POLISH MARITIME RESEARCH 4 (112) 2021 Vol. 28; pp. 142-150
10.2478/pomr-2021-0056

AN ADAPTIVE ISLAND MODEL OF POPULATION FOR NEUROEVOLUTIONARY SHIP HANDLING

Mirosław Łącki*
Gdynia Maritime University, Poland
* Corresponding author: *m.lacki@wn.umg.edu.pl (M. Łącki)*

ABSTRACT

This study presents a method for the dynamic value assignment of evolutionary parameters to accelerate, automate and generalise the neuroevolutionary method of ship handling for different navigational tasks and in different environmental conditions. The island model of population is used in the modified neuroevolutionary method to achieve this goal. Three different navigational situations are considered in the simulation, namely, passing through restricted waters, crossing with another vessel and overtaking in the open sea. The results of the simulation examples show that the island model performs better than a single non-divided population and may accelerate some complex and dynamic navigational tasks. This adaptive island-based neuroevolutionary system used for the COLREG manoeuvres and for the finding safe ship's route to a given destination in restricted waters increases the accuracy and flexibility of the simulation process. The time statistics show that the time of simulation of island NEAT was shortened by 6.8% to 27.1% in comparison to modified NEAT method.

Keywords: artificial neural networks, evolutionary algorithms, neuroevolution, ship movement control, ship manoeuvring

INTRODUCTION

The safety of maritime transport is a key factor in the manoeuvres of seagoing vessels. Due to human errors, a lack of information, bad weather or high vessel traffic, there is still a high risk of ship collision, potentially resulting in a threat to life, cargo and the environment. There are various tools, procedures and manoeuvring decision support systems that have evolved over time and are still being adapted to new conditions, for example, to support unmanned ships (Maritime Autonomous Surface Ships).

Intelligent adaptive computer decision support systems with evolutionary algorithms (EAs) are also used in this field to accelerate decision processes and to reduce the impact of human errors. Determining the parameters of evolutionary processes is often the most important factor in tuning the efficiency of the EA for a certain task. The automation of this process allows the solution to be found more rapidly without the redundant designer influence and is strictly related to another problem in heuristic search methods, like EAs, which is premature convergence. The problematic result of premature convergence may be getting stuck in a local extremum [1]. Thus, in an evolutionary system, it is important to maintain the diversity of the population during the entire search for the global optimum [2].

The motivation for this work is the desire to find a new approach to solve navigational tasks that would provide improved results in comparison to the standard single-population approach. In order to achieve this goal, an island model of population, composed of islands of equal sizes, performing independently of each other, with adaptive dynamic evolutionary parameters, is proposed. The island model approach is often described in the literature to be more effective than the tasks evaluated on a single population [3]we consider popular evolution schemes of panmictic (steady-state. This has inspired the author to use it in a neuroevolutionary ship handling system to automate its adjustment for different navigational situations.

This study is organised as follows. The related works are briefly presented, followed by a description of the simulation models of the vessels. The results of the simulation are then presented and the conclusions are gathered in the final section.

RELATED WORKS

The neuroevolutionary method is a combination of three main techniques, namely, artificial neural networks (ANNs), EAs and reinforcement learning (RL). All these techniques are well known and have been used in different combinations in many fields of research. The main focus of this research is the usage of neuroevolution in ship manoeuvrings and control, but it can be used in other tasks as well.

In related works, researchers have investigated the feasibility of various types of neural network methods, including for the performance and emission characteristics of diesel engines fuelled with biodiesel-based fuels [4]. ANN techniques have also been widely applied for navigational tasks, for example, ship fuel consumption prediction with back-propagation networks [5], predicting both fuel consumption and travel time [6], vessel position and trajectory prediction with generalised regression neural networks [7], classifying inland water vessels with the GoogLeNet Network Toolbox [8], data-driven models of ANNs for the time series prediction of ship motion [9], a radial basis function ANN in ship dynamic positioning system [10] and the training of marine control engineering professionals [11].

EAs with the island model of population were used in [12], where the island-based population was transformed into a multi-agent system capable of learning and adapting the inter-island links based on the experience obtained during the evolutionary process. Another usage of EAs with islands was described in [13], where each island modified a fragment of the chromosome that encoded a possible solution of the multi-objective optimisation problem. The important factors of the island model are the number of islands and island population size, as described in [14], where a single run of the largest population possible with multiple small population independent runs of benchmark tests was carried out. The main result suggested that a single large run reaches the solution faster than the small runs. A comparison of multi-population and single-population EAs was made for path planning in maritime collision avoidance [15]. In this case, the multi-population approach improved the results of the path planning task.

An interesting novel approach to the island models of an EA was described in [16], where the island had different sizes and was managed by a differential evolution algorithm. In evolutionary multi-objective optimisation, it is possible to find a set of Pareto-optimal solutions. Such an approach may be applied to multiple real-life navigational problems, including the weather routing of transoceanic vessels [17].

