INFORMED SEARCH PATTERNS FOR ALLEVIATING THE IMPACT OF THE LOCALISATION PROBLEM

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KEYWORDS

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ABSTRACT

The efficiency of locating a target by autonomous underwater vehicles (AUVs) depends on the selected search strategy. The selected search strategy should take into consideration all aspects of the nature and the behaviour of the search agent, which executes the search. It should also take into account the nature of the search environment. The long-term goal of this research is to use a small cooperative swarm of AUVs to locate a phenomenon of interest in a predefined marine environment. In this paper, some characteristics of search models that can promote constructive collaboration between AUVs for effective search are discussed. Two heuristic algorithms to locate a target are proposed. These heuristics do not use the exact location of the AUV to decide on the next search action as a mean to alleviate the impact of the localisation problem. The two heuristics outperform blind search algorithms in a search environment with two targets of different priorities. The impact of the localisation problem is considered by evaluating the performance of the algorithms in the presence of localisation errors. The results show that one of the proposed informed search heuristics is able to improve the search performance even in the presence of localisation errors.

INTRODUCTION

The development of inexpensive autonomous mobile robots becomes possible as a result of rapid evolution in the techniques of micromechanical fabrication, sensors, effector, control and processing (Gage 1992). The advancements in these techniques have enabled the development of different types of autonomous underwater vehicles (AUVs) and facilitated using them in different applications (Paull et al. 2014). AUVs have been used for oceanographic surveys and bathymetric data collection in marine and riverine environments (Wynn et al. 2014). Searching is a part of an important class of AUVs applications. For example, AUVs are used for detecting mines. They are also used for locating groundwater discharge points. Searching for harmful dumped waste and lost ship containers are also examples of these applications (Zielinski et al. 2009).

In these search applications, usually at least one AUV explores a predefined search area to locate mobile or stationary points of interest (Nolle 2015). A huge number of search algorithms has been successfully applied to solve real-world problems. However, selecting a suitable search algorithm to guide an AUV towards a point of interest is not an easy task (El-Mihoub et al. 2018).

Designing a cost-effective system of cooperative AUVs depends on the quality of the sensors, communication quality, performance requirements, energy constraints, localisation and navigation capabilities and others (Tholen et al. 2019). A cooperative search strategy can be used to guide a group of AUVs, as search agents, towards the most promising region. This higher-level search strategy should have the capability to analyse the search information gathered by AUVs to suggest the best path to the target. Different population-based search algorithms have the capabilities of efficient utilisation of search information to locate a global optimum. However, in real-world applications, there might be limitations on the number of search agents that can be used. This narrows down the list of potential search algorithms to only which are efficient with small population sizes. Particle swarm optimisation (PSO) is an example of a search algorithm that can be efficient with a small number of searchers (Tholen et al. 2018a).

The efficiency of a population based search algorithm depends on its ability to utilise the shared search experience to capture a global view of the search problem (El-Mihoub et al. 2006). Building a global view of the search problem depends on the quality of the shared search information. The quality of the search information depends on the quality of the sensors that collect the search information and the value of the information. For example, sharing known or useless information cannot help in guiding the search to better locations. In addition, sharing the search experience requires reliable communication between search agents (Tholen et al. 2019).

Reliable cooperative search algorithms necessitate that each search agent should be able to explore the search space using its own strategy without relying on the shared search information. The search agent should be able to

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use the information that it has to move towards the search target. The search agent should have the ability to proceed in discovering the search space even in the case of lack of useful search information. Blind search patterns can be applied to explore a search space with the aim of locating search targets in the case of no guiding search information (El-Mihoub et al. 2018). Both deterministic and random search models have been applied as search patterns. A pre-planned blind search patterns can locate a point of interest within an expected accuracy taken into account the size of the search space and the available search resources. In random blind search algorithms, a search pattern is defined by taken random steps in the search space aiming to find the search target.

The AUV, as real-time search agents, impose constrains on selecting a suitable search algorithm. The energy constrains of the AUV might necessitate that deciding on exploitation should be taken immediately and should not be delayed for collecting more search information. Such a delay may mean going forwards and backwards between already visited locations. An AUV needs to move to a suggested search location to collect information about the search environment. This limitations on the AUV's movements impose additional constrains on deciding on the next search point. The next selected search point should be reachable within a specific period of time to validate the decision for selecting this search point. For example, genetic search algorithms (Goldberg 1989), which can produce search points scattered over the whole search space, might not an efficient real-time search strategy within these constrains.

