

Intelligent Prediction of Ship Maneuvering

M. Łacki

Gdynia Maritime University, Gdynia, Poland

ABSTRACT: In this paper the author presents an idea of the intelligent ship maneuvering prediction system with the usage of neuroevolution. This may be also be seen as the ship handling system that simulates a learning process of an autonomous control unit, created with artificial neural network. The control unit observes input signals and calculates the values of required parameters of the vessel maneuvering in confined waters. 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 efficiently. The main task of the system is to learn continuously and predict the values of a navigational parameters of the vessel after certain amount of time, regarding an influence of its environment. The result of a prediction may occur as a warning to navigator to aware him about incoming threat.

1 INTRODUCTION

Predicting the movement of ships maneuvering on confined water is essential to the safety of people, equipment, cargo and the environment. Increase of computational power of personal and portable computers allows to implement complex algorithms into advanced decision support systems also in the field of marine navigation.

Such a system should include the following main functions:

- analysis of the navigational situation online, in continuous mode,
- warning before the dangerous situation may take place, e.g. possible collision or exit from a particular limited area in an undesirable direction,
- providing transparent information that can be used in co-operation with local authorities and other auxiliary units of the area,

- it shall give the answers to “what if” and “when” questions, in the field of ship maneuvering actions and navigational situations.

All these requirements may be fulfilled with neuroevolutionary methods. These methods are intensively studied and implemented in different fields of science, including robotics (Haasdijk et al., 2010; Lee et al., 2013), automation processes (Kenneth et al., 2005), multi-agent systems (Nowak et al., 2008), designing and diagnostic (Larkin et al., 2006) and many others. Neuroevolutionary algorithms are successful methods for optimizing neural networks topologies, especially in dynamic continuous reinforcement learning tasks. Their significant advantage over gradient-based algorithms is the capability to modify network topologies along with connection weights.

The basic concept of the system is presented in figure 1.

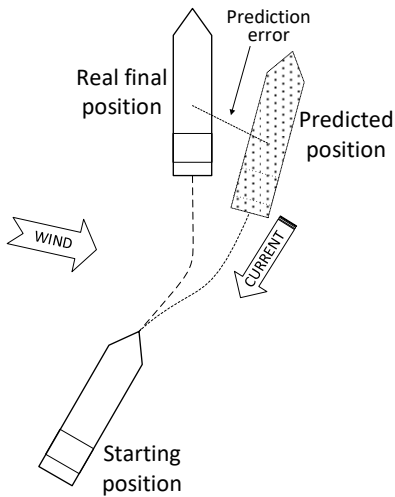


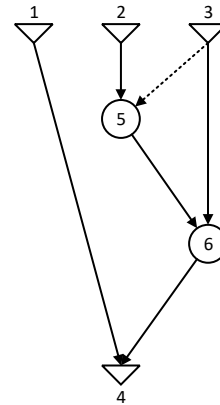
Figure 1. Estimation of a position and course of the vessel as accurate as possible to her final position is the main task of advanced prediction system.

Through continuous learning process, the system shall predict the vessel position and state of the environment after specified time interval as accurate as possible in comparison to final real position of the ship. It is possible to calculate a probable position when there is a simulation model of the vessel available. It is required that simulation model includes the equations and coefficients for wind, current and waves. But in most cases such advanced non-linear simulation model is not available. And again, a good solution for this problem is neuroevolution.

2 ARTIFICIAL INTELLIGENCE WITH NEUROEVOLUTION

Neuroevolutionary methods are part of intelligent computing methods that are inspired by the development of biological nervous systems (Lehman and Miikkulainen, 2013). Neuroevolution is capable of finding solution of complex tasks with artificial neural networks (ANN) created with evolutionary algorithms (EA). Such combination gives an advantage of flexibility and adaptation, which allows to adjust computational structures to dynamically changing tasks.

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 learning process. Each individual begins the process of finding a solution with the same starting parameters. 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.