RL, as described in [18], is one of the basic machine learning paradigms, in which an autonomous agent is able to take actions in an environment in order to maximise its cumulative reward value. Due to the exploration versus exploitation trade-off, RL requires feasible exploration policies, especially in online continuous state problems. The deep RL variant of this method has been applied in various complex tasks, like the automation of security solutions in network systems [19] it is important to investigate the behavior of the attacker after successful exploitation (post-exploitation, where the analysis of the behaviour of the attacker after successful exploitation was performed with the Advantage Actor Critic algorithm compared to the standard RL algorithms.

RL has many advantages in heuristic searches and has been successfully applied in the dynamic motion control of vehicles [20]. RL performs well in combination with ANNs treated as agents taking actions according to RL policy [21].

MATERIALS AND METHODS

For the purpose of this study, two methods of neuroevolution have been implemented and tested, namely, the modified adaptive NeuroEvolution of Augmenting Topologies (NEAT) (mNEAT) and the new modified island-based NEAT (iNEAT) algorithms. Both algorithms, designed and developed by the author, come from the NEAT method introduced by Stanley and Risto [22]. The standard NEAT method starts with a population of small ANNs and allows its topology to augment in an evolutionary process to a feasible size, capable of finishing the given task properly.

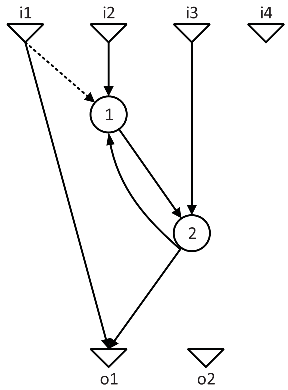
The direct encoding method has been used to create a functional structure of the ANN in NEAT from two genomes containing information on the topology and network connections (Fig. 1). Each value in both genomes (except for the number of inputs and outputs) may be altered in the mutation process.

The simulation was carried out with a computer application created by the author of this work. The computations were performed on a PC with an AMD Ryzen 5 2600 processor and 16 GB of RAM. The simulation was divided into stages for each task consecutively. In each stage, there were the time calculations of reaching the fitness value threshold by the population.

The training process of the NEAT method consists of three main steps, namely, the evaluation of vessel movements, selection and reproduction. The evaluation of each individual was processed during the 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 manoeuvres, i.e., frequent alterations in rpm, leading to improper

movement parameters for the ship, i.e., linear and/or angular velocity becomes too low or too high;
- Moving the vessel away from the goal;
- Reaching the goal.



Topology genome

Inputs	4
Nodes	2
Outputs	2

Connection genome

From	i1	i2	i1	i3	1	2	2
To	o1	1	1	2	2	o1	1
Weight	-0.4	0.02	-0.11	0.9	-1.0	0.52	-0.2
Innov. No.	1	2	4	5	9	12	13
Disabled?	-	-	Yes	-	-	-	-

Fig. 1. An example of direct encoding in the NEAT method. The topology (phenotype) of the ANN is created from connection genomes (genotype)

All these events must be arbitrarily rated, resulting in a reward to an evaluated individual, thus valuating its fitness. The fitness value is important in the evolutionary stage of the algorithm because it affects the chance of reproduction and survival of the individual selected to the next generation.

The evolutionary process of the system consists of three main steps:
- Selection of the best individual (or individuals) of each island;
- Reproduction (with cross-over and mutation sub-processes);
- Replacement (offspring replaces worst individuals on each island).

NEAT modifies the topology of the ANNs using an EA. This approach allows a population of individuals to be obtained that are well suited for the task. In the mNEAT and iNEAT algorithms, there is a small probability of removing a node or connection, thus allowing the individuals to shrink and remove unnecessary genes from genome due to dynamically changing environment. It is also a method to avoid slowing of the learning progress of excessively large phenotypes if some rapid changes occur in the navigational task.

INPUT AND OUTPUT SIGNALS

The number and type of network input and output signals must be determined during the system design phase. A properly designed set of signals included in the model is crucial for the system performance and should provide the most accurate representation of the real navigational situation. The following input signals were considered and implemented in the system with three degrees of freedom of movement of the vessel:
- Course over ground;
- Angular velocity;
- Speed over ground;
- Position of vessel;
- Distance and angle to goal, obstacles and encountered vessel;
- Visibility of goal, obstacles and other vessels;
- Propeller rpm (actual and suggested by ANN);
- Rudders' deflection (actual and suggested).

In the designed system, some other signals from the environment may be considered, if included in the ship model, i.e., wind, sea current, waves, cargo, trim and roll.

There are two output signals of the ANNs that generate control values for the vessel:
- Revolutions of main propeller (in rpm);
- Rudders' deflection.

Some input and all output signals are normalised as real values within the range <0.0; 1.0>. Some input signals are of the Boolean type (e.g., is the goal visible? Is the goal on course? Is an obstacle on course?).

