BLIND SERACH PATTERNS FOR OFF-LINE PATH PLANNING

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KEYWORDS

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ABSTRACT

Path planning is crucial for efficient utilisation of autonomous underwater vehicles. The goal of the mission of an autonomous underwater vehicle determines suitable strategies for path planning. Blind search methods can be used for off-line path planning for unknown environments to locate phenomena of interest. Different blind search patterns have been implemented and evaluated in terms of their ability to reach the mission's goal. A novel blind search pattern that is based on a truncated Lévy distribution is also proposed and compared with other search patterns as path-planning algorithms. The simulations show that Lévy search pattern can outperform other search patterns for small size phenomena. On the other hand, the proposed inverse-Lévy pattern can locate large size phenomena more than other search patterns. The simulations show that the probability of locating the most important phenomenon by a single autonomous underwater vehicle using blind search patterns is much smaller than of a swarm of autonomous underwater vehicles in similar conditions. However, Lévy and inverse-Lévy can be used for the worst-case scenario of no communication nor ability to use feedback information.

INTRODUCTION

Autonomous Underwater Vehicles (AUVs) have attracted significant attention in the last several years and have been widely used in marine geoscience, military, commercial and environmental applications (Wynn et al. 2014). Their ability to operate autonomously makes them the best option for fast and accurate exploration, inspection and search in extreme and unknown environments. They are key players for exploring and searching different water systems where the risks are high. They can be used to locate harmful dumped waste, lost ship containers and collect data in inaccessible or dangerous underwater environments.

Efficient path planning is a crucial issue for modern AUVs. Path-planning algorithms produce feasible trajectories for AUVs to reach their goal. They generate geometric paths, without considering any specified time law (Gasparetto et al. 2015). The goal of the mission of an AUV determines the strategy for path planning. Collecting data from underwater environment, for example, may require a strategy that enables the AUV to pass over all the points of the area or volume of interest within a set of constrains. Different Coverage Path-Planning (CPP) algorithms have been used to determine such trajectories (Galceran and Garreras 2013). Finding locations of harmful garbage, groundwater outflow or lost cargo may necessitate using a different strategy that enables finding the optimal path to these locations with different constrains (Nolle 2015). Efficient CPP algorithms can be used for searching since they usually sample the mission's space to have a complete view of the phenomena of interest. However, they may not be as efficient as artificial search algorithms that utilise minimum samples to reach their goal.

Regardless of the mission's aim, path-planning algorithms should be reliable and enable the AUVs to navigate in both known and unknown environments. Preliminary path is usually defined for an AUV based on the available information of the mission environment and its kinematic constraints. Path and trajectory planning algorithms can used to generate this preliminary path. In off-line path-planning algorithms where the environment is assumed to be known in advance, the AUV follows usually this pre-defined path without any modification. For on-line algorithms, also known as sensor-based algorithms (Noborio et al. 2000), the path is continuously updated through a cognition algorithm that use information from the environment taking into account the characteristics of different sensors and kinematic and communication constraints.

In order to develop an autonomous platform for submarine exploration, which is the final aim of this research, off-line path-planning algorithms should be developed for robust navigation. In this research, a small swarm of AUVs share their individual experience during the search to locate the phenomena of interest and a mechanism for optimal utilization of the cumulative experience will be used to direct the swarm towards the location of those phenomena. However, communication and localization problems can be obstacles in sharing and utilising the cumulative experience of the swarm of AUVs (Tholen et al. 2017). Effective and efficient off-

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line path pattern can help to alleviate these problems towards robust search.

Blind Search and Off-Line Path Planning

This paper builds on the results of another study of the same research that recommends investigating the behaviour of other search algorithms to use in a case of facing problems in communication between AUVs (Tholen et al. 2017). Here, the worst-case scenario of off-line path planning is studied. In this context, path planning refers to the process of producing a geometric path to the highest priority phenomenon. The path of the AUV to find a global optimum is to be pre-defined with no information about the environment, except its boundaries. A set of path planning and search algorithms were implemented and evaluated in terms of their ability to define a preliminary path for AUVs to reach their common goal in an unknown environment. The suitability of using these algorithms by each individual AUV in a swarm to guide the search, in the case of no communication and difficulties in controlling the movement based on the available information, is studied.