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

Figure 2. An example of encoded artificial neural network topology (phenotype) into a connection genome (genotype), due to NEAT method

Evolutionary stage of the system consist three main processes:

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

In case of the evolutionary method the genetic encoding of neural network topology is very important. Author of this paper implemented the modified NEAT method to this system (Figure 2).

NEAT (NeuroEvolution of Augmenting Topologies) adjust the topology of ANN's with EA (Stanley and Risto, 2002a) gradually to given task, allows to obtain a set of ANN's that are best fitted to this task (Łacki, 2009).

Each node 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, as in Equation 1.

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

where:

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

Adding the bias signal of constant value 1, allows to shift the output value of the activation function (Figure 3). Influence of bias may be adjusted through changing weight of this signal, when the mutation stage is performed in evolutionary process during creation of an offspring in the reproduction stage.

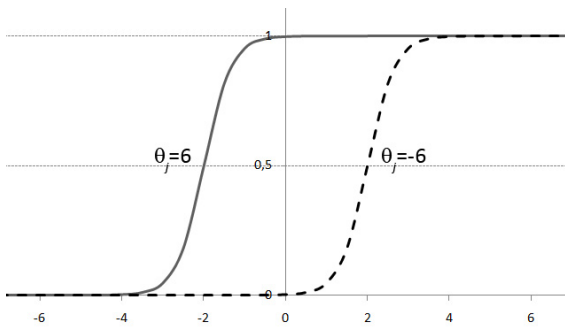


Figure 3. Influence of bias coefficient θ to value of sigmoid function

In this stage two best neural networks are chosen and its genetic material is crossed-over to create two new individuals. Cross-over of disparate topologies is processed in a meaningful way by pairing up genes with the same historical markings, called innovation numbers. With this approach the offspring may be formed in one of three ways:

- In uniform crossover, matching genes are randomly chosen for the offspring genome, with higher probability for better fitted parent.
- In blended crossover, the connection weights of matching genes are averaged.
- In elite crossover disjoints and excesses are taken from more fit parent only, all redundant genes from less fit parent are discarded. All matching genes are averaged.

Genes that do not match with the range of the other parent's innovation numbers are called disjoints (when they occur within the genome) or excesses (when they occur outside of the genome).

These three types of crossover were found to be most effective in neuroevolutionary algorithms in comparison to other crossover methods (Stanley and Risto, 2002b).

Genes that have been disabled in previous generations have a small chance of being re-enabled during new offspring creation, allowing ANNs to make use of older solutions once again (Łański, 2012).

Evolutionary neural network can keep historic trails of the origin of every gene in the population, allowing matching genes to be found and identified even in different genome structures. Old behaviors encoded in the pre-existing network structure have a chance to not to be destroyed and pass their properties through evolution to the new structures, thus provide an opportunity to elaborate on these original behaviors.

The number of inputs and outputs is fixed. During evolution, in mutation stage, the number of internal neurons and connections may change. In classic NEAT method the number of nodes and connections may only increase over time, with possibility to temporary disable the connection. This guaranties to transfer learning experience from ancestors to new offspring and fast learning of new tasks for new population but it may be disadvantageous in such dynamic environments as ship maneuvering in restricted waters. In this case an experience of old population may be insufficient and its learning ability to slow, due to size of experienced ANN's. Through mutation, the genomes in modified

NEAT will gradually get larger for complex tasks and lower their size in simpler ones. Genomes of varying sizes will result, sometimes with different connections at the same positions.

Historical markings represented by innovation numbers allow neuroevolutionary algorithm to perform crossover operation without analyzing topologies. Genomes of different organizations and sizes stay compatible throughout evolution, and the variable-length genome problem is essentially solved. This procedure allows for used method to increase complexity of the structure while different networks still remain compatible.

During elite selection process the system eliminates the lowest performing members of every specialized group of individuals from the population. In the next step the offspring replaces eliminated worst individuals. Thus the quantity of the population remains the same while its quality shall improve according to assumed goals and restrictions of the task.

3 INPUTS AND OUTPUTS OF NETWORKS

Input and output signals of ANN's must be determined at the beginning of designing phase of the system. Proper set of signals considered in the model is crucial for efficient performance of the system and for its fidelity and accuracy in comparison to the real navigational situation.