Each node in the network is a neuron that computes its output value from <0.0; 1.0> as a result of the normalised sum of its input values. The computation is performed using the sigmoid function described with Eq. (1):

$$o_j = \frac{1}{1 + e^{-(S_j \beta + \theta_j)}} \quad (1)$$

where o_j is the output of a neuron, S_j is the sum of the input values x_{nj} adjusted with weights w_{nj}, β is the slope coefficient and θ_j is the bias.

SIMULATION MODELS

The results of the simulation, shown below, are obtained for the VLCC crude oil tanker *Esso Norway II* with a single propeller and rudder and for the container ship *Cape Norman* (shown in Fig. 2). The main parameters of the simulated vessels are given in Table 1. The simulation models consist of three degrees of freedom of movement of the vessel. The main equation (Eq. (2)) of the ships' relative motion was formulated by Fossen [23]:

$$M\nu + C(v_r)v_r + \mathrm{D}(v_r)v_r + \mathrm{g}(\eta) = \tau_p + \tau_{cs} + \tau'_e \quad (2)$$

where M is the mass matrix, C is the centripetal and Coriolis coefficients, D is the damping matrix, v_r is the velocity vector, $g(\eta)$ is the restoring forces vector and τ represents the forces affecting the vessel from the propeller (p), control surfaces (cs) and environmental disturbances (e).

(a)

(b)

Fig. 2. (a) VLCC oil tanker Esso Norway II (1969–1985). Source: http://www.aukevisser.nl.
(b) Container ship Cape Norman. Source: https://www.marinetraffic.com/en/photos/of/ships/shipid:881996

Tab. 1. Main parameters of the oil tanker Esso Norway II and the container ship Cape Norman

Parameter	Esso Norway II	Cape Norman
Overall length	323.8 m	175 m
Length between perpendiculars	304.8 m	170 m
Beam	47.3 m	26.5 m
Max. draft	18.46 m	14.2 m
Deadweight tonnage/capacity	193048 t	1504 TEU
Max. revolutions of propeller	80 rpm	480 rpm
Max. simulation rudder deflection	±20°	±30°

In this simulation, it was assumed that the Esso Norway II encounters a second vessel of similar size moving forward on a steady course. The maximum rudder deflection was limited to ±20° and ±30° regarding the simulation model accuracy. The safety domain was established as a simplified rectangle shape three lengths ahead of the bow, one length behind the stern (Fig. 3) and five lengths in total. The width of this domain is two lengths of the vessel. The domain surface area for the vessel is ~150000 m2.

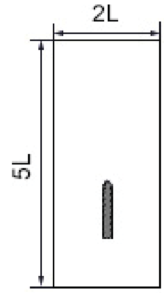


Fig. 3. Simplified safety domain of encountered vessel

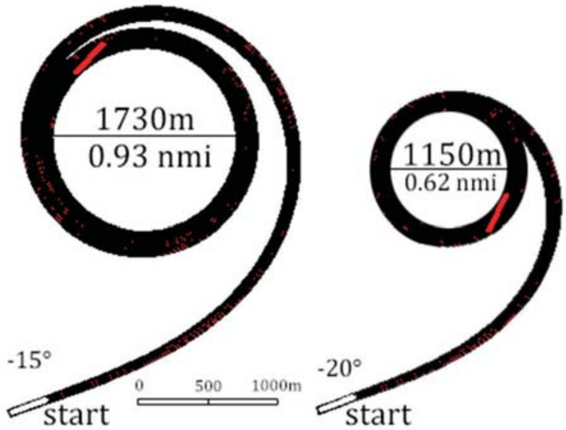


Fig. 4. Simulation results of Esso Norway II turning circle for two rudder deflections

It is noteworthy that the manoeuvrability characteristics of the VLCC oil tanker are very restricted due to its size and tonnage. Its turning circle diameter is ~1150 m (~0.62 nautical miles) for a maximum rudder deflection of -20° (see Fig. 4) and with full speed ahead (80 rpm).

PSEUDOCODE OF NEUROEVOLUTIONARY ISLAND APPROACH (INEAT)

The following list of instructions shows the main steps of the iNEAT algorithm:

1. Generate population p0 with k individuals *i[1..k]*;
2. Give each individual *i* its initial basic structure consisting of *0..n* nodes and *c* connections (*c*>0);
3. Place each individual randomly in one of *g* groups (islands);
4. Start simulation and evaluation;
5. Evolve population regarding selection policy and mutation rates in each island separately;
6. Copy best individuals from each island to separate island *g0*;
7. Cross over individuals from *g0* with random individual from each island and replace the worst individual on the island with the offspring;
8. If the overall fitness value is not obtained: go to 4, else end simulation.

Each island has different and dynamically valued evolutionary parameters. At the beginning, the mutation rate is greater and its value is gradually lowered according to the overall fitness value of the population. If the fitness becomes lower because of rapid environmental changes, then the mutation parameters increase its value proportionally to these changes.