Search for targets should optimise the chances of reaching them. For a stable environment with prior knowledge, deterministic search patterns can be efficient. However, in dynamically changing or unknown environments, probabilistic search methods can be more efficient. In order to study the worst-case scenario with no prior knowledge, no communication and no way to improve the search path utilising feedback information, the seed spreader algorithm (Galceran and Garreras 2013) has been selected as deterministic algorithm to evaluate its ability to guide the search towards the global optimum.

On the other hand, different probabilistic search algorithms can be used for path planning. However, for this study, the search algorithms those comply with off-line path-planning requirements, as described above, are single-point blind search methods. These search methods iterate a single starting solution to reach the optimal solution and do not use any kind of feedback. Two well-known pure random single-point search algorithms, i.e. Lévy flights (Viswanathan et al. 1999) and random walks, have been selected for this purpose. In addition, a third probabilistic search algorithm based on Lévy flights was proposed.

The seed spreader algorithm is a deterministic path-planning pattern for complete coverage of simple regions. It covers the area of interest in a sweeping motion pattern by moving back and forth. It is also known as lawn mowing. This search pattern can guide the AUV to locate the search goal. The seed spreader algorithm, when used as path-planning mechanism to cover the space of interest, decomposes the space into cells and the efficiency of the algorithm depends on the details of the decomposition process. Since one of the objectives of the research is to evaluate the performance of the seed spreader as a deterministic search algorithm, the motion pattern is simulated without decomposition.

Three probabilistic search patterns were selected for path planning. Random search methods can be a valid option for path-planning problems and have been successfully applied in some floor-cleaning robots (Galceran and Garreras 2013). Different random search methods can be used for solving the path-planning problem. Starting from a position, different path patterns can be generated by generating a sequence of random steps in terms of their lengths and directions. The produced search pattern is controlled by the probability distribution used to generate the length and the direction of steps.

In the random walk search for path planning, the AUV follows randomly pre-generated step sizes in random directions within the specified region. The step length and its direction can be randomly selected based on uniform distributions. The x and y coordinates of each step can also be generated using uniform distributed random numbers. By randomly generating the coordinates, the next step length and its direction can be defined. When applying random walk algorithms, the range of the step lengths need to be set according to the problem at hand. Selecting the range of step lengths can affect the search performance.

Another random and well-known biological search is Lévy flights or walks (Sims et al. 2008). Lévy flights represent an optimal solution to the biological search problem in complex landscapes (Reynolds 2015). This model as a search pattern can suits dynamic and complex environments. Lévy search is a kind of a random walk search with unique characteristics. Its search patterns consist of repeated clusters of relatively short step length and rare longer steps. The step lengths of Lévy flight are generated by a probability distribution with a power-law tail. The step lengths can be generated using formula (1)

$$l = r^{\frac{-1}{\alpha}} \tag{1}$$

where l denotes the step length, r a uniformly distributed random number in the range $[0,1]$ and α is a parameter can have any value in the range$[1,2]$.

The step length formula can be applied to generate the step length and its direction can be chosen based on the density function of a uniform distribution. The formula can also be used to produce x and y coordinates of a Lévy step in two-dimensional space.

Solving a problem using Lévy search patterns requires selecting proper parameters for the search. The value of α can impact the search pattern since it affects the step length. The step length equation (1) can produce very large values that can be outside the search range for random numbers near zero. In order to limit the length of the step size to a specific value (l_{max}) within in the search range, the generated random number can be mapped into

a sub-interval of the interval [0, 1]. The new interval is defined by$[r_{min}, 1]$, where r_{min}can be calculated using equation (2).

$$r_{min} = \frac{1}{{l_{max}}^{\alpha}} \tag{2}$$

Limiting the step length of Lévy patterns produced a truncated Lévy search (Xiong and Lam 2010), where $P(x) = 0\,, x > l_{max}\ and\ P(x) = 0, x < 1$. A truncated Lévy search can be more applicable in search, however, it introduces a new parameter that needs to be set and can influence the search patterns.

