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ANT COLONY OPTIMIZATION FOR DATA ACQUISITION MISSION PLANNING

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Abstract

The probabilistic Ant Colony Optimization (ACO) approach is presented to solve the problem of designing an optimal trajectory for a mobile data acquisition platform. An ACO algorithm optimizes an objective function defined in terms of the value of the acquired data samples subject to different sets of constraints depending on the current data acquisition strategy. The analysis presented in this paper focuses on an environment monitoring system, which acquires in-situ data for precise calibration of a water quality monitoring system. The value of the sample is determined based on the concentration of the water pollutant, which in turn is obtained through processing of multi-spectral satellite imagery. Since our problem is defined in a continuous space of coordinates, and in some strategies each point is able to connect to any other point in the space, we adopted a hybrid model that involves a connection graph and also a spatial grid.

Keywords

path planning, environment monitoring, ant colony optimization, data acquisition, navigation control, satellite imagery, constraint-based optimization.

Introduction

Acquisition of the in-situ data for environment monitoring is usually a costly and time-consuming process. In the application area addressed in this paper, which is the monitoring of water quality in large inland water basins, it involves the design of a data collection mission executed by using a specially equipped mobile platform, such as a cruise ship, a glider or a floating robot. For a mission that guides the mobile platform to locations of interest in order to collect a particular type of data, the path is generally planned a priori. Critical to such a mission are reliable, efficient, and adaptive path generation strategies that ensure mobile sensor platforms collect data of greatest value. Large areas covered during the mission, the cost of fuel and manpower, the required timeliness and quality of the data, all this makes the development of optimal navigation path important.

Path finding problem is a well-studied subject. There are various types of applications involving solving the sequential ordering problem with precedence constraints. Among the most known are the Traveller Salesman Problem (TSP) and the Vehicle Routing Problem (VRP), with variants that can include several types of constraints, such as minimum/maximum distance, load capacity, time windows or pick-up and delivery constraints. The existing methods to optimize or intelligently generate navigation paths in monitoring problems include adaptive sampling [1, 2], complete spatial coverage [3], and Self-Organizing Maps [4].

Most of these problems are NP-hard, for which efficient solutions call for the combinatorial optimization approach. The approach that has proved effective in solving combinatorial optimization problems is the use of Ant Colony Optimization, an example of artificial swarm intelligence systems. The ACO is a probabilistic technique, initially proposed in [5] for solving computational problems which can be reduced to finding sub-optimal paths through graphs. The method consists in a parallel search over several local constructive computational threads and a dynamic memory used to record information on previously obtained good solutions. The idea behind finding the best route is based on the ants' behavior; real ants use the trace, called the pheromone, left by other ants while they traverse the paths. The more ants use a path, the higher concentration of pheromone will be left. As the path with the minimum distance will be used more often, its trace will be higher and it will be preferred by the next ants. Several variants of the ACO algorithm have been introduced to improve its overall performance [6–8].

Most of the first ACO applications were devoted to solve the sequential ordering problem (SOP) with precedence constraints in such application as production planning [9], vehicle routing problems with pickup and delivery constraints [10], and transportation problems [11]. TSP and VRP can be treated as special cases of SOP. More recently, the ACO approaches began to be proposed also for problems which are not standard combinatorial optimization applications. Problems linked to spatial data analysis were discussed in [12] and [13].

Our study is motivated by the application of adaptive inland water sampling by mobile platforms for an autonomous algal blooms detection and prediction system [14]. The objective of this work is to maximize the total value of all water samples and to find the optimal planned routing path for the sample acquisition platform. The value of the sample is determined based on the concentration of the water pollutant, which in turn is obtained through processing of multi-spectral satellite imagery. Critical to this research are reliable, efficient, and adaptive control strategies that include the generation of an optimal path using remote sensing data and reactive control of the acquisition platform.

The optimization problem is defined, as opposed to, for instance, the TS problem, in a continuous spatial domain. As proposed in [15], the Continuous Ant Colony System (CACO) divides the search space into regions of interest that have to be visited by the ants. The probability to visit a region is proportional to its pheromone concentration. The ACO_R algorithm, a direct extension of ACO into the spatial domain by using the Probability Density Function, was proposed in [16]. In [17], a solution archive for the derivation of the PDFs over the search space is presented. This archive of k solutions is randomly generated at the beginning of the algorithm and sorted by the cost, ascending or descending, depending on a maximization or minimization aim, respectively. Another adaptation of the ACO is DACOR, proposed in [18].

