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# Indirect Encoding in Neuroevolutionary Ship Handling

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ABSTRACT: In this paper the author compares the efficiency of two encoding schemes for artificial intelligence methods used in the neuroevolutionary ship maneuvering system. 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 an artificial neural network. The helmsman observes input signals derived form an enfironment 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 this project is to evolve a population of helmsmen with indirect encoding and compare results of simulation with direct encoding method.

## 1 INTRODUCTION

Neuroevolution is a combination of two different methods: artificial neural networks (ANN) and evolutionary algorithms (EA). Neuroevolutionary methods are part of intelligent computational methods (Kwaśnicka, 2007) capable of finding solutions to complex tasks by means of artificial neural networks arising from evolution (Lehman and Miikkulainen, 2013). This 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 different fields of science, including:

- robotics (Haasdijk et al., 2010)(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 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 operation of ship maneuvering on confined water is essential to the safety of people, equipment, cargo and the environment. Increase of computational power of electronic devices 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:

- ability to analyze the navigational situation 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,
– ability to find regularities and patterns in complex multi-stage navigational tasks.

All these requirements may be fulfilled with neuroevolutionary methods.

The basic concept of a pattern-finding task is presented in figure 1.

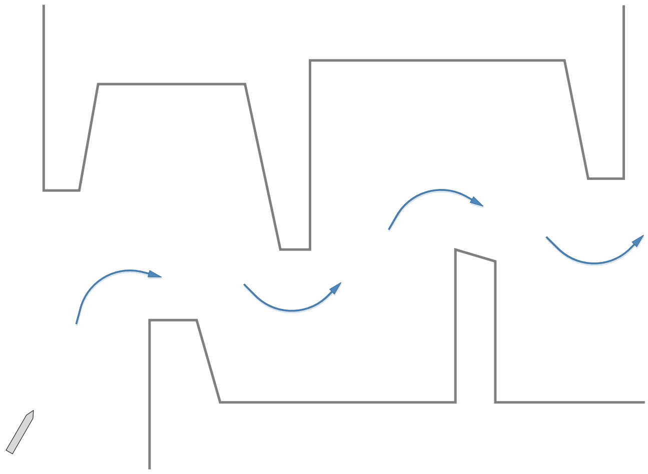


Figure 1. Exploiting regularities on restricted water in a pattern-finding task example.

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 NEUROEVOLUTION WITH DIRECT ENCODING

Neuroevolution is able to find a solution of a complex and dynamically changing task with ANN created and modified with EA.

In neuroevolution ANN is treated as an individual in a population of multiple networks. With direct encoding approach the 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.

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).

The neuroevolutionary method with direct encoding of neural network topology has been implemented in earlier works of the author, with the modified NEAT algorithm (Figure 2).

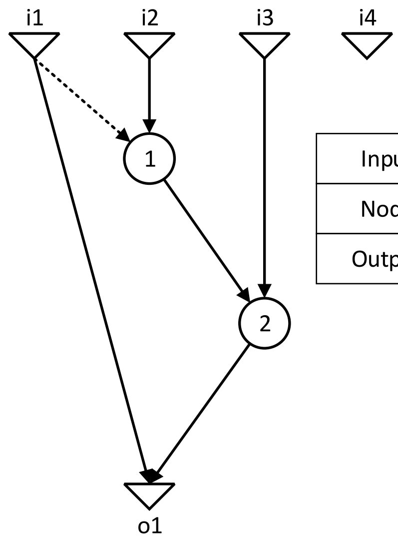
NEAT (NeuroEvolution of Augmenting Topologies) adjust the topology of ANN's with EA (Stanley and Risto, 2002) gradually to given task, allows to obtain a set of ANN's that are best fitted to this task.

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.

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

where:
$o_j$ – output value of an neuron,
$S_j$ – weighted sum of input values $x_{nj}$ with weights $w_{nj}$,
$\beta$ – slope coefficient,
$\theta_j$ – bias.

Adding the bias signal of constant value 1, allows to shift the output value of the activation function. 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.




| | |
|---|---|
| Inputs | 4 |
| Nodes | 2 |
| Outputs | 1 |

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

Figure 2. An example of direct encoding of an artificial neural network topology (phenotype) from a connection genome (genotype) in NEAT method

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, 2002).

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 (Łącki, 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, thus allowing them to interchange genes in a meaningful way. 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 NEUROEVOLUTION WITH INDIRECT ENCODING

First effective indirect encoding of artificial neural networks, called Cellular Encoding, was proposed by Gruau in his PhD thesis (Gruau, 1994). In this method each neuron was represented by a cell connected to other cells. Each cell was able to duplicate in parallel or serial connection of its two offspring. In that approach the neural networks can be generated and developed with modularity. Modular structure is made of several subnetworks, arranged in a hierarchical way. In some cases the same subnetwork can be repeated.

Generally in indirect encoding a genome specifies how to build a topology. It allows to create more compact representation of genes in comparison to direct encoding genomes.

The general set of instruction include commands that allow to create a topology in a meaningful way, i.e.:

– Split connection,
– Add connection,
– Add node,
– Copy connection,
– Remove connection.

The weights of evolved neural networks architectures are trained using backpropagation method.

## 4 INPUTS AND OUTPUTS OF THE 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 method and 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,
– Angle and velocity of a current,
– Angle and velocity of a wind.
– 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. waves, cargo, trim and roll.

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.

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.

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 defined time interval and its fitness value is calculated as a sum of collected rewards (positive of negative values) using Reinforcement Learning (RL) algorithms. The rewards in RL are determined arbitrarily by system designer or user and their values may depend on actual overall performance of the population.

