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Ship course-keeping with neuroevolutionary algorithms

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Abstract

The goal of research presented in this article is to check if a neuroevolutionary method with direct encoding is able to be a part of autopilot of the vessel. One of the important tasks of vessel autopilots is to keep a course as straight as possible or to bring the ship back on the route as efficiently as possible. In this paper, the adaptive neuroevolutionary autopilot is described and tested on a simulation model of a ferry. Neuroevolution is a combination of two different but related fields of artificial machine learning: evolution and neural networks. The combined method is very flexible and can be applied to other ship control tasks. The results of computer simulation of the neuroevolutionary course-keeping system have been included.

Introduction

Autopilot was introduced to merchant ships during the early 1920's. It supported the 'Quartermaster' – an important member of the bridge team, who was responsible to steer the ship according to the Master's and Officer's helm orders (Collinder, 1955). A modern autopilot system is an advanced and technically sophisticated automatic navigational control aid on ships. The autopilot is integrated with the gyro compass and controls the course by adjustments of the angle of the rudder in the required manner. Furthermore, advanced autopilot systems are synchronized with the Electronic Chart system (ECDIS), enabling them to follow the course according to the route plan. This feature reduces the need for manual course changes.

It is known that the PID controllers (proportional integral derivative) traditionally used in the field of motion control have some limitations. One disadvantage of a PID controller is that its performance is optimized to a narrow operating range. With dynamically changing conditions of ship maneuvering, it is often not possible to determine properly the fixed parameters of the controller that will result in good performance. Additionally, in the case of large, non-linear dynamic maneuvers, the result of PID operation may not be sufficient. To deal with the limitations of PID-based motion control systems, adaptive autopilots have been introduced to ship transportation and are still in research and development (Zwierzewicz & Borkowski, 2006; Tomera, 2010).

Efficient and adaptive autopilot operations allow some changes of the vessel's route-trace, but will use fewer and smaller rudder angles to maintain a steady course. This decreases the rudder operations and consequently reduces fuel consumption.

One approach to adaptive autopilots is neuroevolution, which will keep the vessel on its course (Figure 1).

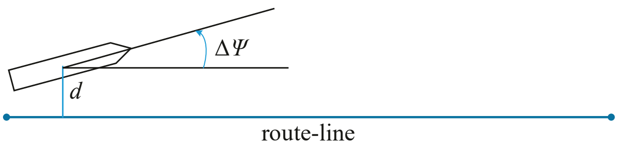


Figure 1. General task of the adaptive neuroevolutionary autopilot is to keep the vessel as close as possible to defined route-line (d → min) with the smallest course changes ($\Delta\Psi$ → min)

Neuroevolution

Neuroevolution is a combination of two different methods: artificial neural networks (ANN) and evolutionary algorithms (EA). Neuroevolutionary methods are a variety of intelligent computing methods that are capable of finding solutions to complex tasks with artificial neural networks created through a process of evolution. This combination gives the advantage of flexibility and adaptability, which allows adjustment of computational structures to dynamically changing conditions of ship maneuvering and many other tasks. Methods include:

- robotics (Haasdijk, Rusu & Eiben, 2010; Lee et al., 2013);
- automation processes (Bagnell & Schneider, 2001; Kenneth et al., 2005);
- multi-agent systems (Nowak, Praczyk & Szymak, 2008);
- designing and diagnostic (Larkin, Kinane & O'Connor, 2006) and many others.

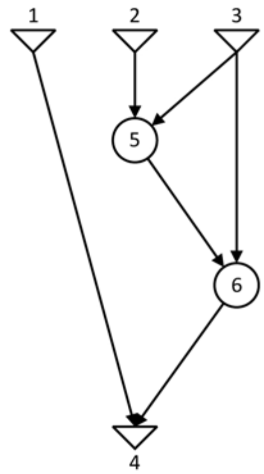
In neuroevolution, ANN is treated as an individual in a population of multiple networks. Basic topologies of the initial population are randomly determined at the beginning of the learning process. Each individual begins the process of finding a solution with the same starting parameters. The action of each individual is usually assessed by reinforcement learning algorithms (Stanley, Bryant & Risto, 2005) and the evolutionary stage of the system selects individuals best suited to the task during a selection stage, which evaluates the whole population to improve its genetic material over time.

The evolutionary stage of the system consist of three main steps:

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

Evolutionary methods require the choice of appropriate genetic encoding of neural network topology to a given task. In this case the NEAT method with direct encoding has been used (Figure 2).

NEAT (NeuroEvolution of Augmenting Topologies) gradually adjusts the topology of ANNs to the given task with EA (Stanley & Risto, 2002), allowing development of a set of ANNs that are best fitted to this task (Łącki, 2009). During evolution, in the mutation stage, the number of internal neurons and connections may change. To cope with the complexity of the adaptive autopilot task, the modified NEAT (mNEAT) method has been implemented. The mNEAT method not only allows gradual augmentation of the topology of the network, but also enables the reduction of redundant elements of the network.