In this work, a hybrid model that involves a connection graph in conjunction with a spatial grid is proposed. The ants in this work can have one of two roles: explorer or collector. While in the explorer role, each time an ant has to select the next node in its route it will check if the corresponding arc already exists and use its pheromone and heuristic information for the calculations. Otherwise, it will create it. If the ant is in the collector role, it will use the pheromone and heuristic information stored in the grids in order to decide about its next move.

The proposed algorithms were verified using information obtained from in-situ measurements performed for Lake Winnipeg in Canada. The initial information on the concentration of water pollutants is obtained in the form of satellite imagery. Each pixel of the multi-spectral image represents a region with an associated value of chlorophyll and Total Suspended Solids sediments (TSS). These values are combined together to form a single value of the objective function over the entire lake.

After a presentation of the objectives and specifics of the sample acquisition mission in the next section, the procedure for path generation is discussed. That section is followed by a more detailed description of the proposed ACO algorithm. In its final part the paper presents experimental results and conclusions.

Data acquisition mission

Information sources

The core approach to the pollutant detection in this paper is automatic analysis of multi-temporal multi-spectral satellite image sequences. The satellite systems used for inland water monitoring was a medium resolution imaging instruments, such as MERIS (Medium Resolution Imaging Spectrometer) carried aboard the ESA's Envisat satellite. This system has 15 spectral bands with center wavelengths ranging from the 390–1040 nm which represent the visible and near infrared part of the electromagnetic spectral. Table 1 represent MERIS lists spectral bands and its potential applications.

The remote sensing data can be complemented by meteorological information, such as temperature and wind speed. Given that those additional data do not change the methodological approach, our study relates to the detection of the level of concentration of chlorophyll-a and TSS only [19].

Table 1
MERIS spectral bands.

Band	Band centre [nm]	Potential Applications
1	412.5	Yellow substance, turbidity
2	442.5	Chlorophyll absorption maximum
3	490	Chlorophyll, other pigments
4	510	Turbidity, suspended sediment, red tides
5	560	Chlorophyll reference, suspended sediment
6	620	Suspended sediment
7	665	Chlorophyll absorption
8	681.25	Chlorophyll fluorescence
9	705	Atmospheric correction, red edge
10	753.75	Oxygen absorption reference
11	760	Oxygen absorption R-branch
12	775	Aerosols, vegetation
13	865	Aerosols corrections over ocean
14	890	Water vapour absorption reference
15	900	Water vapour absorption, vegetation

Pollution indices

Calculation of the chlorophyll-a concentration can be performed using the MCI index or a similar Fluorescent Line Height (FLH) index. These indices are based on MERIS bands 8, 9 and 10 (681, 709 and 753 nm respectively) and use a linear baseline interpolation between the radiance values at 681 nm and 753 nm [20]. The following equation represents a MCI calculation based on [21]

$$\mathrm{MCI} = L_{709} - L_{681} - 0.389(L_{753} - L_{681}), \tag{1}$$

where L_{xxx} is the radiance value of the respective band. The factor 0.389 is calculated as the wavelength ratio (709–681)/(753–681). The MCI is then used to determine the concentration of chlorophyll-a. An example of the distribution of chlorophyll-a in Lake Winnipeg as shown in Fig. 1.

There is currently no uniform remote sensing model to estimate TSS. It is impossible to select a specific wavelength to evaluate the TSS since in practice clear and turbid waters are often combined together, and TSS size variations affect the choice of the most appropriate wavelength. Many models have been proposed based on the combination of MERIS red and near-infrared bands. A robust quantification of TSS was proposed in [22], where the following equation is used to measure TSS

$$\mathrm{TSS} = 53.7\left[\frac{L_{709}}{L_{560} - L_{665}}\right] - 17.0. \tag{2}$$

This equation was used in our study.

