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Neural anti-collision system for Autonomous Surface Vehicle

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ABSTRACT

Autonomous Surface Vehicles (ASV) are robots destined for the operation at water basins like lakes, canals, harbors and even open sea. They are used for different purposes, e.g. for patrol tasks, as scouts, or as a support for Navy ships. One of the main tasks of ASV is to move along a fixed path to a destination point. To this end, an anti-collision system (ACS) has to be used with the ability to lead ASV along a path and to simultaneously avoid all additional objects present at the basin, e.g. ships, sailing boats, fishing cutters, icebergs. To perform this task, the ACS implemented as an evolutionary neural network can be used. The paper describes architecture of the neural ACS, presents two neuro-evolutionary methods used to build the system, and reports the whole process of constructing it.

1. Introduction

Robots are more and more often present in our life. They successfully perform tasks which until recently have been exclusively a domain of a human being. They are more and more effectively replacing us in tasks in which they are better or cheaper, wherever we cannot reach, or where our life can be in danger. In the beginning, there were only robots which executed exclusively activities strictly programmed by a designer. Such robots are used so far, for example, to produce cars, they work in invariable conditions and for well-defined tasks which do not require intelligence. A next category of robots which also are broadly exploited so far are robots supervised by a man-operator, e.g. unmanned underwater vehicles, sapper robots. Because of variable conditions in which they usually act and diversity of tasks they are responsible for, their behavior cannot be preprogrammed. They work as a continuation of a "human hand" and, often perform tasks which are too danger for a human being. Autonomous robots which constitute a next class of robots are the most technically advanced. Tasks which they execute frequently overlap with tasks of remotely operated robots, however, they work without supervision from outside, each action is initiated by a robot itself. Often, robots are both remotely operated and autonomous. In a typical operational regime, they carry out commands given by an operator, however, in some circumstances, e.g. when a communication system between a robot and the operator is down, they change a work mode into autonomous.

Nowadays, autonomous robots are exploited on shore, at sea, under water, in the air, and even in the space. The robots destined for the operation at water basins like lakes, canals, harbors, open sea, are called Autonomous Surface Vehicles (ASV). They are used for different purposes, e.g. for patrol tasks, as scouts, or as a support for Navy ships. One of the tasks of an ASV, in the case of patrol functions, is to visit a number of basin areas indicated by an operator. An order of the monitored areas and an exact moving trajectory for the vehicle may be fixed automatically or by the operator as well. A similar task is also performed by a remotely operated vehicle which has to autonomously come back to a base-ship due to the breakdown of the communication system. This time, the path to follow by ASV has to be determined by the vehicle itself. It should keep the ASV away from all constant elements of the basin, e.g. land, buoys, shallows, wrecks jutted out of the water, etc. However, to effectively perform the task above, it is insufficient to follow only the path leading to a destination, it is also necessary to avoid collisions with objects which may appear along the way, e.g. ships, sailing boats, fishing cutters, icebergs. For that purpose, the anti-collision system (ACS) which is the main subject of this paper can be applied.

It is assumed that the task of the ACS is to make high-level decisions concerning direction and velocity of move, decisions taken by the ACS are converted into control signals for the ASV engine and rudder by means of low-level controllers (e.g. PID or fuzzy controllers) adjusted to the specific type of the ASV. To work, the system requires external sources of information supplying it with the information about the current position of the vehicle, constant elements of a basin surrounding the vehicle (land, buoys, etc.), and temporary objects visible on the basin (ships, icebergs, etc.). Such information can be provided by devices such as GPS (Global Positioning System), electronic navigational chart (or its simplified black-and-white variant indicating areas accessible and inaccessible for the vehicle), AIS (Automatic Identification System – it provides a detailed information, e.g. course, velocity, exact position, about all objects equipped with this system), and radar. Moreover, in order for the vehicle to not only avoid collisions but

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also to move along a fixed path, the ACS has to know coordinates of the closest turning point which has to be visited (it is assumed that the ASV path is a sequence of turning points whereas a trip along the path is moving from point to point – Line-Of-Sight – LOS guidance law).

Much work has been done on the collision avoidance problem to date, and a lot of different solutions have been proposed [1]. Many of them are planning solutions in the sense that when a collision situation is detected they try to determine a safe path for a controlled vehicle, the path which avoids all dangerous objects. The last point of the path is a point in which there is no danger of a collision. To fix a path, different techniques are used, e.g. heuristic search methods [9,23,22] (A* algorithm, its modifications, and others), evolutionary [4,10,17,18,21], and ant colony algorithms [24].

The main problem with applying these methods to the collision avoidance is their computational complexity which results from their inherent search or population nature. They generally cannot give a guaranty of finding a collision-free solution in an assumed short period, how long they will work mostly depends on conditions they deal with. In most situations at sea they will work properly and without delay, however, there can be situations, e.g. heavy traffic in restricted areas, navigation in the presence of many very fast objects, when they may fail by providing a collision-free plan too late. All this makes the above methods suited rather for either off-line path planning or planning in conditions when there is no need to rapidly make decisions.