A third random search pattern, which combines exploring and exploitation with different aspects from that of Lévy search, can help finding an optimal path to the search goal. In Lévy search, very small steps dominate the search pattern, whereas in the proposed search, the pattern is dominated by long steps. In this mechanism, which is referred to as inverse-Lévy in this paper, the search pattern consists of repetition of a cluster of long steps followed by occasional short steps. Having such pattern can promote exploring the whole area with occasional exploitation. This combination of exploring and exploitation can suit finding a path for the phenomenon of interest in unknown environments. The step lengths are based on a Lévy distribution and derived from equation (1). The step length for Inverse-Lévy is calculated according to equation (3).

$$l_{IL} = l_{max} - r^{\frac{-1}{\alpha}} \tag{3}$$

where l_{IL} denotes the step length of inverse-Lévy, l_{max} is a parameter that defines the maximum step length, r a uniformly distributed random number in the range $[r_{min}, 1]$, where: r_{min} is defined in equation (2), and α is a parameter that can have any value in the range [1,2].

In inverse-Lévy pattern search, two parameters, as in truncated Lévy, can affect the details of these patterns and can influence its ability to plan for optimal paths. However, since step lengths close to the maximum step length are expected to dominate the search pattern, the search pattern will be more sensitive to the value of l_{max} parameter.

SIMULATION

A set of experiments was conducted using different search patterns to locate phenomena of interest with different priorities and different sizes. The seed spreader, random walk, Lévy flight and inverse-Lévy were implemented, tested and evaluated for their ability to locate phenomena of interest in an area of 400m x 400m. These search patterns were tested with different parameter values for different phenomena. The four algorithms exhibit different search patterns while exploring the mission area. Figure 1 shows the search patterns of these algorithms with a maximum step length of 50 meter.