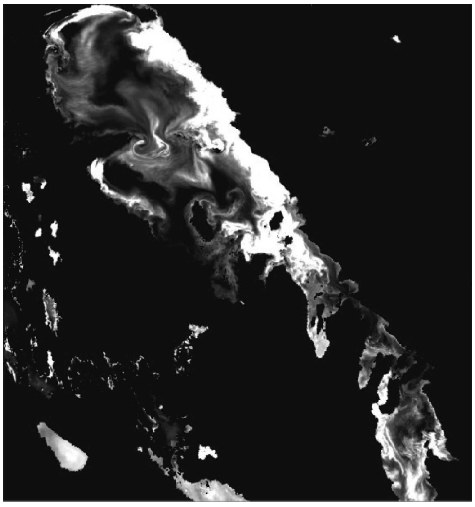

Fig. 1. MCI map for Lake Winnipeg.

Multi-layer maps

The spatial information used in mission planning is combined in the form of a multi-layer map [23]. The map consists of the measured pollutants layers and a bathymetric data layer BM. Figure 2 depicts the place of the multi-layer map in the remote sensing data processing flow chart that leads to the determination of the value of each pixel from the stand point of the optimization strategy. Different strategies produce different map coverage scenarios, which best fit the data acquisition mission goal.

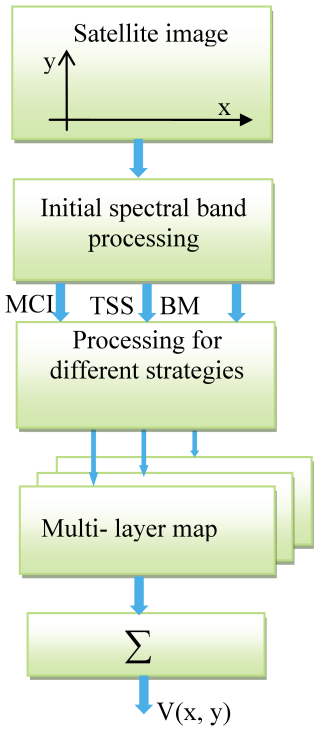

Fig. 2. Remote sensing flow chart.

Acquisition strategies

The acquisition mission can be varied depending on the strategy which applied to collect the samples. The goal is that maximizing the number and the value (weight) of the collected samples. According to a specific strategy the samples weight can vary. The strategies can be classified according to two characteristics, the relationship with the concentration distribution and the acquisition time window which imposes constrain on the acquisition mission. In the first group, the sampling strategies include uniform coverage of high-concentration areas, sampling at local concentration maxima, and sampling along maximum gradient lines. In the second group, one strategy considers the fact that specific samples should be collected within a certain time window. Those samples can be treated as more valuable than the others. The path planning designs a trajectory to collect as many valuable samples as possible. Another strategy assumes that a specific patch contains valuable samples and no time constrains are imposed on sample collection. In the third strategy, time constraint is imposed and a certain number of samples have to be collected in a patch before heading to another patch. The path planning maximizes the collection of the valuable sample according to a specific path which fits the time constrain.

Any strategy can be represented by an objective function which is responsible to evaluate and select the optimal path from the start point to the target point.

Path generation

In many monitoring applications, especially in agriculture or public security [24], the path generation problem is defined in terms of planning covering paths over the monitoring area [25]. The methods presented in literature rely on the sensor footprint, and aim at complete environment coverage. The mobile platform, in our application usually a ship equipped with onboard in situ sensors and sample acquisition instruments, takes only point measurements. Therefore, a complete spatial coverage is infeasible. Our problem implies a combination of spatial coverage and a dynamic TSP.

Generally path planning deals with obstacle avoidance problem. The obstacles are divided into three categories:

- Hard obstacles in the form of islands, coastal areas, ships, and other floating objects.
- Soft obstacles, such as haze, wind and fog. They can affect both local and global navigation.
- Virtual obstacle, such as cloud zones in the satellite image. They can affect both path planning and local navigation.

Problem parameters

Given the description of our problem, Table 2 presents the parameters to be used in our implementation.

Table 2
Parameters of the path generation problem.