In the evolution process, the system selects the individuals best suited to the task during the selection stage and inserts their genetic material in place of the worst performing individuals.

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

The input signals have been divided into two groups – environmental signals 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 ship handling system increases its performance and robustness in simulated environment.

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. 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.

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.

For ship moving forward there are defined terms of relative wind speed $V_{rw}$ and angle of attack $\gamma_{rw}$ (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 serve as technical benchmarks for regional and worldwide exploitation.

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

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 a resultant velocity of speed of the vessel and the velocity of the sea current.

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 result of calculations 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.

## 5 THE EXPERIMENTAL RESULTS

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

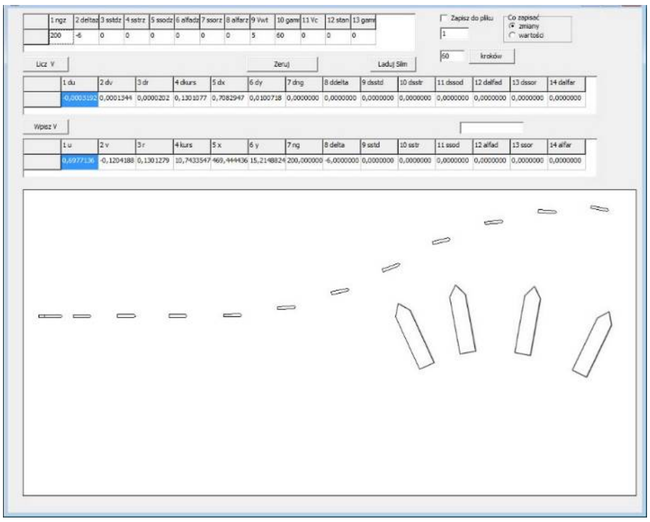


Figure 6. An application for testing behavior of simulation models of different vessels in water current and windy environment

The designed application allows to choose specific model of the vessel, to set a starting parameters of navigational situation in restricted waters, including placement of obstacles, setting speed and direction of a wind and a water current, and run a simulation with observable environmental data and ships parameters and characteristics 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 consists 100 ANNs. The initial content of each genome is determined randomly from available set of instructions with a specific set of rules.

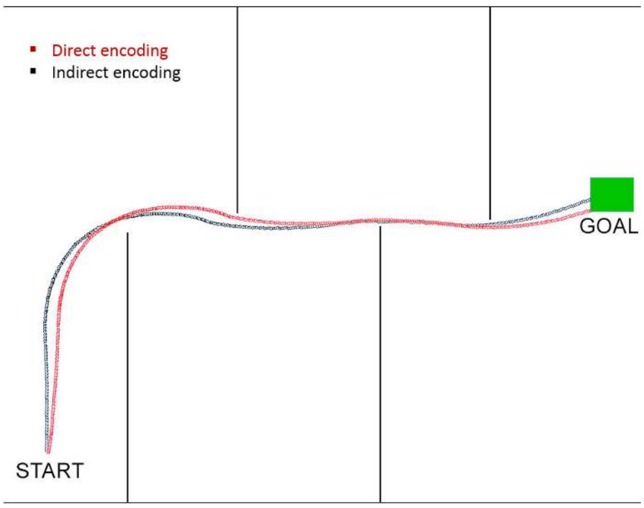



Figure 7. The comparison of two encoding methods in simulation of the container ship maneuvering in restricted area

The simulation example presents the results for 400 generations (Figure 7). The routes of the best helmsmen of two different encoding methods are shown. These simulation results prove a good performance of learning process of a single output neural network for both methods.

Table 2. The time of reaching a goal for two different encodings.

| Encoding | Avg. time | Std dev. | of avg. time |
|---|---|---|---|
| Direct | 00:28:13 | 00:09:25 | 33,4% |
| Indirect | 00:21:01 | 00:02:09 | 10,2% |

The average time of reaching a goal for two different encoding methods is presented in table 2.

Standard deviation of goal reaching time is significantly greater for direct encoding, regarding its greater range of possible predicted speed values.

These two routes illustrates that learning speed in neuroevolutionary algorithms strictly depends on the encoding method. Furthermore the directly encoded population in modified NEAT method adopts faster to new sudden changes due to greater changes in an offspring genomes. But on the other hand, the indirectly encoded population has ability to learn every individual during its lifetime and is able to react to new states relying on learned patterns.

## 6 REMARKS

Neuroevolutionary ship handling system with indirect encoding has properties that distinguishes it from direct encoding system:

- small genotype may create large phenotype,
- it is capable of finding patterns and regularities,
- additional learning process is required for connections weights,
- an individual can learn during its lifetime,
- is capable of implementing scalability and modularity,
- an additional time consuming computation is needed for creating a phenotype.

Intelligent maneuvering pattern-finding system for maritime transport that uses indirect encoding 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 in direct encoding 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. For the simulation study, mathematical model of three-degrees-of-freedom maneuvering container ship and VLCC vessel with the single-propeller and single-rudder were applied to test the pattern-finding 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 input signals related to influence of wind and current allows to simulate complex behavior of the vessel in the environment with much larger state space than it was possible in a classic state machine learning algorithms (Łącki, 2007). Simulation results of maneuvers in variable current and windy conditions for different ship models encourage to further research of the neuroevolutionary methods which may be successfully implemented into advanced navigational systems to increase the safety of navigation.

It is also necessary to introduce and examine additional disturbances from the influence of sea waves on the movement of the vessel in the further research of the neuroevolutionary ship handling system.

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