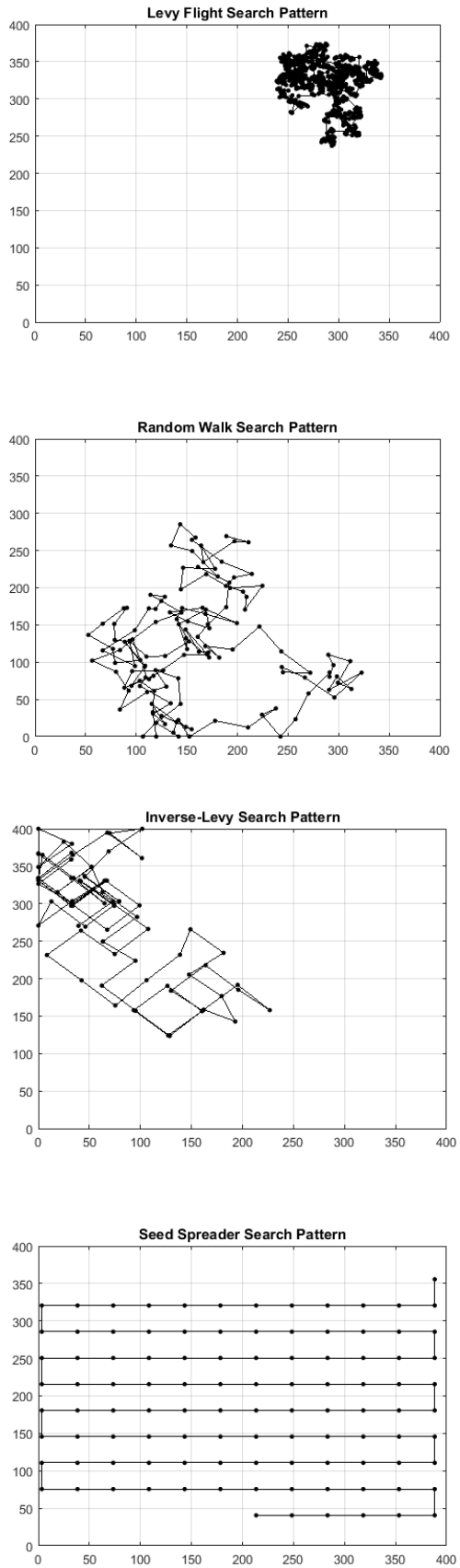

Figure 1: Search Patterns of Different Algorithms

In these experiments to simulate a multimodal search space, three phenomena of interest are assumed having

random locations in the mission area. Since blind search algorithms do not use any gradient information, different priorities instead of fitness score were assigned to different phenomena. The experiments were conducted with phenomena of two different sizes. The performance of each search pattern is evaluated in terms of its ability to find the phenomenon of the highest priority and in terms of finding other phenomena. The ability of the algorithms in locating phenomena of different priorities with the same size were compared.

The stopping criteria for search is either performing the maximum number of steps or travelling for a maximum distance. In all the experiments, the maximum number of steps was set to 1000 and the maximum travelling distance was set to 3600 meters because of the energy constraints of the AUV. Each experiment was repeated for 1000 times.

In the implemented seed spreader algorithm, the step lengths in both directions are equal. The theoretical optimal value of the step length to explore the mission area, given the maximum travelling distance constrain, can be calculated (Tholen et al. 2018) and has a value of about 57 meter. However, using this step length, in the worst-case scenario, the seed spreader algorithms can locate phenomena with a minimum radius of 28.5 meter. The algorithm was tested for different step lengths above and below this value. It was tested for step length values of 5 meters to 100 meters with an increment of 5 meters. The same range of values were also used as maximum step length for random search, Lévy and inverse-Lévy algorithms. In random search, both coordinates of each step are selected randomly from a range of values from zero to a maximum step length. For both Lévy and inverse-Lévy methods, the algorithms were tested using different values of α in the range$[1,2]$.

Walk and Flight Scenarios

While tracking the pattern defined by the algorithm, the AUV can either follow one of two scenarios. The first scenario is to scan the points on its path to the next step location for a phenomenon. The second scenario is to examine only the locations of the steps for phenomena. In the remaining of the paper, when a search pattern uses the first scenario it is referred to as a walk. Random walk, Lévy walk, inverse-Lévy walk and the seed spreader walk scan the path while moving to the next step position. On the other hand, if the search pattern follows the second scenario, it will be referred to as flight. In other words, random flight, Lévy flight, inverse-Lévy flight and the seed spreader flight focus on the location of the next step.

The walk scenario can be applied when the AUV is equipped with sensors that can measure environment data for phenomenon recognition using minimum resources. While the flight scenario can be more suitable for AUVs with sensors that consume considerable amount of resources (Zielinski et al. 2009). However, the experiments were conducting with the assumption that the AUVs are using ideal sensors.

The two different scenarios have been simulated using the different search patterns. In each set of experiments, the search patterns were evaluated for finding phenomena with small and large sizes. The size of large phenomenon is assumed equals to the area of a circle with a radius of 20 meter. The small phenomenon has a radius of one meter.

The starting point of each search pattern is selected randomly for fair comparison between different search algorithms. It is also based on the worst-case situation where the AUV is in the middle of searching and becomes unable to communicate with the rest of the swarm and unable to use environment data to guide the search.

RESULTS

The results of the simulation for finding a path to the mission goal are shown in Figures 2 to 9. These figures show the number of times that each algorithm succeed in finding the phenomenon of highest, second highest and lowest priority. If an algorithm locates more than one phenomenon, it will be assigned to the phenomenon of the highest priority. In other words, the algorithm that managed to locate the highest priority phenomenon may also succeed in locating the second highest and the lowest priority phenomena.