Parameter	Description
n	Number of sample locations
$\mathrm{Cl}_{x,y}$	Chlorophyll concentration at location x, y
$\mathrm{TSS}_{x,y}$	TSS concentration at location x, y
$i_{x,y}$	Location i, that corresponds to coordinate x, y in the area of study, is a collection location in the trip
a_{ij}	Arc segment joining locations i and j
d_{ij}	Distance from i to j
t_{ij}	Time of travel between location i and j
s_i	Sample collection time
D	The maximum allowed distance to be travelled by the vehicle
T	The maximum mission duration time

Objective function

Each pixel that represents a region in the real area has an associated value of chlorophyll and a value of Total Suspended Solids (TSS); we have combined these values together to assign a single value to each region using:

$$V_{x,y} = \omega_{cl}\mathrm{Cl}_{x,y} + \omega_{\mathrm{TSS}}\mathrm{TSS}_{s,y}, \tag{3}$$

where ω_{cl} and ω_{TSS} are the weight coefficients for the chlorophyll and TSS concentration (for the purposes of this work we selected $\omega_{cl} = 0.5$ and $\omega_{\mathrm{TSS}} = 0.5$).

As we want to maximize the value of the collected samples, our objective function is defined over the spatial domain as:

$$V = \max\left(\sum\nolimits_{x,y} V_{x,y}\right). \tag{4}$$

This objective function is subject to constraints summarized in Table 3.

Table 3
Constraints for the path generation problem.

Constraint	Description
$t_{ij} \geq 0 \forall (i,j)$	Time must be positive
$s_i \geq 0 \forall (i)$	Sample collection time in location $i$must be positive
$\sum_{x,y} i_{x,y} \leq 1, \forall i \backslash \{0\}$	Restricts to at most one visit to each location. Could be zero, with the exception of the location of the departure point.
$\sum_{x,y,z} i_{x,y} - i_{y,z} = 0$	Flow conservation equation.
$\sum_x i_{x,0} = 1$	Establishes that the vehicle must arrive to the starting node.
$\sum_y i_{0,y} = 1$	Establishes that the vehicles must depart from the node 0.
$\sum_{i,j} d_{ij} \cdot a_{ij} \leq D$	Restricts the travelled distance to its maximum value.
$\sum_{i,j} t_{ij} \cdot a_{ij} + \sum_i s_i \cdot i \leq T$	Restricts the travelled time to the maximum allowed.

Ant Colony Optimization

Ant behavior

In the standard ACO problem ants traverse arcs connecting nodes in a graph and, depending on the problem, the basic idea is to visit all nodes (or most of them) while minimizing the total cost of the trip (in terms of distance or time). Since in our problem we do not have a graph but a continuous space of coordinates, each point is able to connect to any other point in the space. Thus, creating a graph of all the possible connections is not feasible. Instead, we have opted for using a hybrid model involving a graph and a grid.

Consequently, as the objective is to find a path for a mobile platform that visits several zones in a constrained area to collect samples, the ants have one of two roles, either the collector or the explorer. While in the explorer role, each time an ant has to select the next node in its route it will check if the corresponding arc already exists and will use its pheromone and heuristic information for the calculations, if not, it will create a new node. If the ant is in the collector role, it will use the pheromone and heuristic information stored in the grids in order to decide on its next move.

The collector ant will take small steps (limited by $\Delta coll$) in order to visit near points and collect samples; the collecting process will continue until the product of the collected samples (or visited nodes) and a "load" parameter is over a certain random number (5); if the relation is over the threshold, the ant will change its role from the collector to the explorer and $\Delta expl$ will be used as the maximum step size.

$$\text{role} = \begin{cases} \text{coll} \quad \text{if} & \dfrac{cs^k}{\text{chgRole}} < r0 \\ \text{exxpl} & \text{otherwise} \end{cases} \tag{5}$$

The list of variables and parameters used is shown in Table 4.

Table 4
Parameters used in the ACO implementation.