The islands operate autonomously and they periodically exchange the best individuals among each other during the process of evolution. Such a migration of individuals is carried out regarding the archipelago topology and the defined migration policy. The details of the migration specify the frequency of migration, the quantity of migrants and the method in which migrants are introduced into the target population.

During the simulation, the program runs until the population reaches a certain level of average fitness, calculated with Eq. (3), or its operation is terminated at the user's request. The threshold value of the average fitness of the whole population depends largely on the complexity of a given task:

$$f = \frac{t}{c + t + o + r} \tag{3}$$

where f is the overall fitness value of the population, t is the number of individuals that reached the goal, c is the number of individuals that crashed, o is the number of individuals that left the area and r is the number of individuals that were turning in a circle. The range of the values of f is [0.0, 1.0].

The fitness value threshold for overtaking and crossing situations was set at 0.3. This threshold was different for the third task. In passing through restricted waters, the probability of crashing with an obstacle was greater; thus, the overall performance of the population was lower than in the open sea. This was the reason for setting the fitness value threshold to 0.2 in this task.

RESULTS

This section contains three subsections describing each navigational task. Passing through restricted waters is for the container ship *Cape Norman*, with the assumption that the ship is far away from the bank and other ships. Overtaking and crossing manoeuvres are for the oil tanker *Esso Norway II* according to the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs), published by the International Maritime Organisation in 1972. The mathematical formulations necessary to implement the COLREGs can be described and solved by the algebra of vectors [24] and then manoeuvres can be performed with the proposed EA methods (mNEAT and iNEAT), as compared below.

OVERTAKING

The overtaking manoeuvre is described by Rule 13 in the COLREGs. In the example below, our vessel is heading north with a speed of 5 m/s (9,7 kn) and encounters another vessel located straight ahead at point A (Fig. 6) heading north at 3 m/s (5,8 kn). In this case, an overtaking manoeuvre has to be taken.

Fig. 5. Rudder angle comparison during overtaking manoeuvre: rudder1 (blue) – mNEAT; rudder2 (green) – iNEAT

As shown in Fig. 5, where the rudder angles of the best individuals are compared, there are some differences between the two results. At the beginning, both neural network outputs generate an angle of 5° (5° to port). In the classic mNeat method, there is a gradual change in the rudder angle from 5° to -20°, while the iNEAT change is radical from +20° to -15° and then to -20°, resulting in a longer and wider turning manoeuvre. In this scenario, the mNEAT results are more stable and with better course over ground than iNEAT.

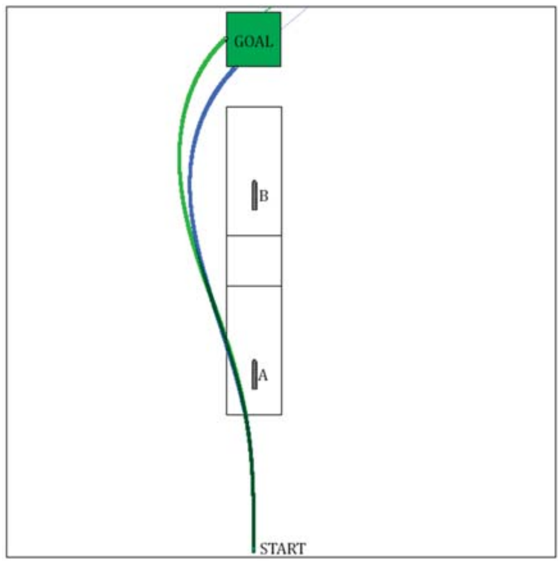


Fig. 6. Registered paths of vessels midship in overtaking situation: blue path – mNEAT; green path – iNEAT. Encountered vessel moves from A to B during whole manoeuvre

The result of this simulation requires further adjustments. The vessels from both solutions reach the goal with course

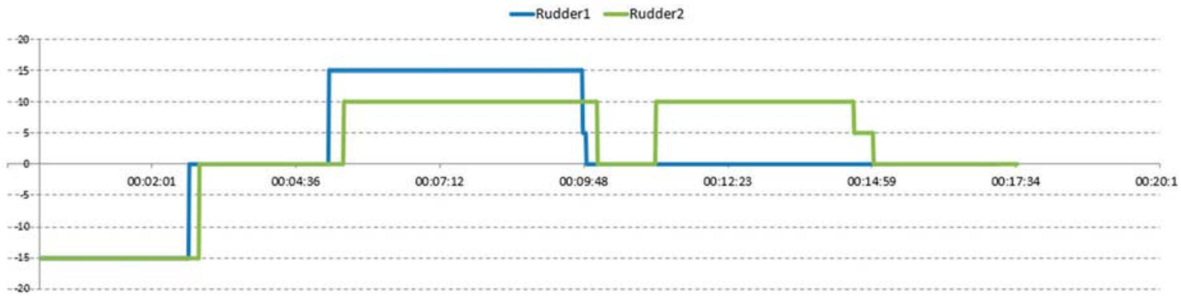


Fig. 7. Rudder angle comparison during crossing situation: rudder1 (blue) – mNEAT; rudder2 (green) – iNEAT