In the graphs that show the performance of the different algorithms, different scale ranges were used to obtain a close view of the performance of the search patterns. For phenomena of small sizes, the maximum value of the scale range is set to 50 for flying scenario and to 180 for walking scenario. Whereas, in the graphs that compare the performance of the algorithms on large sizes phenomena the maximum scale ranges are 700 and 900 for both scenarios, respectively.

Flights to Phenomena

The four search patterns were tested for locating the phenomenon with the highest priority and locating more than one phenomenon. The position of three phenomena have been selected randomly in the search space and tested for the different search algorithms that examine the step locations only for a phenomenon. Search patterns with the concept of flying to the goal were tested with phenomena with equal sizes but different priorities.

The experiments for small size phenomena show that Lévy flight search pattern can find the phenomenon with the highest priority and other phenomena more than inverse-Lévy flights (Figures 2 and 3). On the other hand, Inverse-Lévy flight outperforms Lévy flights for large phenomena sizes. The graphs also show the performance of both search patterns is highly dependent on α.

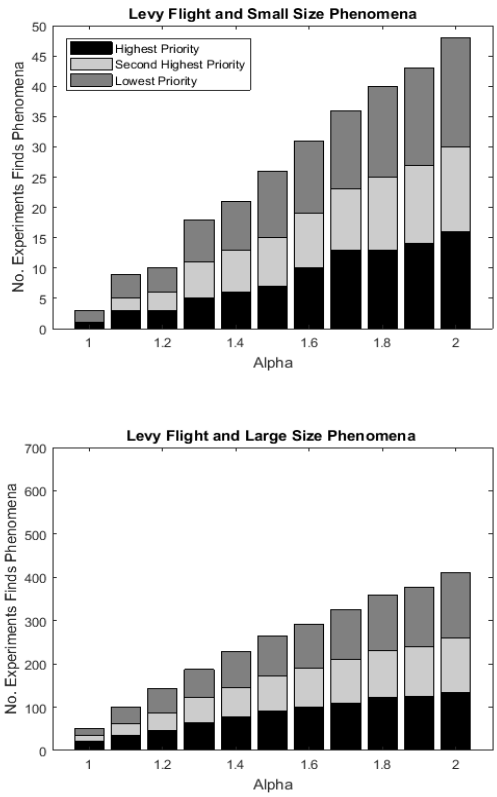

Figure 2: Lévy Flight

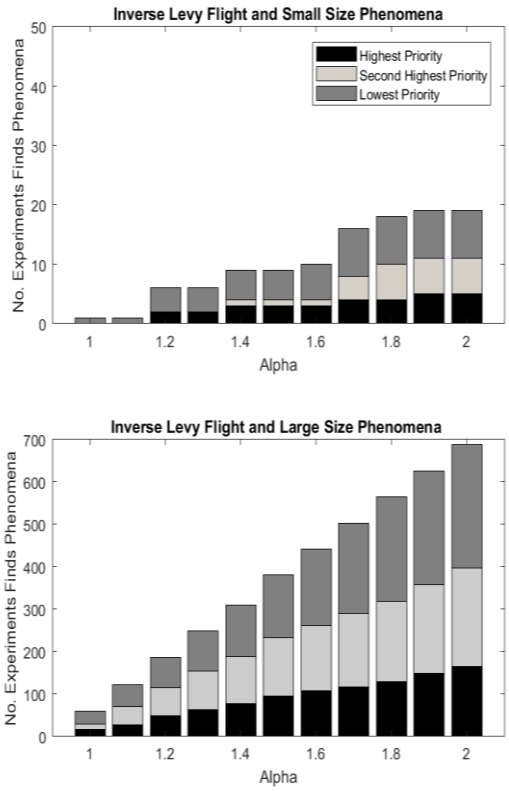

Figure 3: Inverse -Lévy Flight