Parameter	Description
role	Indicates if the ant is collecting or exploring. An ant will dynamically change its role during its search.
chgRole	Load parameter that indicates the maximum number of samples to collect while in the collecting role.
$r0$	Uniformly generated random number used to stochastically control for how long the ant will be in the collecting role.
cs^k	Number of samples collected by the ant k during the current collecting role.
Δexpl	Maximum length of the movement of the ant in the continuous space while it is in the explorer role.
Δcoll	Maximum length of the movement of the ant in the continuous space while it is in the collector role.
Max_neigh	Max number of neighbors to calculate for the current ant point.
$Pt^k_{x,y}$	(x, y) coordinates of the point currently visited by ant k.
R^k	Route of ant k
Z_{length}	Height (and width) of the squared zone.
ACO_ITER	Max number of iterations of the ACO algorithm.
ANTS_ITER	Max number of iterations of each ant, used to construct the route.
MAX_NO_MORE_SOLS	Max number of iterations allowed without an improvement over the best route.
MAX_DIST	Maximum distance to be traveled by the vehicle
$V_{x,y}$	Value of the point (x, y)
τ_{ij}	Pheromone value of the arc connecting points i and j
τ_0	Pheromone initial value
η_{ij}	Heuristic value of the arc connecting points i and j
Clph_i	Amount of chlorophyll in point i
TSS_i	Amount of TSS in point i
Z_i	Set of points inside the same zone of point i
Z_{length}	Defines the width of the squared zones into which the map is divided
α	Weight parameter of the pheromone information
β	Weight parameter of the heuristic information
ρ	Percentage of pheromone that remains after evaporation

Neighbor generation

Since in our continuous problem there are no predefined connections between the nodes, we have to generate them. The generation of the neighbors of the current point for ant k follows equation (6), in which the neighbor coordinates (x, y) correspond to a random point that is at the distance Δ (depending on the role $\Delta expl$ or $\Delta coll$). Following the standard ACO rule, a neighbor cannot be in the current route of the ant.

$$\begin{gathered}\mathrm{Neigh}^k_{x,y} \in (Pt^k_x - \Delta < Pt^k_x < Pt^k_x + \Delta, \\ Pt^k_y - \Delta < Pt^k_y < Pt^k_y + \Delta) \wedge \mathrm{Neigh}^k_{x,y} \notin R^k.\end{gathered} \tag{6}$$

The explorer role will lead the ant to one of the generated neighbors; the parameter $\Delta expl$ should have a value that allows the ant to get out of the current zone and go to a new one to make new collections. The ant will change to the collector role once it has left the zone. The zone is defined as a squared space of the complete continuous space of the problem; so, the space is divided into a grid of zones of dimensions Z_{length}.

Each point of the space has an associated value $V_{x,y}$ which is a function of the amount of chlorophyll and TSS. As stated before, depending on the role, the ant will use the information stored in the arc that departs from the current zone; the heuristic value stored in the arc corresponds to the sum of the heuristic values of all the cells in the destination zone:

$$\eta_{ij} = \sum_{x,y \in j} \omega_{cl} \mathrm{Clph}_{x,y} \cdot \omega_{\mathrm{TSS}} \mathrm{TSS}_{x,y}, \tag{7}$$

where i is the departing zone of the arc, j is the destination zone of the arc, $\mathrm{Clph}_{x,y}$ and $\mathrm{TSS}_{x,y}$ are the chlorophyll and TSS concentrations in cell x, y, and ω_{cl} and ω_{TSS} are the importance weights for the chlorophyll and the TSS concentration. The information stored in each cell of the grid is given by (8).

$$\eta_{x,y} = \omega_{cl} \mathrm{Clph}_{x,y} \cdot \omega_{\mathrm{TSS}} \mathrm{TSS}_{x,y}. \tag{8}$$

ACO implementation

The implementation of Ant Colony Optimization follows the procedures explained in the previous section. The probability value associated to the arcs while the ant is in explorer role follows the approach presented in [15], where the overall pheromone value of the zone is considered. The selection of the next arc is done according to parameter q_0 which leads the process of the exploitation of the space or exploration of the current routes. If the value of a random number is over q_0 then the ant (in any role) will use (9), otherwise it will use (10).

$$j = \arg\max \left\{ (\tau_{iu})(\eta_{iu}) \right\}^{\beta}, \, for\, u \notin M_k, \tag{9}$$

$$\begin{gathered} p_{ij} = \frac{(\tau_{ij})(\eta_{ij})^{\beta}}{\sum\limits_{u \notin M_k} (\tau_{iu})(\eta_{iu})^{\beta}}, \\ \text{if } j \notin M_k, \text{ otherwise } 0, \end{gathered} \tag{10}$$

where τ_{ij} is the current pheromone trace in the arc ij; η_{ij} is the heuristic value of the arc ij. To avoid the repetition of a location in the route, each ant stores the location of the visited nodes in a temporal memory M_k. The pheromone update process is done in two phases; first, each ant updates its own path, and later a global process updates the arcs of the best route, according to (11) and (12), respectively.

