ON A NOVEL SEARCH STRATEGY BASED ON A COMBINATION OF PARTICLE SWARM OPTIMISATION AND LEVY-FLIGHT

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ABSTRACT
The long term goal of this research is to develop a flexible, low-cost and autonomous platform for submarine exploration. Such a platform can be used for locating submarine points of interest. The search for submarine groundwater discharges (SGD) in coastal waters is one of the possible applications for such an observatory. The swarm should be guided by a search strategy. In this research a novel search algorithm based on Particle Swarm Optimisation and inertia Levy-flight is presented. It was demonstrated using a computer simulation that the novel algorithm is capable of improving the search performance compared to the performance of a swarm of homogenous particles or inertia Levy-flight to guide the search of the swarm to locate a source of submarine groundwater discharge.

INTRODUCTION
The aim of this project is to utilize a swarm of autonomous underwater vehicles (AUV) to develop a low cost and flexible environmental observatory. The search for submarine groundwater discharges (SGD) in coastal waters is one of the possible applications for such an observatory. Marine scientists are interested in locating and analysing these discharges because the nutrients discharged by SGD have a significant influence on the marine ecosystem (Dugan, et al., 2010; Moore W., 2010; Nelson, et al., 2015). AUVs can be used for the exploration of medium sized areas and measure some parameters, for example conductivity, temperature or nutrients to locate a SGD (Zielinski, et al., 2009). The interaction of the swarm must be managed by a search strategy. In this research, the behaviour of the swarm will be guided by a combination of particle swarm optimisation (Nolle, 2015) and Levy-flight (Tholen, et al., 2018).

Submarine Groundwater Discharge
Submarine groundwater discharge (SGD) consists of a flow of fresh groundwater and the recirculation of seawater from the sea floor to the coastal ocean (Moore W., 2010). The fresh water and the sea water discharges commingle in the so-called mixing zone (Figure 1) (Evans & Wilson, 2016).

Figure 1: Submarine Groundwater Discharge of Fresh- and Recirculating-Water, modified after Evans and Wilson (2016)

Test Environment
The aim of the AUV is to localise a point of interest, for example SGDs. There is a constant input of different substances, i.e. nutrients or fluorescent dissolved organic matter (FDOM) (Nelson, et al., 2015) due to SGDs to the marine environment. While substances are discharged into the ocean, the concentration of these substances will be a function of the position and the time because of mixing processes in the water (Stedmon, et al., 2010). Dynamic behaviour could be simulated while using numerical models (Evans & Wilson, 2016) or a model based on cellular automata (Tholen, et al., 2017). However for fair comparison between the different algorithms, a static fitness function is used during this research. The conductivity in milli-Siemens per centimeter (mS/cm) was chosen as tracer, to describe the distribution of the water mass inflow on a SGD in this work. The values of the conductivity are based on the measurements at the Black Point SGD in Maunalua Bay Hawaii (Richardson, et al., 2017).
The value of the conductivity in the search space is simulated as follows:

\[ f(x) = a \cdot e^{b \cdot x} + c \cdot e^{d \cdot x} \]  

(1)

Where:
- \( f(x) \): conductivity in mS/cm,
- \( x \): Euclidean distance between AUV and SGD,
- \( a \): scale parameter (45.62 mS/cm),
- \( b \): gradient parameter (0.00079),
- \( c \): scale parameter (-36.88 mS/cm),
- \( d \): gradient parameter (-0.3896),
- \( max \): maximum conductivity (53.42 mS/cm).

The search area is limited to 400 m x 400 m. The position of the SGD was set to position \( r_3 = (50 \text{ m} / 50 \text{ m}) \). Figure 2 shows the shape of the described fitness function. As shown, gradient information are only sparsely available. This makes it a difficult test environment for direct search algorithms. During the search, the AUV moves through the search space and measure the conductivity after each second. To make the simulation more realistic, noise were added to the values of the fitness function (1), using a normal distribution with the measurement value as mean value and a standard deviation of 0.2 mS/cm. Furthermore, the measurement accuracy of the AUV is limited to a value of 0.01 mS/cm.

**Particle Swarm Optimisation**

PSO is modelled on the behaviour of collaborative real world entities (particles), for example fish schools or bird flocks, which works together to achieve a common goal (Kennedy & Eberhart, 1995; Bansal, et al., 2011). Each individual of the swarm searches for itself. However, the other swarm members also influence the search behaviour of each individual.

