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SWARM OF AUTONOMOUS UNDERWATER VEHICLES – PRELIMINARY RESULTS OF THE CONTROL SYSTEM

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Abstract. A swarm of autonomous underwater vehicles can be a valuable alternative for fully equipped and very expensive super-vehicles. A distributed system of tightly cooperating vehicles can be cheaper, simpler in maintenance, more reliable, more flexible and universal than traditional single-vehicle systems. However, keeping a tight formation of underwater vehicles in the condition of the sea current, unclear environment, and rare inter-vehicle communication is a very challenging problem, which requires an effective vehicle control system. The paper proposes a solution to the above-mentioned problem, which is based on neuro-evolution. Moreover, the paper also presents the first results of the proposed system.

Keywords: swarm; autonomous underwater vehicles; neuro-evolution; neural networks

Introduction

The underwater environment is increasingly explored by man. There are different goals of the exploration, e.g. pipeline/oil rigs/wind farms maintenance/monitoring, mine haunting, living organisms' observation. In addition to Remotely Operated Vehicles (ROV) which seem to be already a standard in underwater exploration, Autonomous Underwater Vehicles (AUV) are also increasingly applied for tasks which are impossible for ROV's to perform due to their limited operational range. The other advantage of AUV's is also the fact that they do not need any supporting infrastructure and human involvement, which often makes them cheaper in exploitation compared to ROV's.

AUV's can perform their tasks individually or together with other vehicles forming loosely cooperating teams or tight swarms. In the case of the latter, the vehicles operate in formations which require special skills from members of swarms (McColgan 2018; Ramp 2009). One type of swarm formation is a leader-following formation which consists of a leader-vehicle and its followers (Bikramaditya et al. 2016; Ciu et al. 2009; Ciu et al. 2010; Toonsi 2019). In order to keep this type of formation, each follower AUV (FAUV) has to be able to determine its position relative to the leader AUV (LAUV). To this end, different techniques and sensors can be used. In the paper, a follow-leader solution is proposed which is based on an acoustic communication system (CS) for the distance to the leader estimation and a glimmer-camera (GC) for the distance and bearing to the leader estimation. Since the frequency of the information acquired from CS is very low and GC is a short-range sensor, the system proposed in the paper has also to rely upon the predictions (P) of the state of both LAUV and FAUV. This way the system is able to constantly estimate the relative distance and bearing to the LAUV even in periods in which the information from the CS and GC is inaccessible.

In order to control the FAUV based on the estimations provided by CS/GC/P, an evolutionary artificial neural network (EANN) is applied. It is trained by means of a neuro-evolutionary algorithm called Assembler Encoding with Evolvable Operations (AEEO) (Praczyk 2015). To test the solution proposed in the paper, the simulation experiment was carried out with the use of MOOS-IvP simulation environment[1)] which is dedicated for marine applications and offers a lot of software tools which make designing the system and its testing in simulation conditions very comfortable. The preliminary results of the experiments are presented in the further part of the paper.

Outline of the system

In the system, the assumption is made that the LAUV is the only vehicle in the swarm that is equipped with an accurate dead-reckoning and long-distance navigation system (NS) based on an optical gyro, Doppler Velocity Log (DVL), and a depth sensor. In turn, the remaining vehicles are equipped with a low-cost and short-distance NS mainly based on an inertial sensor (IMU), odometry and the depth sensor.

In order to follow the LAUV, each FAUV constantly estimates LAUV position and its own position in the global coordinate system. To make it possible, the following information is necessary: position of the LAUV, position of the FAUV relative to the position of the LAUV, and moving parameters of the FAUV and LAUV, i.e. at least heading and speed.

The position of the LAUV as well as its momentary moving parameters are provided by the CS in messages, which are periodically sent by the LAUV to all FAUVs. This way, each FAUV is able to make short-term predictions of the LAUV position.

In turn, in order to determine its own position, each FAUV uses three sources of information, i.e. the messages received from the LAUV which are also applied to estimate the distance to the latter, the GC to estimate the distance and bearing to the LAUV and the NS which indicates heading and depth.

The estimations of LAUV and FAUV positions in the global coordinate system make it possible to constantly estimate FAUV position relative to the LAUV, i.e. bearing and distance to the leader at each point of the voyage, even between signals from the sensors. This in turn, makes it possible to keep the desired distance and bearing to the LAUV, or in other words, to keep the swarm formation by each FAUV.

As already mentioned, to control the FAUV and keep the swarm formation, a feed-forward EANN is applied which evolves according to AEEO (detailed specification of AEEO is given in (Praczyk 2015). It has four inputs, two outputs, and maximally M hidden neurons. The connections between all the neurons in the network depend completely on the decisions of the neuro-evolutionary algorithm.