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

- Ships' course over ground,
- Ships' angular velocity,
- Ships' speed over ground,
- Ships' position,
- Angle and velocity of a current,
- Angle and velocity of a wind.
- Main propeller revolutions (current and preset),
- Rudders' angle (current and preset).

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

Output signals of ANNs shall generate the values for important parameters that may change after certain amount of time. Most important signals in prediction process are:

- Ships' position,
- Ships' course over ground,
- Ships' speed over ground,
- Ships' angular velocity.

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

Computational flexibility and ability to adapt a network topology to a given task allows to design complex sets of inputs and outputs of ANN's.

Since the neural network with multiple outputs learns slower than one with only one output, the proposal of the author is to divide a population of ANNs into different specialized groups of networks, designed to calculate a predicted value of a single particular output signal (Figure 4).

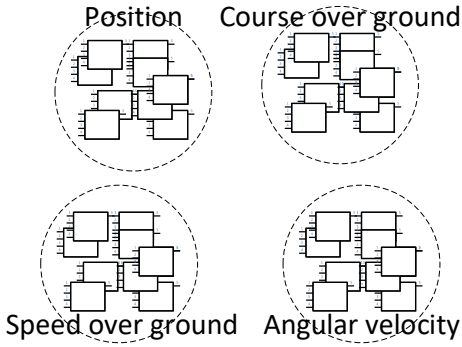


Figure 4. Division of population into specialized groups of ANNs

This is a very sophisticated neuroevolutionary method that can deal with premature convergence that preserves diversity and gradual complexity of explored solutions.

Each group has separate ranking list and individuals compete only within their own group. This approach requires much more memory allocation for higher amount of genetic material but eliminates unnecessary influence of unwanted input signals to output values.

Performance of each individual is measured in predicted time interval and its fitness value is calculated as a difference between real and predicted value (Formula 2).

$$f_i = (r_n - p_i)^2 \leftarrow \min \quad (2)$$

where: f_i – fitness value of an individual i (a cost criteria), r_n – real value of a signal of n -group, p_i – predicted value of a signal of an individual i .

In this case the individuals with least fitness value are more likely to reproduce their genetic material in next generation.

General algorithm for data flow to prediction system is presented on figure 5.

Input signals have been divided into two groups – environmental and steering signals. Group of environmental signals consist all data incoming from vessels surroundings (i.e. winds and currents speed and direction) which creates an input state vector for the system.

Implementation of mathematical model of wind to the motion control in neuroevolutionary prediction system increases its performance and robustness in simulated environment.

Under pressure of wind force, depending of the ships' design (location of the superstructure, the deployment of on-board equipment and cargo, etc.) she tends to deviate from the course, with the wind or into the wind. The smaller the speed and draft of the ship, the greater the influence of wind. Of course, the size of the side surface exposed to wind is essential to the ships movement.

When the ship moves forward the center of effort of the wind (wind point, WP) is generally close to amidships, away from pivot point (PP). This difference creates a substantial turning lever between

PP and WP, thus making the ship, with the superstructure deployment at stern, to swing the bow into the wind.