When navigate to explore the search space, AUVs are prone to localisation and navigation errors (Paull et al. 2014). There are different ways to overcome localisation and navigation problems. Different algorithms have been proposed to correct the AUV positioning errors (Jian-hua et al. 2015). However, an effective search strategy for directing an AUV to the most promising region of the search space should consider these errors. The exact location of the global optimum is required as an end result of the search process. However, a search strategy, which avoids using exact location information to decide on the next search action, can help to alleviate the impact of localisation errors on the search results. Blind search patterns can be an example of search algorithms that do not use location information to decide on the next search action. However, these patterns do not benefit from the available search information to accelerate locating the search target.

In this paper, two local search strategies that do not rely on the exact AUV's position are proposed. The impact of the localisation problem on their performance is studied. This paper also explores the effect of localisation errors on the actual value of the fitness function of the search environment.

SEARCH ALGORITHMS AND LOCALISATION ERRORS

Search algorithms aim to maximise the chances of locating a search target. Deterministic search patterns can be followed to increase these chances. Since there is no prior knowledge about the location of the target in the search space, a predefined path, in these deterministic search methods, is selected to minimise the maximum distance between this path and each point in the search space. On the other hand, random search patterns assume that implicit relations exist between the locations of the search target of any search space and the random steps taken. The success of deterministic or random patterns depends on the details of the search problems and the performance requirements (El-Mihoub et al. 2018).

The performance of both deterministic and random search patterns can be improved by making use of search information to refine search decisions. The performance of Levy search was boosted by incorporating some information about the search progress within the inertia-Levy flight algorithm (Tholen et al. 2018b). A smart utilisation of search progress information can improve the search capabilities of the search agents. However, in the case of using an AUV as a search agent, the search information should be handled with care due to the localisation and navigation problems.

Autonomous mobile robots need to estimate their true location in space in order to navigate in their mission space. The localisation process is characterised by inherent uncertainty and operational bias that lead to estimation errors. These errors depend on the properties of the emitted signals, the characteristics of the surrounding environment, the details of the localisation task, and the capabilities of the signal receiver (Letowski and Letowski 2011). For AUVs, navigation and localisation in underwater environments is particularly challenging. The attenuation in the radio frequency signals of the Global Positioning System (GPS) and low bandwidth and unreliable underwater communications due to the unstructured nature of the marine environment aggravate the localisation problem (Paull et al. 2014).

However, promising underwater localisation algorithms have been proposed by applying simultaneous localisation and mapping technology (SLAM) and making use of the advancements in acoustic communications (Jian-hua et al. 2015). Nevertheless, some of these methods are still not well formalised and tested (Paull et al. 2014).

Different strategies can be followed to tackle the impact of the localisation problem on an AUV as a search agent. The first strategy is to minimise this impact by minimising the localisation errors and then use search algorithms considering only other constrains imposed by using an AUV as a search agent. Another possible strategy is to study the impact of localisation errors on the different potential search strategies and adapt these search strategies to minimise its impact on the search results. It is also possible to combine both strategies to alleviate the influence of localisation problem in locating the search target. In this paper, the possible impact of the localisation problem on the behaviour of the search algorithm behaviour is investigated. This investigation can help in proposing search methods that are robust against localisation errors.

HEURISTIC INFORMED SEARCH METHODS

The search strategy that can be followed by an AUV as a search agent to locate a point of interest should avoid using the exact location of the AUV. It should also have the capabilities discussed in the introduction section. The required capabilities can be summarised in the following:

- The algorithm should be able to decide on the next search location even in the case of no useful search information.
- The next search location should be reachable by the AUV to validate the decision taken before taking the next search decision.
- The algorithm should be able to utilise the search information, but not the exact location information, to decide on the next search location.

Blind deterministic and random search methods can explore the search space without any feedback from the search process. These search methods can be, easily, modified to use search information to explore the promising regions of the search space (Tholen et al. 2018b). These methods can switched back to the blind mode if no further search information can be extracted. Simple methods can be used to utilise the search information within the mentioned above constrains. The search can be directed towards the promising search area based on the fitness of that region and using its relative position with respect to the current position of the AUV.

Two heuristic search algorithm are proposed. Both follow an initial deterministic path to explore the whole search space taking into account the energy constrains.

