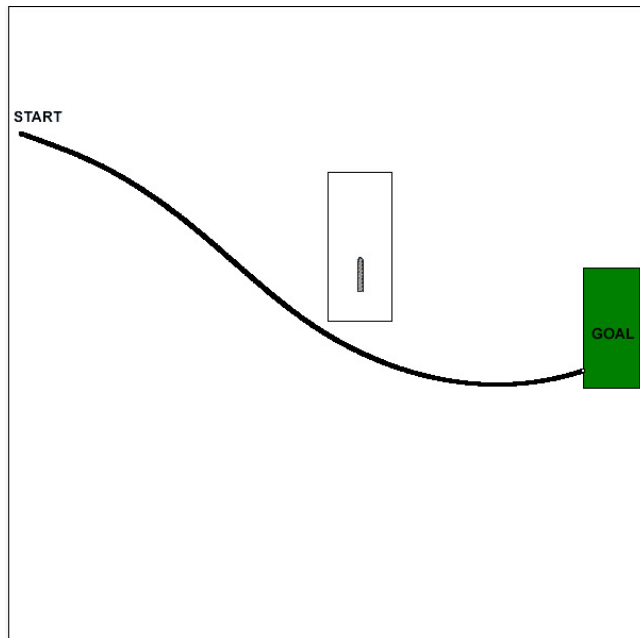


Figure 13. Final route of the best individual

The results of simulation are presented as final route of the best individual and its actions and parameters in figures 14-18.

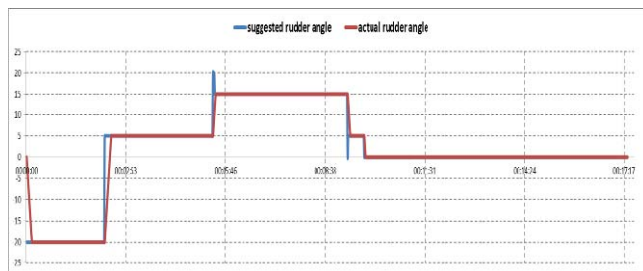


Figure 14. Suggested and actual rudder angle

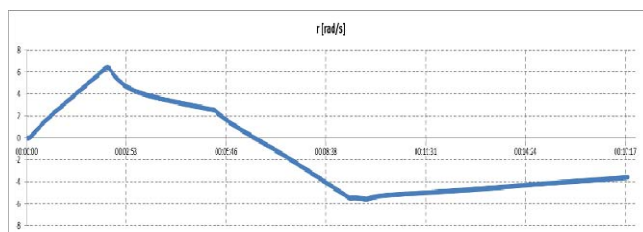


Figure 15. Angular velocity

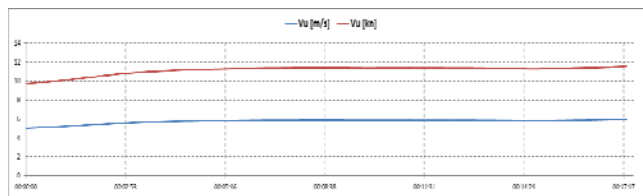


Figure 16. Linear velocity in m/s and in knots

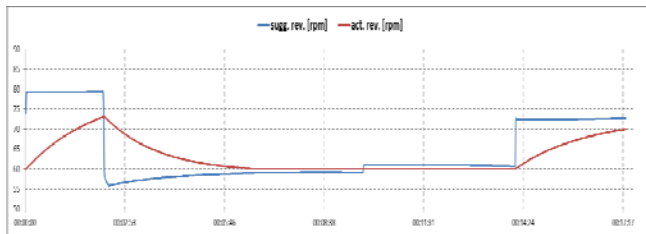


Figure 17. Suggested and actual revolutions [rpm]

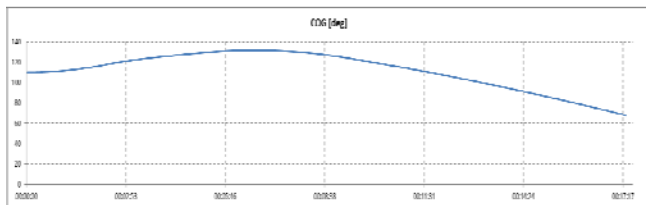


Figure 18. Course over ground

Ship of that size has very limited maneuverability, what implies higher awareness of early orders of changing her rudder deflection or/and propeller thrust. Simulation results show that change of thrust has no big impact of ships' speed in considered situations. More important is rudder angle, which is limited to $\pm 20^\circ$.

4 REMARKS

Many discussions on COLREGs have raised and been continued since its creation and first submission related to its application. There are some proposals of improvements in the maritime education to reduce the negative impacts during the implementation of the COLREGs (Demirel and Bayer, 2015).

Neuroevolutionary approach to ship handling during cross-over or overtaking of encountered vessel may improve a quality of maneuvers and safety of navigation. For the simulation study, mathematical model of three-degrees-of-freedom VLCC crude oil tanker with the single-propeller and single-rudder has been used to test the performance of the system. In comparison to a classic state machine learning algorithms (Łacki, 2007) the artificial neural networks based on modified NEAT method may increase complexity and performance of considered model of ship maneuvering according to COLREGs. Neuroevolutionary ship handling system brings some valuable benefits to this approach:

- increase of the safety of navigation by improving the data analysis for decision-maker during maneuvers,
- reduction of operating costs of vessels due to reduced number of extreme and unnecessary maneuvers,

- minimization of the occurrence of human errors,
- reduction of the harmful impact of transport on the environment
- finding some new solutions related to heuristic characteristics of neuroevolution.

It is important to notice that all these benefits in neuroevolution strictly depend on proper adjustment of evolutionary parameters and processes, the size of ANNs population and the encoding methods of signals considered in serviced environment.

Successful simulation results encourage to further research of the neuroevolutionary methods with additional disturbances from the influence of sea waves, ocean currents and winds, for different ship models, which may be successfully implemented into advanced navigational systems to increase the safety of navigation.

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