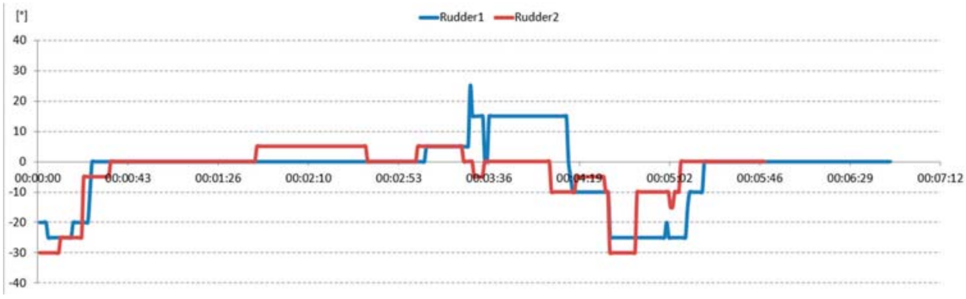


Fig. 9. Rudder angle comparison during passing through restricted waters: rudder1 (blue) – mNEAT; rudder2 (red) – iNEAT

over ground far from 0° (38° for mNEAT and 54° for iNEAT). Perhaps a stronger negative reinforcement value shall be inflicted to individuals with a high COG (Course Over Ground) value at the destination.

CROSSING SITUATION

The crossing situation is described by Rule 15 in the COLREGs. In this scenario, the Esso Norway II is a give-way vessel, forced to take proper manoeuvres to avoid collision with another vessel on its starboard.

Both results (Fig. 7) of the suggested rudder deflection are acceptable and the final choice of the solution may be determined by the impact of the penalties for the maximum rudder deflection or the rewards for the straight ahead course (0°).

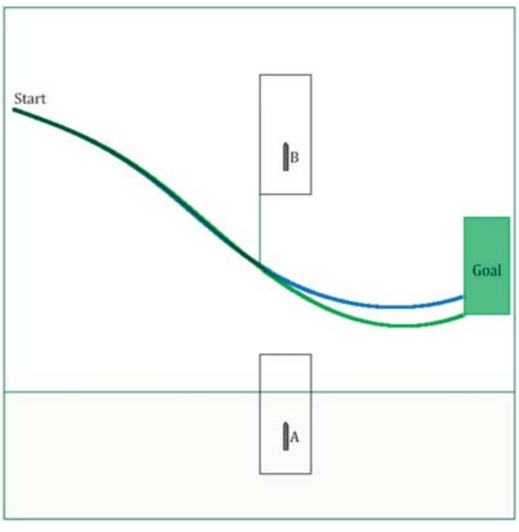


Fig. 8. Two paths of the vessel during crossing manoeuvres: blue path – mNEAT; green path – iNEAT. Encountered vessel is moving steadily from A to B

The final trajectories do not differ much (see Fig. 8). The mNEAT route seems to be flatter with a better final COG. In this task, there was a quantitively stable group of vessels that had chosen a relatively safe circulation manoeuvre, instead of the risk of going towards the forbidden domain of the encountered vessel or area boundaries. This group was too weak to dominate the population but also too strong to be completely eliminated from the population during selection and reproduction.

PASSING THROUGH RESTRICTED WATERS

The simulation model of the Cape Norman was assigned to this task. One of the hardest manoeuvres was the narrow turn on starboard near the destination zone (see Fig. 11).

The results clearly show that iNEAT (red) is better than mNEAT (blue) in terms of the number of manoeuvres (rudder deflection values and alterations, Fig. 9), propeller suggested revolutions (Fig. 10) and the trajectory shape (Fig. 11).

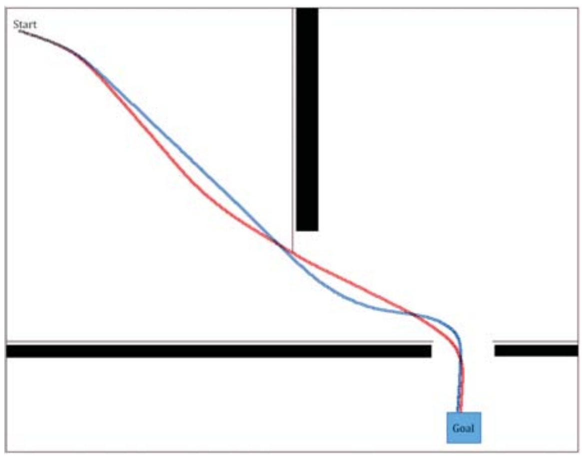


Fig. 11. Path of the midships of the vessel comparison during passing through restricted waters: blue path – mNEAT; red path – iNEAT