At each time step of the control loop, the network is fed with the errors in the distance and bearing to the LAUV:

$$In1(t) = ED(t) = \frac{D(t) - D_d(t)}{D_{max}} \qquad (1)$$

$$n2(t) = EB(t) = \frac{B(t) - B_d(t)}{180} \qquad (2)$$

$$In3(t) = ED(t-1) \qquad (3)$$

$$In4(t) = EB(t-1)) \qquad (4)$$

where, t is a time step, In1..In4 are network inputs, ED is the distance error, D is the true distance to the LAUV, D_d is a desired distance, Dmax is the maximum acceptable error in distance, EB is the bearing error, B is the true bearing to the LAUV, and B_d is the desired bearing.

Both errors are positive if the current parameter values, i.e. the current distance or bearing to the LAUV, are larger than the desired parameter values, and they are negative otherwise.

The task of the network is to determine the desired speed and heading of the FAUV. To this end, the network uses two output neurons, i.e. the speed neuron of sigmoid type and the heading neuron of hyperbolic tangent type. The output signal of the speed neuron is multiplied by maximum speed of the vehicle V, whereas the output signal of the heading neuron is multiplied by 180:

$$S_d(t) = V * Out1(t) \qquad (5)$$

$$H_d(t) = 180 * Out2(t) \qquad (6)$$

where, Sd is a desired speed, Hd is a desired heading, and Out1, Out2 are outputs of the neural network.

Experiments

Conditions of the experiments

In order to initially verify the effectiveness of the proposed control system based on EANN, experiments in simulation conditions were carried out. In the experiments, the task of the EANN was to control a MOOS-IvP FAUV whose model is implemented in the form of a MOOS-IvP application called uSimMarine[1)]. The parameters of the vehicle were as follows: V=2 m/s, ThrustMap=0:0,20:1,40:2, TurnLoss = 0.85, TurnRate = 70, MaxAcceleration = 0.5, MaxDecceleration =0.5, RotatedSpeed=0, MaxRudderV=40, whereas the simulation step was equal to 0.1 s.

The task of the FAUV was to follow the twin MOOS-IvP LAUV which moved with the constant speed equal to 1 m/s along two different trajectories consisting of five waypoints: learning trajectory – (50,50)->(100,0)->(150,0)->(140,50)->(100,0), testing trajectory – (20,30)->(20,80)->(60,80)->(90,60)->(90,100). The starting positions of both vehicles in the two above trajectories were as follows: (0,3) – LAUV, (0,0) – FAUV. During the voyage, the vehicles moved on the horizontal plane without change of the depth and the desired bearing and distance to the LAUV were equal to -60deg, 3m, respectively.

All the on-board systems of the FAUV used to estimate the vehicle navigation parameters produced noisy information. The maximum errors of each system were as follows: NS speed error=0.3 m/s, NS heading error=15deg., GC distance error = 1m, GC bearing error=5deg, CS distance error=0.5 m. The range of GC was equal to 5 m, whereas the CS had no range limitations. The viewing angle of the GC amounted to ±60 deg. and the system was mounted along vehicle axis – 0 deg. corresponded to vehicle heading. Both the CS and GC provided the information with the minimum frequency equal to 2Hz and 1Hz, respectively.

With regard to EANN, it had maximally 50 neurons, including input and output neurons. The remaining architecture of the network was an effect of the evolutionary process.

In order to evolve the network, AEEO used the following fitness function:

$$F(EANN) = \frac{1}{1+ED_{max}+EB_{max}} \qquad (7)$$

where, ED_{max} and EB_{max} are the maximum ED and EB errors during the vehicle voyage.

Results of the experiments

The example results of the experiments are presented in Figure 1 and 2. They show that it is generally possible to keep the follow-leader swarm formation by FAUVs equipped with the CS, GC, P, and simple NS for navigation purposes and EANN for control purposes.

The vehicles generally had no problems with following the leader on the straight segments of the trajectories. In this case, the greatest ED errors amounted to about 1.5m, whereas EB errors did not exceed 10deg. However, each turn caused problems in keeping the formation. In spite of applying wide-angle camera on the FAUV board, the greatest deviations from the formation always appeared on sharp turns where the FAUV often lost sight of the leader and was forced to rely mainly on predictions. In this case, ED errors amounted even to 12m whereas EB errors reached up to 50 deg.

In order to improve the effectiveness of the system proposed in the paper, instead of one wide-angle camera, a number of cameras can be used. This way, the angle of view of the FAUV can be extended and probability of losing the LAUV decreased.