The first algorithm, which is referred to as algorithm-A in this paper, can leave the defined path when finding a promising region. A decrease in the fitness value can be an indication of leaving a promising region. The algorithm, in this case, starts exploiting the neighbourhood by changing the AUV direction to a new direction that is nearly perpendicular to the current direction of the current path. The AUV will continue exploiting this area by moving in this new direction if there is no decrease in the fitness. The AUV starts exploring the area on other side of the predefined path if a decrease in the fitness value is found. The AUV will return to its predefined path if there is no further improvement in the fitness. The predefined path can have a horizontal, vertical or spiral pattern. Pseudocode of algorithm-A is provided in Figure 1.

The second algorithm is referred to as algorithm-B. This algorithm explores the search space using a spiral pattern as a predefined path. The algorithm divide the search space into equally sized sub-areas. It estimates the fitness of different sub-areas through evaluating the fitness of points on the edges of these sub-areas. The fitness of the current evaluated sub-area is compared with the expected fitness of the sub-areas to be explored. This comparison can be used to decide to further explore this sub-area using a horizontal or a vertical pattern if it is a promising region. A kind of tournament between the current evaluated sub-area and the remaining sub-areas is conducted. The tournament size can be defined based on the budget allocated for exploitation, the aimed accuracy of the exploitation and cost of exploitation. A tournament selection might lead to exploring under-average sub-areas. This can increase the possibilities of finding the search target in the case that the fitness of the edges does not reflect the fitness of the sub-area. This algorithm starts by passing through the edges of the search space and use the fitness of these points as a base for expecting the fitness of the edges, which have not evaluated yet.

```
start
path=define deterministic path (Horizontal, Vertical or Spiral)
set the AUV position to the position of the first point in the
path
set the AUV direction to follow the path
read the sensor to evaluate the fitness of the current position
while the AUV is moving
    if the fitness of the new position < the fitness of the last
    position
      explore the area around the current position : by changing
      the  direction of the AUV to a direction that is
      perpendicular to the current direction
      change the direction back to follow the predefined path
    end if
end while
stop
```

Figure 1: Pseudocode of Algorithm-A

Pseudocode of algorithm-B is provided in Figure 2. The energy budget for exploration and exploitation need to be defined before starting the algorithm.

```
start
path=spiral deterministic path
divide the search area to sub-areas of equal sizes based on the
energy budget for exploration and cost of movement and change
direction
expect the cost of exploring a sub-area given the aimed accuracy
and using the energy budget for exploitation
determine the tournament size
set the AUV position to the position of the first point in the
path
initiate the AUV direction
while the AUV is moving
  while the AUV on the edges of the search area
    evaluate the fitness of the edges and assign them to their
    sub-areas
  end (while the AUV on the edges…)
  assign the average fitness of the evaluated edges as the
  expected fitness of all unvisited edges
  for all the sub_areas
    evaluate the fitness of the current_sub_area
    winner=tournament(current_sub_area,tournament_size)
    if cuurent_sub_area is winner
      further explore the current_sub_area
    end if
    amend tournament_size
    go back to the main spiral path
  end for all the …
end while (the AUV is moving)
stop
```

Figure 2: Pseudocode of Algorithm-B

Figure 3 shows a sample run of algorithm-A for a specific search space with two optima. A sample run of algorithm-B on the same search space is shown in Figure 4.

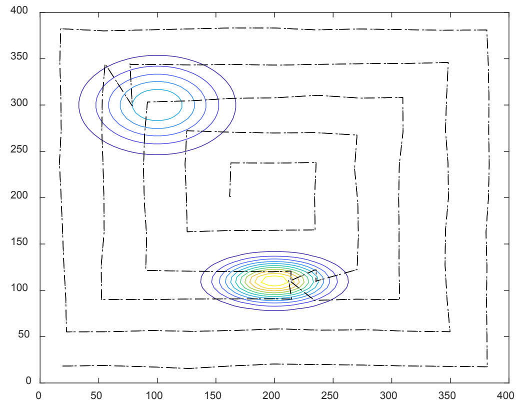

Figure 3: A Sample Run of Algorithm-A

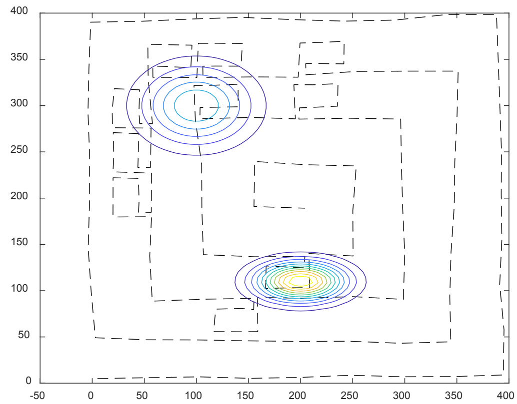

Figure 4: A Sample Run of Algorithm-B.