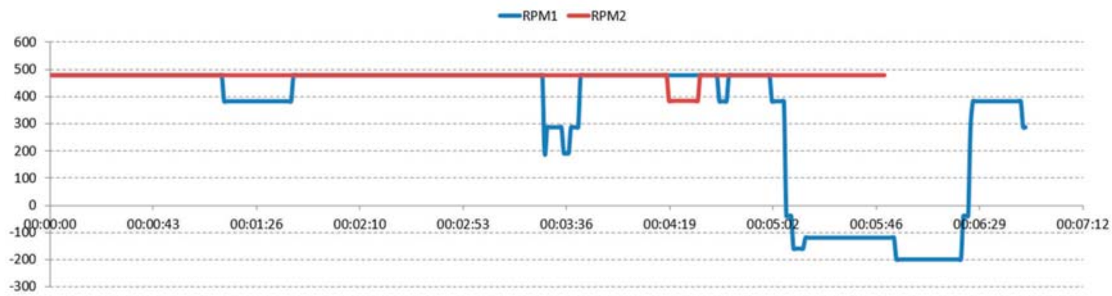


Fig. 10. Propeller revolution comparison during passing through restricted waters: RPM1 (blue) – mNEAT; RPM2 (red) – iNEAT

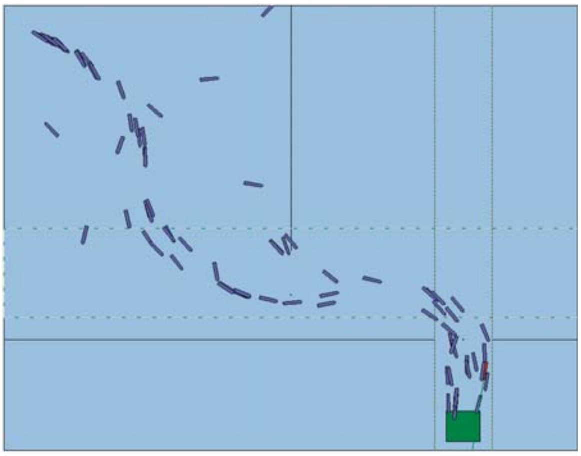


Fig. 12. Example of an ongoing simulation

An example of the evolutionary learning process during the simulation is presented in Fig. 12. As shown, a situation occurs where the population has already learned how to reach the goal and most of the individuals follow the best helmsman (marked as red). The tuning process now begins with a stricter selection threshold. Some of the vessels explore new solutions, which eventually may be better rewarded than actions taken by the current best helmsman. A comparison of the time statistics for all navigational tasks for the first simulation run is presented in Fig. 13 and Table 2.

Tab. 2. Time statistics for simulated navigational tasks

Manoeuvres	Average time of acquiring fitness value threshold, 20 runs		Improvement rate	Median absolute deviation	
	mNEAT	iNEAT		mNEAT	iNEAT
Overtaking	0:05:10	0:04:25	14.4%	0:00:50	0:01:34
Crossing	0:07:58	0:07:25	6.8%	0:01:05	0:00:50
Restricted waters	0:13:02	0:09:30	27.1%	0:01:55	0:01:22

The time statistics show that the iNEAT approach is faster, particularly for the passage through restricted waters (Fig. 13(c)), despite the fact that it requires additional time for island management operations. The example in Fig. 13(d)