The simulations also show that Lévy flight outperforms the other two search patterns, i.e. the seed spreader flight (Figure 4) and random flight (Figure 5) for phenomena of small sizes. Nevertheless, for large phenomenon sizes, the seed spreader algorithm performs better than other search algorithms, in most cases, in terms of finding at least one phenomena. However, for specific values of α and maximum step length, the inverse-Lévy method outperforms other algorithms. The experiments show that for large phenomena, the seed spreader algorithm in most cases guides the search to the lowest priority phenomenon. Whereas, each phenomenon has the same chance to be located by other algorithms.

Walks to Phenomena

The same set of experiments was repeated with scanning for phenomena while moving to the next position. In these experiments, an AUV scans the search pattern every meter for a phenomenon.

The simulations show an improvement in locating phenomena for all algorithms as expected (Figures 6 to 9). The simulations demonstrate that for specific values of α and step lengths, inverse-Lévy walk (Figure 6) outperforms other search walks.

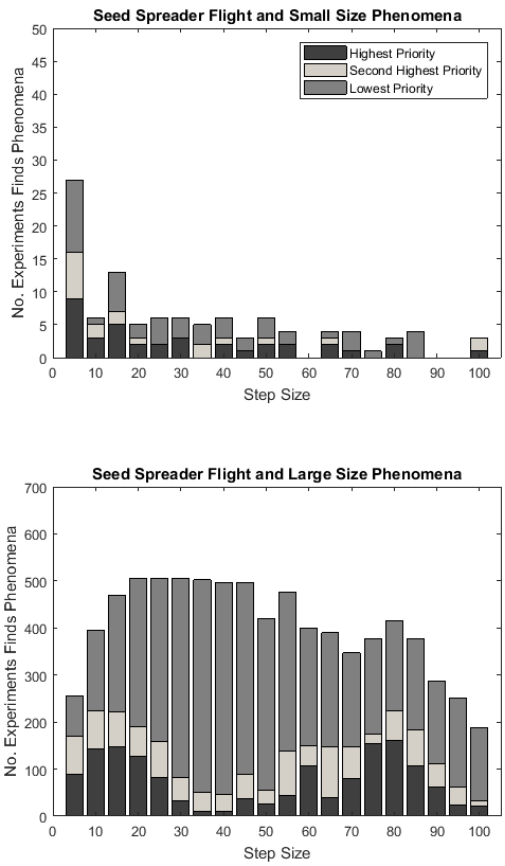

Figure 4: The Seed Spreader Flight

The experiments demonstrate the same trend, noticed in the experiments of fly to the goal, where the seed spreader algorithm (Figure 7) usually guides the search to the lowest priority phenomenon in contrast to other algorithms.