Other methods use neural networks or/and fuzzy logic to determine the collision risk and to select an object to avoid. Then, they identify a collision situation (out of a number of well-defined situations) and use COLREGs[1] to maneuver the vehicle [3].

As before, these methods cannot be applied in highly complex and highly dynamic environments.[2] First of all, they assume that each collision situation, even the one with many colliding objects, can be considered as a combination of simple one-object avoidance collision problems. Moreover, to solve different collision problems, they use a number of standard maneuvers, each of which is adjusted to a pattern situation. The problem is, however, when a collision situation is far from each pattern and it cannot be reduced to a combination of standard maneuvers.

A next approach to collision avoidance is to copy maneuvers which appeared to be effective in a previous collision situation, or in other words, to use the so-called case base reasoning (CBR) technique [8]. The main problem, in this instance, is time consuming analysis of sample collision cases included in the database. This feature of CBR approach makes it inappropriate for highly dynamical environments when situation at sea may change rapidly and lightning decisions are sometimes necessary.

Rule-based expert systems [6,7] and fuzzy expert systems [5,11] can be considered as a next class of collision avoidance techniques. In this case, we deal with decision rules, each of which corresponds to some collision situation and proposes a solution to this situation. If more than one rule matches an input collision case, a maneuver is proposed which is usually a compromise between decisions of all matching rules.

To create the systems, navigators' experience, traffic regulations, encountered collision scenarios or navigation theory are used. The way of preparing the systems seems to be main reason for their restricted applicability only to cases which already took place or can take place in the opinion of navigators. Since they are built by a human being and based on learning data which are result of human being experience, collision avoidance expert systems may have problems with generalization in unusual collision situations which are not taken into account by designers while preparing the systems.

V-obstacle [16] is an algorithmic collision avoidance technique. It searches for anti-collision maneuvers in the velocity domain taking into consideration the behavior of all colliding objects. Knowing motion parameters of the objects the v-obstacle determines for each of them a cone-shaped area (linear variant of v-collision) which represents collision risky velocities of the own vehicle. To avoid collision, it is necessary to select maneuvers which do not correspond to any of such areas.

The drawback of this method is that it looks only one step forward, that is, when calculating a next move it takes into account only a current situation, which means that it does not propose a solution to a whole collision problem but it only indicates maneuvers which in a given point in time are safe. For more complex collision problems, such an approach may produce trajectories far from optimality, in some circumstances, a sequence of v-obstacle maneuvers may even lead to a dead-end situation in which there will not be any collision-free maneuver.

In the paper, a new collision avoidance solution is proposed. Since its main application is to avoid collisions in very complex, multi-object, rapidly changing environments, e.g. during military operations in the presence of many fast alien objects, it differs from all the solutions presented above. First, due to speed requirements, it does not plan a motion trajectory, as the planning path solutions, but it indicates a single maneuver which should be performed to avoid collision in a given situation. Second, because of multi-object environment in which we cannot expect the other objects to obey COLREGs, the solution proposed in the paper is not restricted by any kind of regulations and it can produce any collision-free maneuver. Third, to prepare the system to work in different conditions, sometimes even unusual conditions, conditions which are assumed to be difficult to predict, it was trained based on diverse collision scenarios designed by a navigator, navigational dilettante, and even a genetic algorithm. Fourth, even though the system does not look forward and makes decisions based on the information from a single point in time, it is sensitive to not perform maneuvers which in the future may lead to dead-end situations. This property of the system is achieved thanks to training process during which the system learns which collision-free maneuvers can be in a given situation inappropriate and should be avoided.

The ACS described above is implemented as an evolutionary neural network. The network calculates the course and the speed for the ASV based on the appropriately processed information from different ASV devices. To build the network, two neuro-evolutionary techniques are used: Assembler Encoding with Evolvable Operations (AEEO) and Cooperative Co-Evolutionary Neural Networks (CCENN). They were selected out of many other methods because of their effectiveness confirmed in experiments with underwater vehicles.[3] They appeared to be more efficient in evolving neuro-controllers for a team of the vehicles than Neuro-Evolution of Augmenting Topologies [19,20], i.e. one of the most successful state-of-the-art neuro-evolutionary methods of recent years.

To produce a reliable anti-collision network, each neuro-evolutionary method was run many times. In each run, a very intensive "training" process took place during which the networks were tested on many different training tasks. Networks which brought the ASV to a destination point without any collision and wandering in all the tasks were then put to a generalization tests. Their

[1] International Regulations for Avoiding Collisions at Sea – The COLREGs describe potential collision scenarios such as crossing, head-on, and overtaking and suggests possible maneuvers to avoid a collision.

[2] A lot of fast objects with unpredictable behavior, e.g. objects which want to intentionally lead to a collision.

[3] Description of both methods is given in the papers which are currently under review.