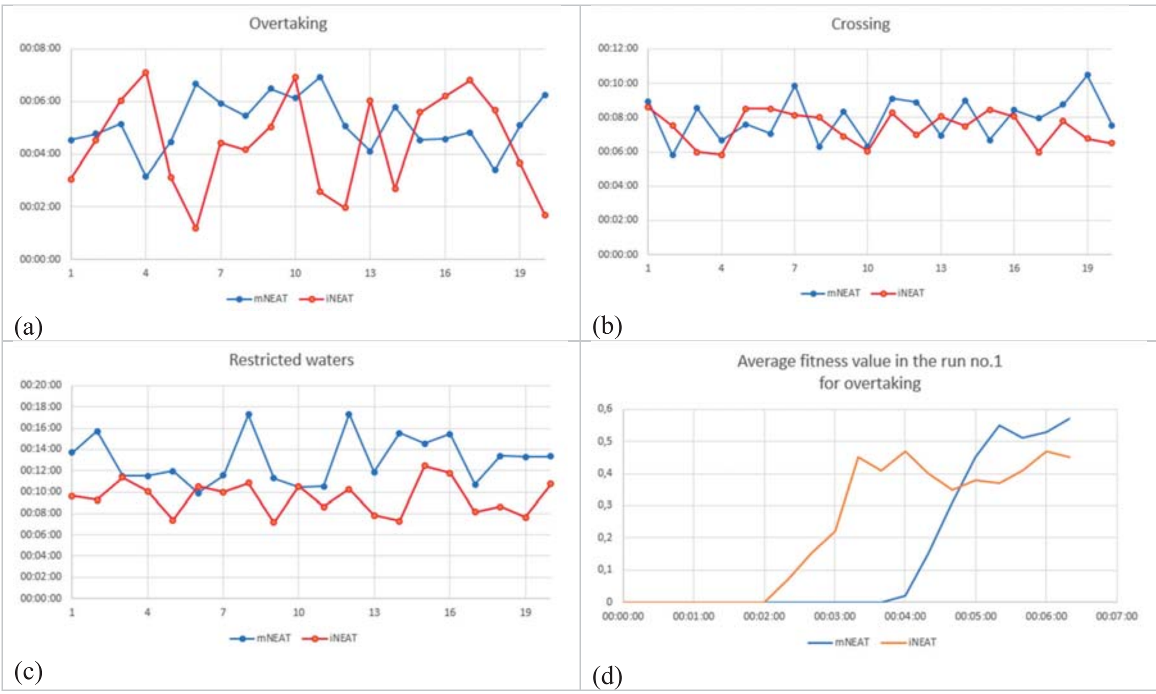


Fig. 13. Time of fitness value threshold acquisition in 20 runs for overtaking (a), crossing (b) and passage through restricted waters (c). An example fitness value acquisition process for the first run in overtaking (d). The threshold value for this task is 0.3.

shows that mNEAT is able to achieve higher average fitness values of ~0.55 for mNEAT and ~0.45 for iNEAT at the sixth minute of the simulation. This is due to the fact that the evolutionary parameters in iNEAT take a wider range of values, resulting in wider search space exploration and a potentially higher percentage of failures for some individuals.

CONCLUSIONS

The proposed new iNEAT method increases the accuracy and flexibility of the simulation process. This system allows for the simulation of the complex behaviour of the ship in a dynamic environment in a much larger space of states than is possible in classical reinforcement learning algorithms [18].

The simulation results show that the island separated population in an evolutionary ANN may slightly accelerate some complex and dynamic navigational tasks. The time statistics show that the time of simulation of island NEAT was shortened by 6.8% to 27.1% in comparison to modified NEAT method.

The proposed system has several important advantages that positively affect the efficiency of maritime transport. These are, among others:

- Possibility of usage on manned and unmanned vessels, which may lead to better automation of processes in the sea navigation;
- Providing additional data useful for decision makers during manoeuvres;
- Reduction of ship operating costs, human errors and detrimental impact of maritime transport on the environment.

All these benefits are strictly dependent on the size and dimensions of the search space, the number of signals analysed, the size of the ANN population and the encoding methods of the signals considered in the simulated environment. The population divided into islands with different evolutionary parameters allows the individuals to spread over a wider search space, resulting in a better chance of finding an optimal or sub-optimal solution. The diverse genetic pool is also much more flexible in dynamic environments. The drawback of this solution is the lower average fitness value of the population and additional procedures required for island management.

Due to the dynamic parametrisation of the island separated population, it is possible, in some cases, to find the correct solutions that allow us to reduce the number of manoeuvres, like rudder deflections or rpm alterations, resulting in lower fuel consumption.

The island model requires the topology of the migration and the migration policy to be established, which are tasks that require additional time and preparations. There are some proposals for the future research directions in ship handling neuroevolutionary methods, such as:

- Implementation of multi-size island model without migration;
- Introduction of environmental disturbances from influence of wind, current and waves on the moving vessel;
- Combining island model with indirect encoding neuroevolutionary methods;
- Evaluation of different population sizes on the algorithm's efficiency.

DATA AVAILABILITY

The simulation data used to support the findings of this study are available from the author upon request.

CONFLICTS OF INTEREST

The author declares that he has no conflicts of interest.

FOUNDING STATEMENT

This research was funded by the statutory activities of Gdynia Maritime University, grant number WN/2021/PI/2.

REFERENCES

1. D. Whitley, S. Rana, and R. Heckendorn, "The Island Model Genetic Algorithm: On Separability, Population Size and Convergence," Journal of Computing and Information Technology, vol. 7, 1998.

2. H. M. Pandey, A. Chaudhary, and D. Mehrotra, "A comparative review of approaches to prevent premature convergence in GA," Applied Soft Computing, vol. 24, pp. 1047–1077, 2014, doi: https://doi.org/10.1016/j.asoc.2014.08.025.

3. E. Alba and J. M. Troya, "An analysis of synchronous and asynchronous parallel distributed genetic algorithms with structured and panmictic Islands," in Parallel and Distributed Processing, Berlin, Heidelberg, 1999, pp. 248–256.

4. A. Hoang et al., "A review on application of artificial neural network (ANN) for performance and emission characteristics of diesel engine fueled with biodiesel-based fuels," Sustainable Energy Technologies and Assessments, Jun. 2021, doi: 10.1016/j.seta.2021.101416.

5. S. L. Boung Yew and K. K. Kee, "Artificial Neural Network Back-Propagation Based Decision Support System for Ship Fuel Consumption Prediction," 2018. doi: 10.1049/cp.2018.1306.