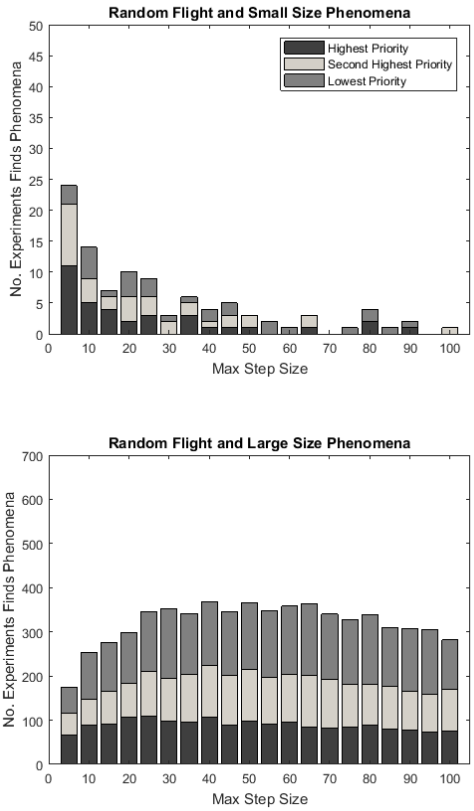

Figure 5: Random Flight

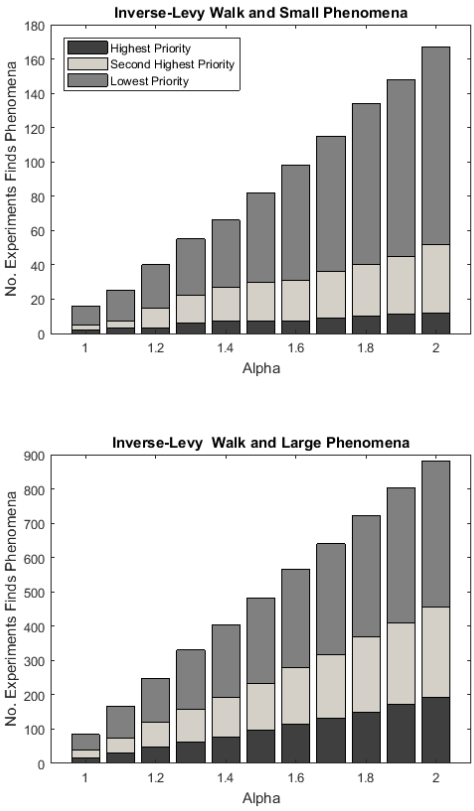

Figure 6: Inverse-Lévy Walk

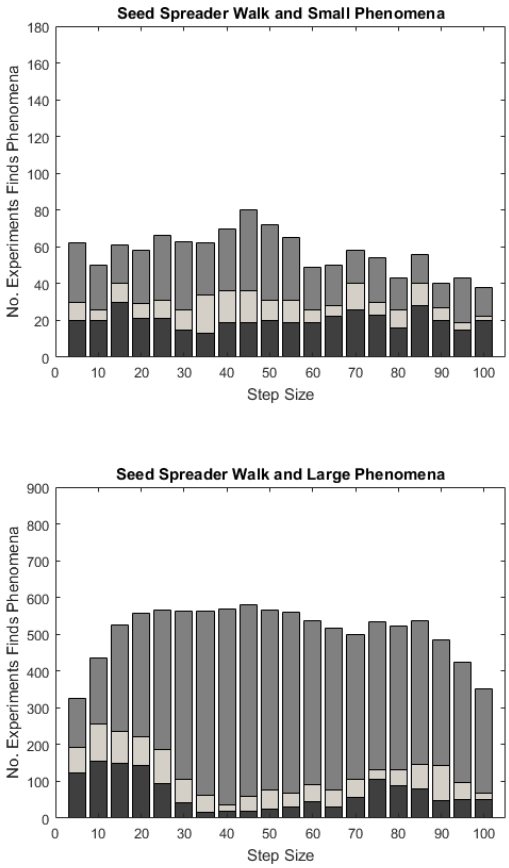

Figure 7: The Seed Spreader Walk

The experiments for locating small size phenomena demonstrate that for Lévy walks with $\alpha \geq 1.4$ Lévy patterns (Figure 8) slightly outperform other search patterns and inverse-Lévy has the worst performance

The performance of random walk (Figure 9) in finding phenomena of small size is much better than random flights (Figure 5). However, for locating phenomena of large sizes there is no significant improvement in the performance compared with random flights.

CONCLUSION AND FUTURE WORK

The experiments clearly show that the probability of locating the phenomenon of interest using a single AUV with blind path-planning algorithms is very small even for phenomena with considerable large sizes. If this probability compared to that of a Particle Swarm Optimisation (PSO) with three AUVs (Tholen et al. 2017), working in perfect conditions as that of the simulation in this paper, blind path-planning algorithms cannot be used alone to locate points of interest.