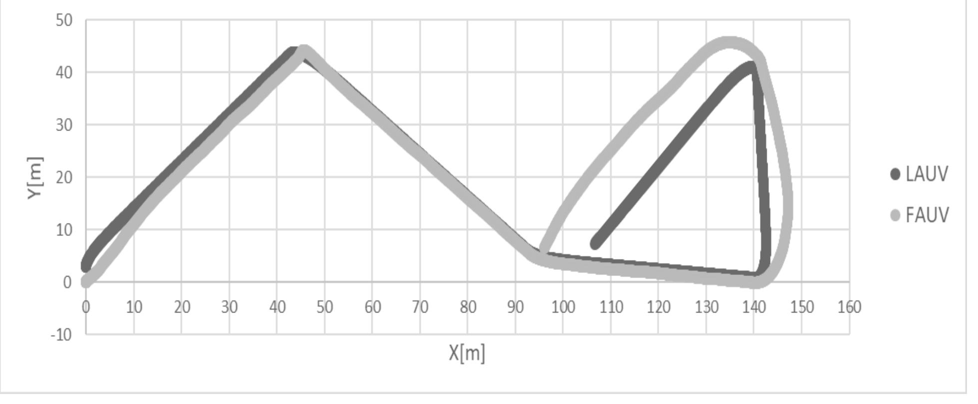

Figure 1. Example vehicle learning trajectories

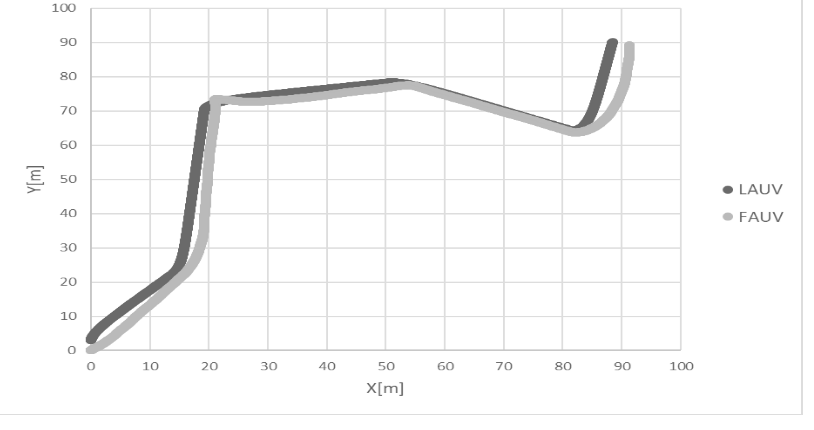

Figure 2. Example vehicle testing trajectories

Moreover, the visibility of the LAUV can also be improved by fitting its color to the water environment and by applying an extra laser on the LAUV and a laser detector on the FAUV.

The other solution which can extend the FAUV range of vision is a sonar or a system of echo-sounders. However, in this case, the problem is to differ the LAUV echo from echoes of other objects.

In the current variant of the system, in order to predict the future states of the vehicles, the simplest vehicle kinematic model is applied. In order to improve the performance of the system, more advanced solutions can be used, for example, Extended Kalman Filter (EKF).

The other possible improvement is a recurrent neural network which can replace the feed-forward one. In order to effectively control the FAUV, the network has to know the complete state of the vehicle at each point in time. To this end, in the current variant of the system, the feed-forward EANN is supplied with some parameters from two neighboring time steps, which roughly estimate the state of the vehicle. Meanwhile, the recurrent network is able to determine the state of the vehicle by its own, using recurrent connections for that purpose. More accurate estimations of the vehicle's state may improve effectiveness of the whole system.

The ban on sharp turns for the LAUV is a next method for improving the performance of the system. Gentle turns will give the FAUV time to adopt to new moving direction of the swarm and in consequence will increase the ability to keep a tight formation.

Conclusions

The paper outlines the system responsible for the leader-following behavior of the AUV. The system consists of: the Communication System with the extra role to provide distance to the leader, the Glimmer-Camera system with the task to estimate the distance and bearing to the leader, the Navigational System with the task to estimate and predict navigational parameters of both the leader and the follower, and Evolutionary Neural Network with the task to control the vehicle.

The paper also reports preliminary experiments on the system that were carried out in simulation conditions. The results of the experiments are promising, on the one hand, they revealed the potential of the system, but on the other hand, they also showed its imperfection. As it appeared, the system works properly on straight segments of the swarm trajectory and losses formation on turns. The sharper the turn, the more serious the problems with keeping a tight swarm formation are. In order to eliminate all shortcomings of the system that appeared during the experiments, further research is necessary.

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NOTES

1. https://oceanai.mit.edu/ivpman/pmwiki/pmwiki.php?n=IvPTools.USimMarine

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Appendix: Abbreviations

AEEO – Assembler encoding with evolvable operations – neuroevolutionary method to train neural networks

AUV – Autonomous underwater vehicle

B – True bearing to the LAUV

CS – Communication system

D – True distance to LAUV

DVL – Doppler velocity log

EANN – Evolutionary artificial neural network

EB – Bearing error

ED – Distance error

EKF – Extended Kalman Filter

FAUV – Following autonomous underwater vehicle (the vehicle whose task is to follow the leader vehicle)

GC – Glimmer-camera system
LAUV – Leader autonomous underwater vehicle (the vehicle whose task is to lead the swarm)
NS – Navigation system
P – prediction system
ROV – Remotely operated vehicle

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