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \rho \tau_0, \tag{11}$$

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \rho \cdot \Delta\tau_{ij}(t). \tag{12}$$

In order to benefit from the intrinsic parallelism of ACO, our implementation creates a new process thread for each ant in the system; they find their own route in a parallel fashion, and later the main loop of the algorithm waits for the termination of all the ants in order to continue iteratively with the next steps. The pseudocode of our implementation is presented in two parts. Algorithm 1 shows the ACO structure and Algorithm 2 shows the find_route procedure performed by each ant.

```
   while iter < MAX_ITER and
   num_better_sols < MAX_NO_MORE_SOLS
do
     for k = 1, …, kmax
        Antk->find_route()
     end for
     for k = 1, …, kmax
        Antk->join()
        if Antk->route_val > Best_val then
           Best_val = Antk->route_val
           Best_route = Antk->route
           num_better_sols = 0
        end if
     end for
     pheromoneUpdate(Best_route)
     num_better_sols = num_better_sols + 1
   end while
```

Fig. 3. Algorithm 1 – ACO pseudocode.

```
i = start_xy
Neighs = i->find_neighbors( )
while iter < ANTS_ITER and Neighs.count >
0 and route.dist < MAX_DIST do
   q = rand(0, 1)
   if q > q0 then
     j = i->find_best_neighbor( )
   else
     j = i->find_random_neighbor( )
   end if
   route.add(j)
   if role == collector then
     num_iter_coll = num_iter_coll + 1
     r0 = rand(0, 1)
     if num_iter_coll / chgRole > r0 then
        role = explorer
     end if
   else
      role = collector
   end if
   i = j
   Neighs = i.find_neighbors( )
   iter = iter + 1
end while
```

Fig. 4. Algorithm 2 – *find_route*() function pseudocode.

A local search is made within the best_neighbor and random_neighbor procedures. The objective of this search is to find the best replacement for each neighbor in the array. In order to accomplish this, the procedure searches, in the vicinity of the neighbor, the point with a higher value and uses it as a replacement. After selecting a new neighbor, the best_neighbor uses (9) to select the best option among the neighbors. The random_neighbor procedure computes the probability values of each neighbor according to (10), and the selection is made with a Roulette Wheel procedure. It is important to notice here that a neighbor for an explorer ant corresponds to an arc departing from its current zone; for a collector ant, a neighbor is another cell.

In order to avoid the overexploitation of arcs exiting from the origin point and to explore the most of the search space, the ants are forced in the first iteration of Algorithm 1 to move almost completely at random (by setting q_0 to 0.2) over the arcs and the cells leaving the corresponding pheromone trace, using only the heuristic information as a guidance. In iteration 2 the value of q_0 is set to 0.5, and from iteration 3 on the behavior of the ants is regular.

Experimental results

The tests of our proposed implementation of ACO were made over the data of the zone located in the southern part of Lake Winnipeg. Two sections with areas of 1.369 km^2 and 13.210 km^2 were extracted at coordinates 53°21'19" N, −98°30'9" W; they will be later referred as set #1 and set #2. The data acquisition strategy followed the maximum gradient following scenario.

The parameter values used in all experiments are given in Table 5. The variable parameters specific to the tests are: the minimum and maximum distance, the maximum time of the mission, the minimum number of samples to collect, and the number of ants in the system, these are exposed in Table 6.

Table 5
Parameter values common to all experiments.

Parameter	Value
α	1
β	0.8
ρ	0.9
ACO_ITS	50

Table 6
Parameter values for experiments.

Experiment	Set	Max dist. [km]	Max time [sec]	Min samples	Ants
1	1	100	28.800	100	10
2	1	100	28.800	100	200
3	2	250	50.000	100	200

Table 7 shows the value, the trip time, the trip distance and the number of collected samples for each experiment specified in Table 6.