From	1	2	3	3	4	6
To	4	4	4	6	6	4
Weight	–0.4	0.02	–0.11	0.9	–1.0	0.75
Innow. num.	1	2	4	5	9	10
Disabled?	No	No	Yes	No	No	No

Figure 2. An example of an artificial neural network topology (phenotype) and its connection genome (genotype), using the direct encoding NEAT method

The ANN consists of 3 types of nodes: the input, output and hidden nodes. Each hidden node represents a neuron that produces a real value between 0 and 1 as a result of the normalized weighted sum of its inputs. Normalization of the weighted sum is performed with a sigmoid function, as in Equation 1.

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

where:

o_j – output value of a neuron;
S_j – weighted sum of input values x_{nj} with weights w_{nj};
β – slope coefficient;
θ_j – bias.

The influence of a bias may be adjusted by changing the weight of this signal when the mutation stage is performed in the evolutionary process during creation of an offspring in the reproduction stage.

During the reproduction stage, the best neural network (regarding its top position in the ranking) is chosen and its genetic material is crossed-over with a random individual from the population to create a new individual, which will replace the worse one, according to the current ranking. The performance of each individual is measured at pre-determined time intervals.

Ranking is created according to main fitness function equation ($f_i \rightarrow$ min):

$$f_i = w_1 \cdot \Delta\Psi + w_2 \cdot d \tag{2}$$

where:

f_i – fitness value of an i-individual;

w_1, w_2 – weights of considered values (values of these weights varied from 0.3 to 0.7, correlatively);

$\Delta\Psi$ – course deviation;

d – vessel's distance to course-line.

Cross-over of disparate topologies is processed in a meaningful way by pairing up genes with the same historical markings, called innovation numbers.

The maneuvering model of the vessel is designed in a scheme of three degrees of freedom.

The input signals of the system are as follows:

- course over ground;
- angular velocity;
- speed over ground;
- distance to route-line;
- difference of current and required course of the vessel;
- angle and velocity of water current;
- two main propellers' revolutions (current and preset);
- two rudders' angles (current and preset).

In future research other signals from the environment will be taken into account, i.e., wind, waves, cargo, trim and roll.

Output signals of ANNs generate four values for steering the vessel:

- rpm for left main propeller,
- rpm for right main propeller,
- left rudder deflection,
- right rudder deflection.

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

Neuroevolutionary course-keeping system

The advanced adaptive neuroevolutionary autopilot should be able to work on different types of vessels, with adjustable parameters, features and limits, such as:

- rate of turn – The officer can set a value of turn rate between 0–360°. When turning, the rudder will move as much as it takes to attain the required turn rate without exceeding the set value. The officer must take into account the vessel's maneuvering characteristics and set a safe value for the vessel;
- rudder limits – a value from 1° to the max rudder angle. During maneuvering, the rudder deflection will not exceed more than the set limit;
- turning by radius – the user can input turn radius in nautical miles;
- off-course alarm – a notification to the officer that there is a significant difference in the set course and the actual heading of the vessel, that requires manual control or adjustment of the system's limitations;
- manual mode – in this mode, the vessel is steered manually by the operator (often used during maneuvering on restricted waters and areas with high traffic density or in case of emergencies);
- traffic density – a parameter that will automatically switch autopilot off (to manual mode) when the numeric of fuzzy value of current traffic density set by the user has been exceeded. The automatic mode may not be efficient in collision avoidance maneuvers while navigating in restricted areas with high traffic density;

Figure 3. *Stena Vision* ferry (previously *Stena Germanica* (maritimbild, 2010) and its simplified model with the best artificial neural network from the neuroevolutionary ship handling system

- minimum speed – autopilots work inefficiently on reduced speeds. This parameter allows the system to warn the operator that the minimum speed value has been reached and the current situation requires manual control of the vessel;
- integration with important alarms and signals – the auto pilot will be integrated with failure or reduction in the power control system, with sensor status monitoring and with the heading control system. In any case of emergency, power blackout or gyro failure the system should be immediately switched to manual mode and the course continued by magnetic compass and other available methods and devices.

A mathematical model of the *Stena Germanica* ferry implemented in a computer simulation has been used to test the neuroevolutionary autopilot system. Currently, this ferry is in service on the Gdynia-Karlskrona route, under its new name, *Stena Vision* (Figure 3).

Goal of the task: stable and relatively fast passage through the area with the course deviation as small as possible ($\Delta\Psi \rightarrow$ min and $d \rightarrow$ min).

The main assumptions:

- initial course: 80°;
- desired course: 90°;
- keeping the vessel as close as possible to the assigned course-line;
- simulation with and without external environmental disturbances (a water current).