SIMULATION AND RESULTS

A set of experiments was conducted using the proposed heuristic search algorithms to locate the global optimum in a search space of two optima with Gaussian shapes (Nolle, 2015). The area of the search space is set to 400m x 400m (El-Mihoub et al. 2018). The stopping criteria for search is consuming the energy stored on the AUV. The energy is translated in terms of meters travelled by the AUV which is set to 4500 meter (Tholen et al. 2018b). The cost of changing the direction is expressed in meters depending on the angle of change in the direction. The cost of changing the direction by an angle of 180° is assumed to be equivalent to travelling 4 meters. The locations of the two optima are chosen randomly in the search space. The experiments were conducting with the assumption that the AUVs are using ideal sensors and the AUV can navigate with zero navigation error. The algorithms' performance criterion is defined as the distance between the global optimum and the best solution found by the algorithm.

The first set of experiments compares the performance of algorithm-A with the pure pre-defined path patterns, referred to as algorithm-C, without considering the localisation problem. The algorithms were executed 100 times using the mentioned above search environment and randomly selected locations for the two optima.

The results of these experiments are shown in Figure 5. The figure shows that algorithm-A outperforms the algorithm-C with three different patterns. Algorithm-A was able to locate the global optimum with an accuracy of less than 5 meters in about 80% of the experiments. On the other hand, algorithm-C was able to find the global optimum with the same accuracy in less than 30% of the experiments.

The performance of algorithm-B was evaluated in the absence of localisation errors. This algorithm was tested with a ratio of exploration to exploitation budgets of 7:3. The performance of algorithm-B, in most cases, is better than algorithm-C using the spiral pattern. Algorithm-B was able to locate the global optimum with an accuracy of less than 5 meters in more than 60% of the experiments. However, its performance is outperformed by algorithm-A using the same pattern (Figure 6).

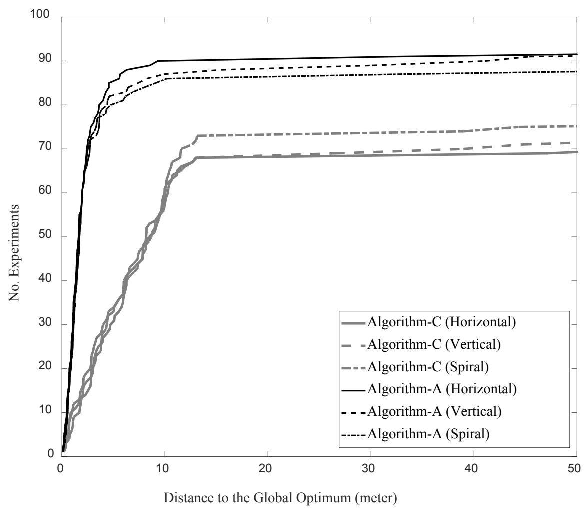

Figure 5: Comparing the Performance of Algorithm-A and Algorithm-C without Considering Localisation Errors

Another set of experiments was conducted to investigate the impact of the localisation errors on the heuristics performance. In these experiments, 100 randomly selected locations for the two optima were combined with pairs of 20 randomly selected basin sizes to produce 2000 different search environments. The performance of algorithm-A is compared with algorithm-B and algorithm-C using the spiral pattern only for fair comparison.

An accumulated localisation error is assumed in these experiments. The localisation error is assumed to be a result of errors in estimating the current navigation direction and estimating the AUV speed. The standard deviation of the error in estimating the AUV speed was set to 0.5 cm (Paull et al. 2014). The standard deviation of the error in estimating the current navigation direction is set to 2° (Paull et al. 2014).