However, they might be used as backup search in the worst-case scenario. In that case, for small phenomena, Lévy search patterns with specific values of α can be used since it can direct the search toward the most interesting phenomenon compared to other algorithms. For large sizes phenomena, inverse Lévy may be a good

option. However, the performance of Lévy and inverse-Lévy depends on the settings of the control parameters, i.e. the maximum step length and α. Inverse-Lévy search patterns are more sensitive to the maximum step length than Lévy search. Using feedback information about the search progress can help in self-adapting the control parameters and might improve their performance.

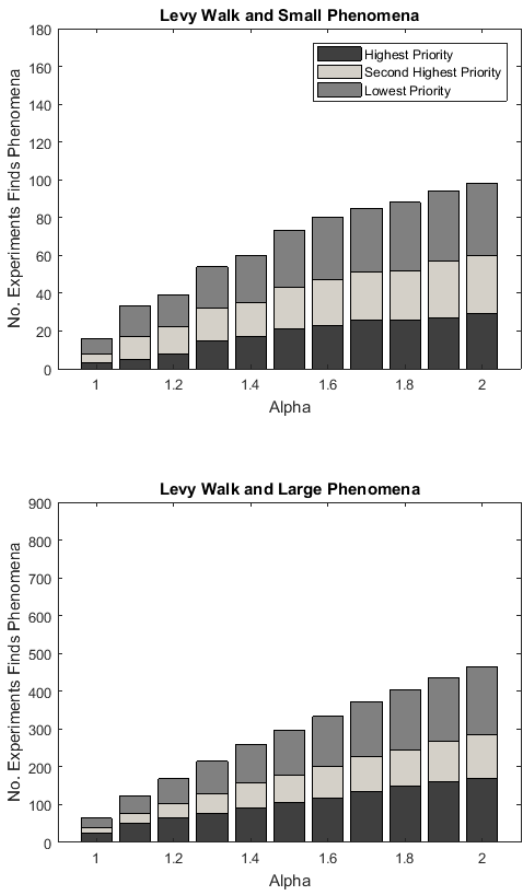

Figure 8: Lévy Walk

Studying different self-adaptive techniques and the possibilities of applying them to Lévy or inverse-Lévy search patterns is the next step of this research. There are different ways to make these search patterns self-adaptive. A possible adaptive technique for inverse-Lévy is to control its maximum step length by increasing it when there is no improvement in the search to promote exploration while reducing exploitation. Adaptation can also be done by extending the search space of the search algorithm to include the two control parameters of inverse-Lévy or Lévy, i.e. l_{max} and α, and redefining the problem as to find the best parameters and the location of the most important phenomenon.

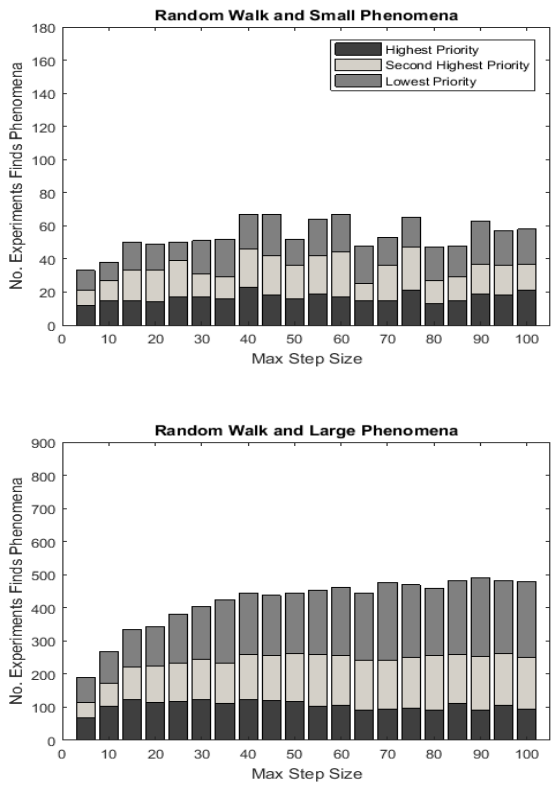

Figure 9: Random Walk

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