Table 7
Results of experiments.

Experiment	Value	Trip time [sec]	Trip dist. [km]	Collected samples
1	220	20.494	102.47	107
2	280	22.895	114.48	128
3	286	51.955	259.776	117

As it can be seen from Table 7, with 200 ants the algorithm generates the best trip for the test set #1; the distance and time constraints in experiment #1 were broken in 2.47%. It is worth noting that although experiment #2 exceeds the trip time and distance only a little more than experiment #1, the value of $V_{x,y}$ is incremented by almost 30%, with 20% more of samples collected. Figures 5 and 6 show the resulting trips for experiments 1 and 2, respectively.

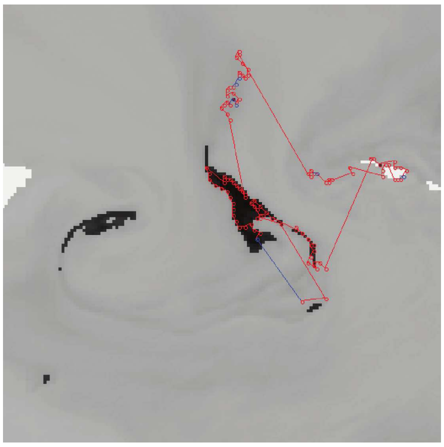

Fig. 5. Path generated for experiment 1.

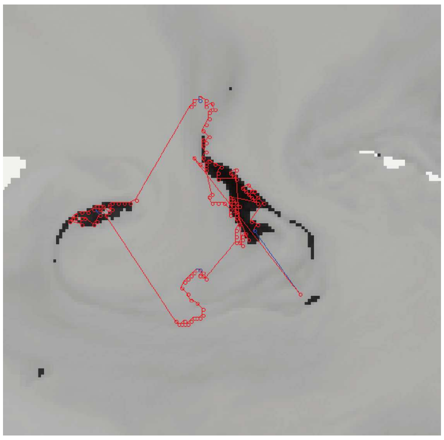

Fig. 6. Path generated for experiment 2.

The third experiment was performed with a similar parameter configuration, in set #2 which represents a bigger zone. In this case, the time and distance constraints increased by 3.91%.

However, as it can be seen in Fig. 7, the path leads the ship through non-traversable zones. This issue has to be resolved by the implementation of a reactive control scheme that executes the path generated here at the deliberative control level.

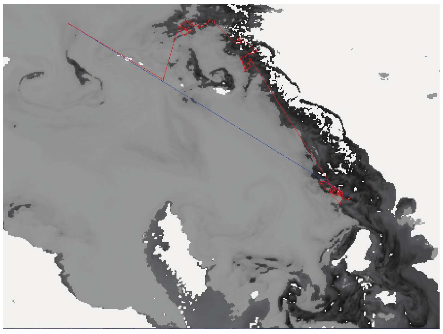

Fig. 7. Path generated for experiment 3.

Conclusions

The results presented in this paper showed that the Ant Colony algorithm can be applied to the optimization of an environment monitoring mission in different map coverage scenarios. The main contributions of this paper are the following. An ACO algorithm was presented to plan a closed path that passes through areas of high sensory interest. The objective function can be modified depending on the data acquisition strategy. The form of constraint functions was proposed to achieve higher sample density in areas of higher scientific interest, and, at the same time, uniform sampling coverage of these areas. In our hybrid graph-grid model the ants can have one of two roles: explorer or collector. The hybrid grid-graph implementation also reduces the computing time, since is not necessary to create connections between all the possible points in the search space.

The algorithms were validated by implementing the computed strategies in the context of monitoring water quality in large inland water basins in combination with satellite imagery. The satellite data were used to calculate the concentration of environmental features that were subject of the monitoring. The specific features were chlorophyll-a and Total Suspended Solids.

In the future work we will consider additional ancillary information, including meteorological data, in order to compensate for the impact of such factors as temperature or wind strength in the mission planning stages. Also, applications of the proposed optimization schemes will be investigated in the area of transportation systems using autonomous vehicles.

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