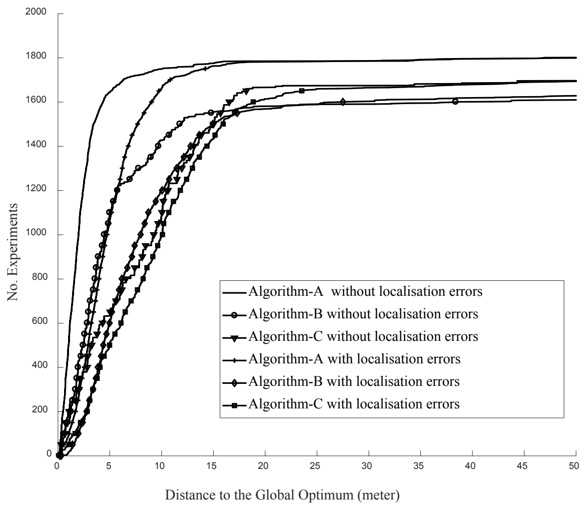

Figure 6: The Impact of the Localisation Problem on the Search Algorithms

The results show that the localisation errors degrade the performance of the search algorithms. However, the algorithm-A outperforms algorithm-B and algorithm-C in the presence of the localisation problem. The experiments also show that the localisation problem has its least impact on the performance of algorithm-C, which is a blind algorithm. There is no significant difference between the performance of algorithm-B and algorithm-C in the presence of localisation errors. The degradation in the performance of algorithm-B can be due to the impact of the localisation errors on dividing the search space to sub-areas. The division process depends on location information. Algorithm-B uses implicit location information more heavily than algorithm-A.

Relying on the current position information with localisation errors to navigate through the pre-defined path can lead to errors in the navigation. The influence of the navigation errors as a result of localisation errors on the performance of the different algorithms is shown in Figure 7. This graph shows the distance between the real position of the best found solution and the global optimum by each algorithm while navigating using position information with localisation errors. This graph shows that the effect of this navigation problem is small compared to that of the localisation errors.

CONCLUSION AND FUTURE WORK

The impact of localisation error on the search can be lightened by designing an algorithm that relays on other search information rather than the exact position of the promising solutions. Algorithm-A, which uses the fitness value of the current solution and the relative position of any promising region without using the exact location of the solution, was able to maintain its superiority over algorithm-B and algorithm-C even in the existence of localisation errors. On the other hand, the performance of algorithm-B, which does not use the exact location of the solution, was comparable with the blind search algorithm-A in the presence of localisation errors. Algorithm-B uses implicit location information more heavily than algorithm-A. The decision for exploitation in algorithm-B depends on the implicit position relations of a large number of points that define the sub-area edges.

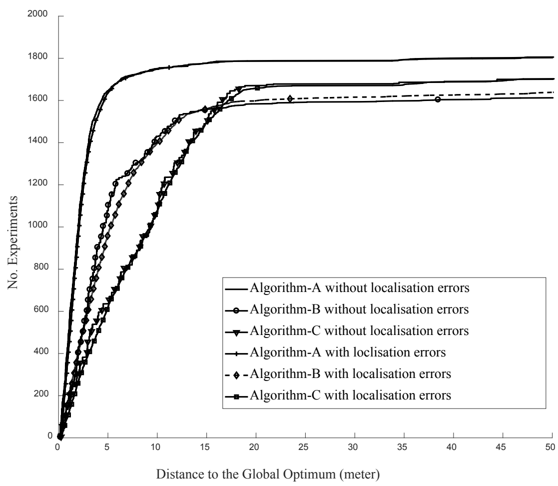

Figure 7: The Effect of the Navigation Errors on the Algorithms Performance

Figure 8 shows the impact of the localisation on a fitness function. In Figure 8, two graphs that illustrate the impact of a normal distributed localisation error with two different standard deviation values and their impact on the fitness function of two optima with Gaussian shapes. The graphs show that localisation errors can introduce noise in the fitness functions. Search algorithms that are able to locate global optima in noisy environments might help to tackle the localisation errors in searching applications.

The next step in this research is to combine these heuristic algorithms using a cooperative search strategy. The impact of the localisation and communication errors on the performance of this combination will be studied and investigated.

Another possible direction of the current research is to study search algorithms, which can succeed in exploring noisy environments. Selecting and utilising the most suitable algorithm to locate search targets in the existence of the localisation problem will be evaluated and investigated.