6. W. Tarełko and K. Rudzki, "Applying artificial neural networks for modelling ship speed and fuel consumption," Neural Computing & Applications, vol. 32, pp. 17379–17395, 2020. doi: 10.1007/s00521-020-05111-2

7. J. Liu, G. Shi, and K. Zhu, "Vessel Trajectory Prediction Model Based on AIS Sensor Data and Adaptive Chaos Differential Evolution Support Vector Regression (ACDE-SVR)," Applied Sciences, vol. 9, p. 2983, 2019, doi: 10.3390/app9152983.

8. K. Bobkowska and I. Bodus-Olkowska Izabela, "Potential and Use of the Googlenet Ann for the Purposes of Inland Water Ships Classification," Polish Maritime Research, vol. 27, pp. 170–178, 2020. doi: 10.2478/pomr-2020-0077

9. G. Li, B. Kawan, H. Wang, and H. Zhang, "Neural-network-based modelling and analysis for time series prediction of ship motion," Ship Technology Research, vol. 64, 2017, doi: 10.1080/09377255.2017.1309786.

10. T. Niksa-Rynkiewicz and A. Witkowska, "Analysis of impact of ship model parameters on changes of control quality index in ship dynamic positioning system," Polish Maritime Research, vol. 26, no. 1(101), pp. 6–14, 2019. doi: 10.2478/pomr-2019-0001

11. J. Lisowski, "Computational Intelligence in Marine Control Engineering Education," Polish Maritime Research, vol. 28, no. 1, pp. 163–172, 2021, doi: doi:10.2478/pomr-2021-0015.

12. R. Lopes, R. Pedrosa Silva, F. Campelo, and F. Guimarães, "A Multi-agent Approach to the Adaptation of Migration Topology in Island Model Evolutionary Algorithms," in Proceedings - Brazilian Symposium on Neural Networks, SBRN, 2012, pp. 160–165. doi: 10.1109/SBRN.2012.36.

13. P. García-Sánchez, J. Ortega, J. González, P. A. Castillo, and J. J. Merelo, "Distributed multi-objective evolutionary optimization using island-based selective operator application," Applied Soft Computing, vol. 85, p. 105757, 2019, doi: https://doi.org/10.1016/j.asoc.2019.105757.

14. E. Cantú-Paz and D. E. Goldberg, "Are Multiple Runs of Genetic Algorithms Better than One?," in Genetic and Evolutionary Computation — GECCO 2003, Berlin, Heidelberg, 2003, pp. 801–812.

15. R. Śmierzchalski, Ł. Kuczkowski, P. Kolendo, and B. Jaworski, "Distributed Evolutionary Algorithm for Path Planning in Navigation Situation," TransNav, the International Journal on Marine Navigation and Safety of Sea Transportation, vol. 7, pp. 293–300, 2013, doi: 10.12716/1001.07.02.17.

16. A. Skakovski and P. Jędrzejowicz, "An island-based differential evolution algorithm with the multi-size populations," Expert Systems with Applications, vol. 126, pp. 308–320, 2019, doi: https://doi.org/10.1016/j.eswa.2019.02.027.

17. J. Szlapczynska and R. Szlapczynski, "Preference-based evolutionary multi-objective optimization in ship weather routing," Applied Soft Computing, vol. 84, p. 105742, 2019, doi: https://doi.org/10.1016/j.asoc.2019.105742.

18. L. P. Kaelbling, M. L. Littman, and A. W. Moore, "Reinforcement Learning: A Survey," Journal of Artificial Intelligence Research, vol. cs.AI/9605, pp. 237–285, 1996, doi: 10.1613/jair.301.

19. R. Maeda and M. Mimura, "Automating post-exploitation with deep reinforcement learning," Computers & Security, vol. 100, p. 102108, 2021, doi: https://doi.org/10.1016/j.cose.2020.102108.

20. R. De Nardi, J. Togelius, O. E. Holland, and S. M. Lucas, "Evolution of Neural Networks for Helicopter Control: Why Modularity Matters," Evolutionary Computation, 2006. CEC 2006. IEEE Congress on, pp. 1799–1806, 2006, doi: citeulike-article-id:4142097.

21. N. T. Siebel and G. Sommer, "Evolutionary reinforcement learning of artificial neural networks," International Journal of Hybrid Intelligent Systems - Hybridization of Intelligent Systems, vol. 4, pp. 171–183, 2007.

22. K. O. Stanley and M. Risto, "Efficient Reinforcement Learning Through Evolving Neural Network Topologies," presented at the Proceedings of the Genetic and Evolutionary Computation Conference, 2002.

23. T. I. Fossen, Guidance and control of ocean vehicles. Chichester, UK: Wiley, 1994.

24. R. Zaccone, M. Martelli, and M. Figari, "A COLREG-Compliant Ship Collision Avoidance Algorithm," Jun. 2019, pp. 2530–2535. doi: 10.23919/ECC.2019.8796207.

CONTACT WITH THE AUTHOR

Mirosław Łącki
e-mail: m.lacki@wn.umg.edu.pl

Gdynia Maritime University
Morska 81/87
81-225 Gdynia
Poland