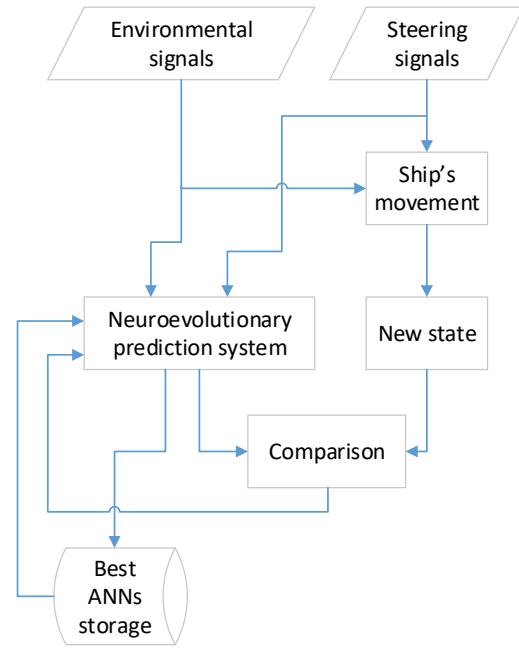


Figure 5. General algorithm of prediction system with neuroevolutionary method

For ship moving forward there are defined terms of relative wind speed V_{rw} and angle of attack γ_{rw} (Isherwood, 1973). Wind forces acting on symmetrical ship are in general calculated from data as ship's overall length, surfaces affected by the wind, air density and coefficients calculated from available characteristics of ships model, i.e. from wind loads data of Oil Companies International Marine Forum (OCIMF, 1977). This organization identifies safety and environmental issues facing oil tankers, barges, terminals and offshore marine operations, and develops and publishes recommended standards that will serve as technical benchmarks for regional and worldwide exploitation.

Additional forces that affect ships movement are water flows from current and tides. In this case the water moves in relation to the bottom of a river, sea or an ocean.

Position of the Moon and the Sun in relation to the Earth affects mostly waters in the oceans. Many naval ports of the world have their locations at a river estuaries. Currents of that rivers may be often affected by ocean tides. Tidal force is determined by the difference in forces at the Earth's center and surface. Tidal forces are mostly available from local authorities if a form of timetable sets and charts.

Tidal charts are grouped in sets, each set covers the time interval between two consecutive high tides in the area. These charts they give the average tidal flow information for desired time span for the ship maneuvering area. Information on a tidal chart consists of direction and average flow speed in knots for specified tides.

An alternative to the tidal charts is the tidal diamonds method, which may be found on most nautical charts. With this method one can relate

certain points on the chart to a table that will calculate the direction and velocity of tidal flow and according to this flow the estimated position of the vessel can be calculated regarding the direction of the tide.

The gravitational tides are not the only one affecting flow of the water, there are also terrestrial tides, atmospheric tides and thermal tides. Atmospheric tides are caused by the radical effects of weather and solar thermal tides and in most cases they reinforce oceanic tides.

Under the pressure of a current a ship is drifting together with the water, relative to the ground and any fixed objects. When the ship is moving in current the speed over ground is resultant velocity of ship speed and velocity of the current.

Stronger water flows may cause the tendency to swing the ship with the stern or bow towards the side, which may lead to dangerous situation. This might be particularly difficult to overcome when working in following tide because of the small effectiveness of the rudder at low speed.

Steering signals consist data that may be changed by a user of the system (i.e. a navigator or a commander on the bridge). Steering signals include propellers revolutions or thrust and rudders angles.

All these input signals affect ship's movement which creates a new state of the environment with the moving vessel in it.

At the same time the similar new state parameters are being calculated in the neuroevolutionary system, regarding the same input signals. The real and predicted values are compared and the result of comparison provides substantial information for the system that allows to elaborate the quality of created ANN's and overall performance of whole population. During evaluation the ranking of ANNs it created and the best networks are stored for future exploitation.

4 SIMULATION MODELS AND RESULTS OF PREDICTION

For the purpose of a ship movement simulation an application has been created by the author (Figure 6).

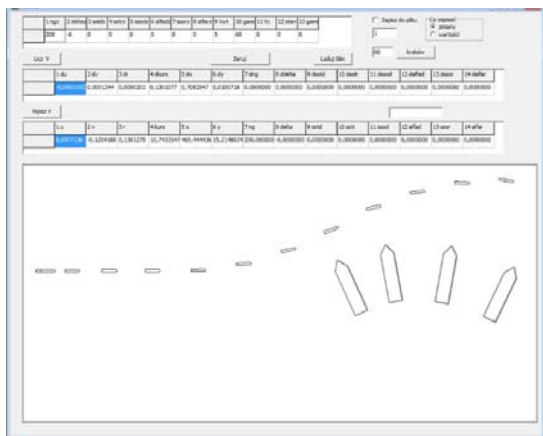


Figure 6. An application for testing behavior of simulation models of different vessels

The designed application allows to choose specific model of the vessel, to set a starting parameters of navigational situation in restricted waters, including speed and direction of a wind and a water current, and run a simulation with partially observable prediction values that can be saved to a file and analyzed offline after the simulation.