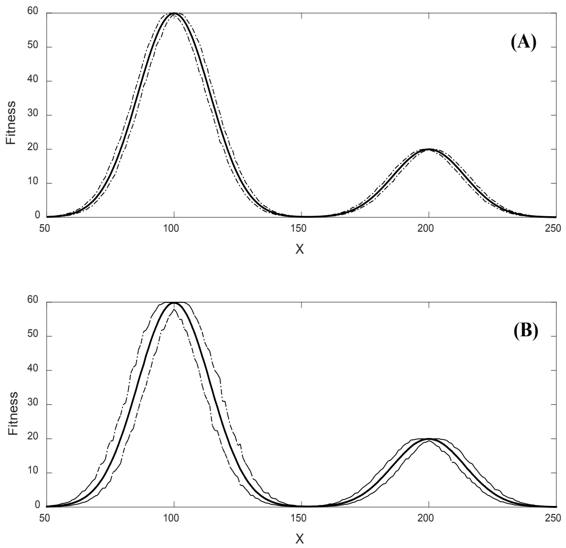

Figure 8: Impact of the Localisation Errors on the Fitness Function with Different Standard Deviations; (A) σ = 0.5 and (B) σ= 1.0

REFERENCES

El-Mihoub, T. A.; Hopgood, A. A.; Nolle, L; and Battersby, A. 2006. “Hybrid Algorithms: A review”. *Engineering Letters* 3, No. 2, 12-45.

El-Mihoub, T. A.; Tholen, C.; and Nolle, L. 2018. “Blind Search Patterns for Off-line Path Planning”. In *Proceedings of the 32nd Conference on Modelling and Simulation 2018*, (Wilhelmshaven, Germany, May 22-25), 121-128.

Gage, D. W. 1992. “Command Control for Many-Robot Systems”. *Unmanned Systems*, 28-34.

Goldberg, D. E. 1989. *Genetic Algorithms in Search, Optimization, and Machine Learning.* Addison-Wesley Longman Publishing Co, Boston, MA, USA.

Jian-hua, C.; Hai, Z.; De-hong, G.; and Zheng-dong, G. 2015. “An AUV Positioning Error Correct Algorithm Based on Acoustic Propagation Time Compensation”. In *Proceedings of the 2015 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC)*, (Ningbo, China, Sep 19-22), IEEE, 1-5.

Letowski, T. and Letowski, S. 2011. “Localization Error: Accuracy and Precision of Auditory Localization”. In *Advances in Sound Localization*, Strumillo P. (Eds.), InTechOpen, 55-77.

Nolle, L., 2015. “On a search strategy for collaborating autonomous underwater vehicles”. In *Proceedings of Mendel 2015, 21st International Conference on Soft Computing,* (Brno, Czech Republic, Jun 8-10), Springer, 159-164.

Paull, L.; Saeedi, S.; Seto, M.; and Li, H. 2014. “AUV Navigation and Localization: A Review”. *IEEE Journal of Oceanic Engineering* 39, No. 1 (Jan), 131-149.

Tholen, C.; El-Mihoub, T. A.; and Nolle, L. 2018a. “On A Novel Search Strategy Based On a Combination of Particle Swarm Optimisation and Levy-Flight”. In *Proceedings of the 32nd Conference on Modelling and Simulation 2018*, (Wilhelmshaven, Germany, May 22-25), 190-194.

Tholen, C.; El-Mihoub, T.; Nolle, L; and Zielinski, O. 2018b. “On the Robustness of Self-adaptive Levy-flight”. In *Proceedings of the OCEANS’18 MTS/IEEE Kobe/Techno-Ocean*, (Kobe, Japan, May 28-31), IEEE, 1-5.

Tholen, C.; Nolle, L.; and Werner, J. 2019. “On the Influence of Localisation and Communication Error on the Behaviour of a Swarm of Autonomous Underwater Vehicles”. In *Recent Advances in Soft Computing. MENDEL 2017. Advances in Intelligent Systems and Computing*, Matoušek R. (Eds.), 837, Springer, Cham, 68-79.

Wynn, R. B.; Huvenne, V. A. I.; Le Bas, T. P.; Murton, B. J.; Connelly, D. P.; Bett, B. J. B.; Ruhl, J. H. A.; Morris, K. J.; Peakall, J.; Parsons, D. R.; Sumner, E. J.; Darby, S. E.; Dorrell, R. M.; and Hunt, J. E. 2014. “Autonomous Underwater Vehicles (AUVs): Their past, present and future contributions to the advancement of marine geoscience”. *Marine Geology*, 352 (Jun), 451-468.

Zielinski, O.; Busch, J.; Cembella, A.; Daly, K.; Engelbrektsson, J.; Hannides, A. K; and Schmidt, H. 2009. “Detecting marine hazardous substances and organisms: sensors for pollutants, toxins, and pathogens”. *Ocean Science*, 5 (Sep), 329-349

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