In the beginning of a search, each particle of the swarm starts at a random position and a randomly chosen velocity for each direction of the n-dimensional search space. Then, the particles move through the search space with an adjustable velocity. The velocity of a particle is based on its current fitness value, the best solution found so far by the particle (cognitive knowledge) and the best solution found so far by the whole swarm (social knowledge) (2):

\[ \vec{v}_{i+1} = \vec{v}_i \omega + r_1 c_1 (\vec{p}_b - \vec{p}_i) + r_2 c_2 (\vec{g}_b - \vec{p}_i) \]  

(2)

Where:
- \( \vec{v}_{i+1} \): new velocity of a particle,
- \( \vec{v}_i \): current velocity of a particle,
- \( \omega \): inertia weight (2.0),
- \( c_1 \): cognitive scaling factor (1.4),
- \( c_2 \): social scaling factor (1.4),
- \( r_1 \): random number from range [0,1],
- \( r_2 \): random number from range [0,1],
- \( \vec{p}_b \): current position of a particle,
- \( \vec{g}_b \): best known position of the swarm.

After calculating the new velocity of the particle, the new position \( \vec{p}_{i+1} \) can be calculated as follows:

\[ \vec{p}_{i+1} = \vec{p}_i + \vec{v}_{i+1} \Delta t \]  

(3)

Where:
- \( \vec{p}_{i+1} \): new position of a particle,
- \( \vec{p}_i \): current position of a particle,
- \( \vec{v}_{i+1} \): new velocity of a particle,
- \( \Delta t \): time step (one unit).

In (3) \( \Delta t \), which always has the constant value of one unit, is multiplied to the velocity vector \( \vec{v}_{i+1} \) in order to get consistency in the physical units (Nolle, 2015). In this research the control parameter values were chosen as follows (Tholen & Nolle, 2017):

\begin{align*}
\omega &= 2.0, \\
c_1 &= 1.4, \\
c_2 &= 1.4.
\end{align*}

**Inertia Levy-flight**

Biologists have observed that animals, like sharks, bony fish, sea turtles and penguins, often move in patterns that can be approximated by Levy-flights (Reynolds, 2014) following the Levy-flight foraging hypotheses. This hypotheses states that natural selection should have lead to adaptations for Levy-flight foraging, because Levy-flights can optimise search efficiencies (Viswanathan, et al., 2008). Since there is experimental, evidence for inherent Levy search behaviour in foraging animals (Kölzsch, et al., 2015), Levy-flight has been selected as a search strategy for a single AUV. While using Levy-flight, the AUV has to choose a random direction as well as a random step length for each iteration. The direction is chosen from a uniformly distribution in a range of 0 to 360 degree. However the chosen step length is based on a power law cumulative distribution function:

\[ s = r^{-\frac{1}{\alpha}} \]  

(4)

Where
- \( r \): random number from the range [0,1],
- \( \alpha \): parameter from the range [1,2].

When using Levy-flight as a search algorithm, the value of \( \alpha \) has to be chosen off-line by the user before the search. The value of \( \alpha \) has direct impact on the step length \( s \) calculate in each iteration. Therefore, the search behaviour of the AUV depends heavily on the chosen...
value of $\alpha$. Instead of manually tuning of $\alpha$, a self-adaptive scheme to tune this parameter $\alpha$ is used. The AUV in each step calculate a value of $\alpha$ based on the information gained from the environment (Tholen, et al., 2018) as follows:

$$\alpha = \frac{g_c - g_w}{g_b - g_w} + 1$$

(5)

Where:

$g_c$: current fitness value,

$g_w$: worst score fitness found so far,

$g_b$: best score fitness found so far.

Furthermore, the AUV stores the fitness value of the previous iteration $g_{t-1}$ and compare this value with the fitness value in the actual time step $g_t$. If there is an improvement, the AUV will keep its direction. Otherwise, it will choose a new direction randomly.

**Combination of Particle Swarm Optimisation and inertia Levy-flight**

Sometimes a scout vehicle can improve the success of a search in difficult search areas (Nolle, 2015). In this research, the inertia Levy-flight will be used as search strategy for the scout vehicle, to guide the search of the other particles using PSO as search strategy. During the search, the scout will move through the search space. In each step, it will measure the conductivity. The scout vehicle shares its best position with the swarm.

The movement of the scout vehicle is not affected by the search results of the other swarm particles. Hence, this allows an independent search for the scout vehicle, the scout will be able to reach new areas even if the other particles of the swarm will trapped into a local optima or stuck in an area without any gradient information.

**EXPERIMENTS**

To compare the performance of the proposed search algorithm, simulations were carried out, using the described test environment.

Three different algorithms with different configurations was evaluated using a swarm of four AUVs. In the first configuration, all particles were guided by a PSO. In the second configuration, the search of the AUVs were guided by the inertia Levy-flight. In this configuration the AUVs do not exchange any information about the environment. For the third configuration, three of the AUVs perform a PSO, while the fourth AUV perform an inertia Levy-flight.

For each configuration, 1,000 simulations were carried out. The search time is limited to 5,400 seconds, due to the limitations of the operation time of the hardware platform. In each run, the $g_{best}$ value of the whole swarm is stored during the search.