Two simulation models of ships with three-degrees-of-freedom had been used in the system for the purpose of systems performance test. Main parameters of ships has been compared in table 1.

Table 1. Main parameters of simulation ship models.

Name	Blue Lady	Cape Norman
Type	VLCC	Container ship
Scale	1:24	1:1
Length	13,78 [m]	175 [m]
Beam	2,38 [m]	26,5 [m]
Draft	0,86 [m]	14,2 [m]
Capacity/Tonnage	22,83 [T]	1504 [TEU]
Max. speed	3,1 [kn]	20,4 [kn]

The sets of output data of ANN's has been calculated and recorded during task evaluation in every generation as the results of simulation. The population consist four separate groups of ANNs, with 50 individuals each, resulting in 200 ANNs in total.

The chart presents evaluation of the simulation for 200 generations (Figure 7). Since there is always only one optimal solution for every parameter in the prediction system, the algorithm tends to converge quickly to this solution. These simulation results prove a good performance of learning process of a single output neural network.

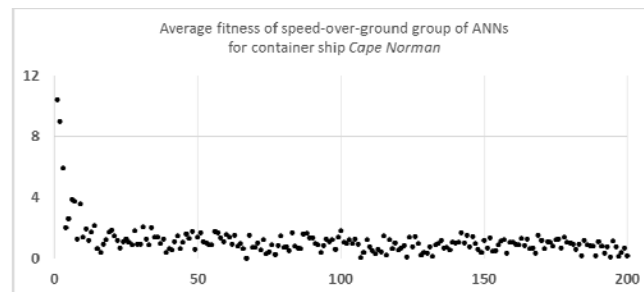
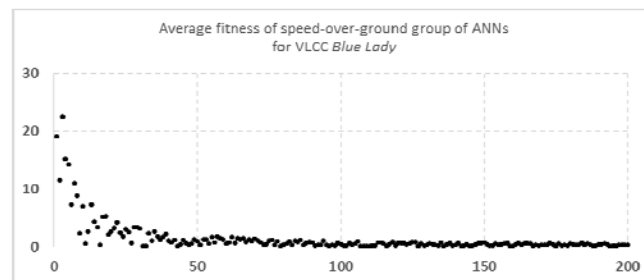


Figure 7. The examples of average fitness values of specialized groups of ANNs

For two different models of the vessels the average fitness values become at stable levels after about 20-40 generations, which took about few minutes of simulation on a standard PC.

Spread of average fitness for speed over ground is greater for container ship, regarding its greater range of possible predicted speed values.

Additional characteristics of learning process are shown on figure 8.

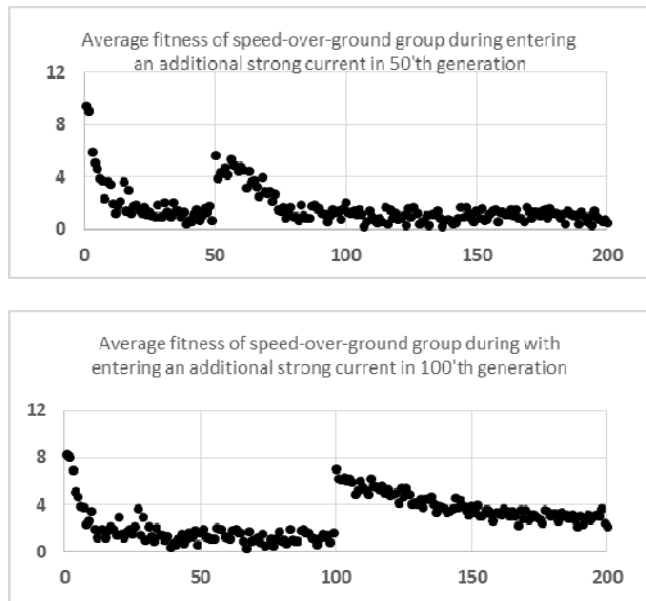


Figure 8. The comparison of learning speed during entering a strong current after different generation number.