During the simulation, the evolutionary neural network controls the revolution of the two main, independent propellers (with revolution steps of 10 rpm) and deflection of the two rudders (with deflection interval of 5°).

Measurement of course deviation was performed and registered for the best artificial helmsman in the population of 100 neural networks with 3 seconds time interval. All networks were simulated and evaluated simultaneously regarding the Reinforcement Learning reward system (Stanley & Risto, 2002) and the characteristics of the ferry model (Table 1).

The first series of measurements concerned a task of keeping the ferry on course by an artificial helmsman without any environmental disturbances.

In the case of no disturbances from the environment, the measured average course deviation for the best helmsmen decreased from 9.5° to about 1° (Figure 4). It clearly shows the learning ability of the system.

The second series of measurements concerned a task of keeping the ferry on course by the system with a water current influencing the vessel's movement. The value of the current varied from 0.1 to 1.0 m/s (0.19–1.94 knots) in a perpendicular channel, with direction of 180°.

In this case, with disturbances from a water current, the measured average course deviation for the best helmsmen decreased from 11° to about 2°

Table 1. *Stena Germanica* ferry general characteristics

Parameter	Symbol	Value
Length overall	LOA	175 [m]
Length between perpendiculars	L	154.2 [m]
Beam	B	29 [m]
Draught – loaded	TLOADED	6.65 [m]
Tonnage	ΔLOADED	38,772 [T]
Weight under ballast	ΔBALLAST	176,600 [T]
Max speed	V	20 [kn]

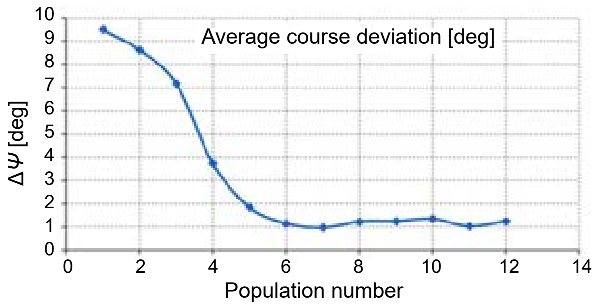


Figure 4. Average course-over-ground deviation of the ferry, divided in 12 groups of 50 measurements of best helmsmen, without environmental disturbances

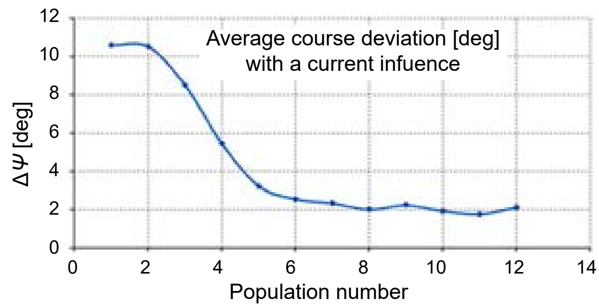


Figure 5. Average course-over-ground deviation of the ferry, divided in 12 groups of 50 measurements of best helmsmen, with environmental disturbances from a water current

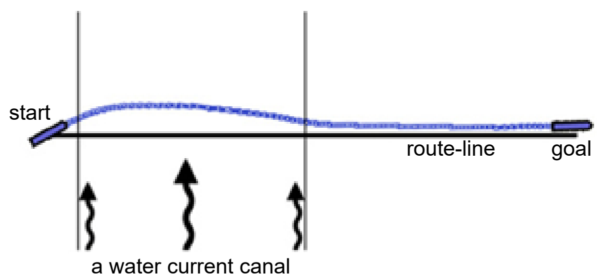


Figure 6. Trace route of the vessel with a water current canal influencing her maneuvers

(Figure 5), with standard deviation decreased from 8.6° to 1.4°.

The additional result of the simulation is the registered trace (the blue line) of the ferry's movement, as shown in Figure 6.

Conclusions

The adaptive neuroevolutionary autopilot system for maritime transport may add some valuable benefits when successfully implemented:

- improvement of the data analysis for the decision-maker during maneuvers,
- improvement of the automation processes of navigation,
- reduction of operating costs of vessels,
- minimization of the occurrence of human errors,
- reduction of the harmful impact of transport on the environment.

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

For the simulation study, a mathematical model of three-degrees-of-freedom maneuvering a ferry vessel with twin propellers and double rudder was applied to test the autopilot's performance. Artificial neural networks based on a modified NEAT method increased the fidelity and performance of the selected model ship maneuvering in autopilot mode.

Implementation of additional input signals related to the influence of a water current allowed simulation of complex behavior of the vessel in a dynamic environment with much larger state space than was possible in classic-state, machine-learning algorithms (Łącki, 2007).

Reduction of vessel fuel consumption is possible and highly required, through effective autopilot usage.

Further research of the neuroevolutionary autopilot is required, particularly with the influence of wind and waves on the vessel. Comparison to other methods is also required, e.g., with the LQR regulator.

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