**RESULTS**

The results of the 1,000 simulations were classified into three categories, to compare the performance of the different search algorithms. The minimal distance between the SGD and a particle during the search will be used for the classification. However, the $g_{best}$ value of the swarm can be used for the classification process. Due to the specific nature of the search topology this distance information is transformed into conductivity values using equation (1). Table 1 shows the attributes of different classes in terms of the minimum values and the maximum values the distance to the SGD and conductivity values. Experiments with results that fall within class one can be named as successful runs, while others can be referred to as unsuccessful runs.

**Table 1: Attributes for Classification**

<table>
<thead>
<tr>
<th>Class</th>
<th>Min-Value</th>
<th>Max-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$x$ (m)</td>
<td>$f(x)$ (mS/cm)</td>
</tr>
<tr>
<td>1</td>
<td>0.0</td>
<td>8.74</td>
</tr>
<tr>
<td>2</td>
<td>&gt;0.4</td>
<td>14.08</td>
</tr>
<tr>
<td>3</td>
<td>&gt;5</td>
<td>40.55</td>
</tr>
</tbody>
</table>

Figure 3 shows the results of the simulations, using the classification described above. It can be observed from the figure, that the swarm guided by PSO was not able to find the SGD during specified search time. While using the inertia Levy-flight, the swarm is able to find the SGD in 595 runs. Furthermore using the combination of PSO and inertia Levy-flight, the swarm is able to find the SGD during 685 runs.

![Figure 3: Frequency Diagram sorted by classes](image)

Figure 4 shows the trajectories of the AUVs during the search for the three different algorithms. The graphs on the left hand side show the trajectories of the runs with the best performance. While the ones on the right hand side show the trajectories of the runs with the worst performance.
a) PSO

b) Inertia Levy-flight

c) Combination

Figure 4: Trajectories of the AUVs during the search for the best run (left) and the worst run (right) for the three search algorithms

DISCUSSION

It can be observed from Figure 4-a that the PSO was unable to explore the search area. The particles of the swarm using inertia Levy-flight do not exchange any information and each particle explores the search area by itself. If one of the particles is able to find the SGD, the run will be successful (left). In the combination configuration, the particle using inertia Levy-flight adds extra exploring capabilities to the swarm. That has a great impact on the performance as depicted in figure 4-c. If this scouter particle moves near the SGD, it can redirect the swarm towards the SGD even if all the swarm is far from it. The combination can fail to find the SGD if both the swarm fails to approach the SGD or this particle fails to scout the SGD as in the case shown in figure-c right.

The experiments show that a search strategy based on PSO is not able to guide a swarm of four AUVs to a SGD due to the specific topology of the search space. While the performance of a swarm using the inertia Levy-flight is much better. However, by using a combination of both algorithms, the search performance of the swarm can be improved.

Table 2 summarise the results of the simulations. It can be depicted from the table, that the average performance of the inertia Levy-flight is better than for the combination. However the median value of the combination is better than the value of the inertia Levy-flight.

Table 2: Aggregation of Statistical Parameters

<table>
<thead>
<tr>
<th></th>
<th>PSO</th>
<th>Levy-flight</th>
<th>Combination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>51.2</td>
<td>8.70</td>
<td>8.38</td>
</tr>
<tr>
<td>Max</td>
<td>52.76</td>
<td>52.67</td>
<td>52.70</td>
</tr>
<tr>
<td>Average</td>
<td>52.42</td>
<td>17.74</td>
<td>19.76</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.36</td>
<td>11.46</td>
<td>17.75</td>
</tr>
<tr>
<td>Median</td>
<td>52.61</td>
<td>13.15</td>
<td>9.25</td>
</tr>
</tbody>
</table>

CONCLUSION AND FUTURE WORK

A novel search algorithm based on PSO and inertia Levy-flight was developed to guide the search of a swarm of AUVs for a submarine point of interest, i.e. a SGD. It is shown, using a computer simulation, that this algorithm is capable to improve the search performance of a small swarm of AUVs during its search. With the sparsely availability of gradient information, a swarm of AUVs guided by PSO is not capable to reach the SGD during the limited search time. However, the inertia Levy-flight in general is able to help the swarm of AUVs to locate the SGD. When using the inertia Levy-flight, the AUVs do not exchange any information. The proposed configuration enable sharing knowledge about the environment without limiting the exploring capabilities of inertia Levy by allowing the scouter to provide information to the swarm without taken any commands from the swarm that can limit its exploring ability.

Further simulations will be done to evaluate the ability of the proposed algorithm to locate SGD in different search topologies and to fine tune the control parameters of the search algorithm. The algorithm will also be tested using the AUV platform that is currently under development.

REFERENCES


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AUTHOR BIOGRAPHIES

CHRISTOPH THOLEN graduated from the Jade University of Applied Science in Wilhelmshaven, Germany, with a Master degree in Mechanical Engineering in 2015. Since 2016 he is a research fellow at the Jade University of Applied Science in a joint project of the Jade University of Applied Science and the Institute for Chemistry and Biology of the Marine Environment (ICBM), at the Carl von Ossietzky University of Oldenburg for the development of a low cost and intelligent environmental observatory.

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