These two charts illustrates that learning speed in neuroevolutionary algorithms strictly depends on the age of population. Younger population adopts faster to new sudden changes due to smaller genome of individuals. But on the other side the older population is more experienced and is able to react to new states relying on learned patterns.

5 REMARKS

Intelligent maneuvering prediction system for maritime transport has some valuable benefits:

- increase of the safety of navigation in a restricted water area by improving the data analysis for decision-maker during maneuvers,
- improvement of the operation of ships in port, due to the increased bandwidth,
- 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 size of ANNs population and the encoding methods of signals considered in serviced environment.

Neuroevolutionary approach to ship handling in confined waters improves a quality of maneuvers and safety of navigation effectively (Łacki, 2008). For the simulation study, mathematical model of three-degrees-of-freedom maneuvering VLCC tank ship with the single-propeller and single-rudder was applied to test the prediction performance of the

system. Artificial neural networks based on modified NEAT method increase complexity and performance of considered model of ship maneuvering in confined waters.

Implementation of additional input signals related to influence of wind and current allows to simulate complex behavior of the vessel (Łacki, 2012) in the environment with much larger state space than it was possible in a classic state machine learning algorithms (Łacki, 2007). simulation results of maneuvers in variable wind and current conditions of different ship models encourage to further research of the neuroevolutionary methods which may finally be implemented into advanced navigational prediction systems to increase the safety of navigation.

REFERENCES

- Haasdijk, E., Rusu, A.A. & Eiben, A.E. 2010. HyperNEAT for Locomotion Control in Modular Robots.
- Isherwood, J.W. 1973. Transactions of Royal Institution on Naval Architects, Wind resistance of merchant ships, vol. 115, 327-332.
- Kenneth, S., Nate, K., Rini, S. & Risto, M. 2005. Neuroevolution of an automobile crash warning system, Washington DC, USA.
- Larkin, D., Kinane, A. & O'Connor, N. 2006. Towards hardware acceleration of neuroevolution for multimedia processing applications on mobile devices, Hong Kong, China.
- Lee, S., Yosinski, J., Glette, K., Lipson, H. & Clune J 2013. Applications of Evolutionary Computing, Evolving gaits for physical robots with the HyperNEAT generative encoding: the benefits of simulation.
- Lehman, J. & Miikkulainen, R. 2013. Neuroevolution, Scholarpedia, vol. 8, 30977.
- Łacki, M. 2007. Machine Learning Algorithms in Decision Making Support in Ship Handling, Katowice-Ustroń, WKŁ.
- Łacki, M. 2008. Neuroevolutionary approach towards ship handling, Katowice-Ustroń, WKŁ.
- Łacki, M. 2009. Ewolucyjne sieci NEAT w sterowaniu statkiem. Inżynieria Wiedzy i Systemy Ekspertowe, Warszawa: Akademicka Oficyna Wydawnicza EXIT, pp. 535-544.
- Łacki, M. 2012. TransNav - International Journal on Marine Navigation and Safety of Sea Transportation, Neuroevolutionary Ship Handling System in a Windy Environment, vol. 6.
- Nowak, A., Praczyk, T. & Szymak, P. 2008. Zeszyty Naukowe Akademii Marynarki Wojennej, Multi-agent system of autonomous underwater vehicles - preliminary report, vol. 4, 99-108.
- OCIMF 1977. Prediction of Wind and Current Loads on VLCCs, Oil Companies International Marine Forum.
- Stanley, K.O. & Risto, M. 2002a. Efficient evolution of neural network topologies.
- Stanley, K.O. & Risto, M. 2002b. Efficient Reinforcement Learning Through Evolving Neural Network Topologies.
- Stanley, K.O., Bryant, B.D. & Risto, M. 2005. IEEE Transaction on Evolutionary Computing, Real-time neuroevolution in the NERO video game, vol. 9, 653-668.