Multi-Strategy Navigation for a Mobile Data Acquisition Platform Using Genetic Algorithms

Submitted: 5th December 2016; accepted: 25th January 2017

Fadi Halal, Marek B. Zaremba

DOI: 10.14313/JAMRIS_1-2017/4

Abstract:
Monitoring of biological and chemical pollutants in large bodies of water requires the acquisition of a large number of in-situ measurements by a mobile sensor platform. Critical to this problem is an efficient path planning method, easily adaptable to different control strategies that ensure the collection of data of the greatest value. This paper proposes a deliberative path planning algorithm, which features the use of waypoints for a ship navigation trajectory that are generated by Genetic Algorithm (GA) based procedures. The global search abilities of Genetic Algorithms are combined with the heuristic local search in order to implement a navigation behaviour suitable to the required data collection strategy. The adaptive search system operates on multi-layer maps generated from remote sensing data, and provides the capacity for dealing with multiple classes of water pollutants. A suitable objective function was proposed to handle different sampling strategies for the collection of samples from multiple water pollutant classes. A region-of-interest (ROI) component was introduced to deal effectively with the large scale of search environments by pushing the search towards ROI zones. This resulted in the reduction of the search time and the computing cost, as well as good convergence to an optimal solution. The global path planning performance was further improved by multipoint crossover operators running in each GA generation. The system was developed and tested for inland water monitoring and trajectory planning of a mobile sample acquisition platform using commercially available satellite data.

Keywords: *genetic algorithms, path planning, monitoring system, remote sensing, navigation control, heuristic search*

1. Introduction

Acquisition of a large number of in-situ measurements by a mobile platform is a basic task in the process of monitoring biological and chemical pollutants in large bodies of water. Monitoring of environmental phenomena in inland waters requires measuring a variety of physical processes, such as nutrient concentration, wind effects, and solar radiation [26]. Remote sensing (RS) techniques provide significant advantages in terms of spatial and temporal coverage and cost-efficiency. The maps of large environment areas are often obtained through the processing of satellite imagery. The multi-spectral data can subsequently be used to obtain models of water pollutants, such as the concentration of chlorophyll (Chl-a) or total suspended sediments (TSS) [17], by applying such measures as the maximum chlorophyll index (MCI) [10] or the ocean chlorophyll 4 algorithm (OC4v4) [21]. In many situations the remote sensing data have to be augmented and updated by *in situ* measurements. This is due to the need for precise local measurements, for the calibration of satellite imagery in varying water conditions, and for the purpose of precise local decision making.

Critical to this sample acquisition problem is an efficient path planning method, easily adaptable to different control strategies that ensure the collection of data of the greatest value. Acquisition of different types of samples may require appropriate behaviours that implement different collection strategies. Designing a multi behaviour search system for a mobile sample acquisition platform requires answering the following questions. Which is the suitable navigation mode for a specific water pollutant? How to compute the cost of the solution? How can the solution of the path planning problem deal with multiple patches of high concentration of the pollutant?

In general, the path planning procedure designs a trajectory that visits a given set of points such that the optimisation process minimises the total travel distance. This task can be defined in terms of a combinatorial optimization problem with a globally optimal solution that satisfies all hard and soft constraints. The optimal solution or a set of globally optimal solutions minimises or maximises the objective function. The path finding problem is typically defined in terms of the Travelling Salesman Problem (TSP) [7] or a more general Vehicle Routing Problem (VRP) [4]. Determining the optimal solution is an NP-hard problem, so the size of problems that can be solved optimally is limited [3]. In the situation of environment monitoring systems, the problem is even more complex because exact positions of the sampling points are not known a priori. In practice, therefore, solutions to optimal path planning problems have to incorporate heuristic methods.

A variety of heuristic methods have been investigated. Evolutionary algorithms have been employed in many variants. In [6] an ant colony optimization system was presented to solve the problem of designing an optimal trajectory for a mobile data acquisition platform. Luo *et al.* [20]an intelligent mobile vehicle is required to reach multiple goals with a shortest path that, in this paper, is capable of being implemented in TSP (Traveling Salesman Problem proposed a hybrid GA and D* algorithm for real-time map building and navigation for multiple goals purpose. Yoshikawa and Terai [32] proposed a car navigation system using hybrid genetic algorithms and D algorithm. Their system finds a route which has several passing points before arriving at the final destination. In [18] the path planning problem for a submarine navigation application was solved using the artificial bee colony algorithm. The use of a cultural hybrid algorithm to solve the mission planning was reported in [33]. An improved simulated annealing artificial network to plan the path for a mobile robot was employed in [8].

Genetic algorithms have been frequently used in NP-hard problems due to their flexibility and high quality of the search results [25]. They can provide a solution without any advance knowledge about the environment, and are largely unconstrained by the limitations of the classical search methods [24]. By mimicking natural evolution processes, they have the ability to adaptively search large spaces in near-optimal ways. In practical terms, GA methods are easy to interface with simulation models. An important feature that should be considered in implementing GA techniques is that they are problem specific. Due to the constraints of a particular problem and the operation of crossover and mutation mechanisms, feasible offsprings often cannot be obtained by applying exclusively genetic algorithms. In order to ensure the feasibility, additional algorithms should be incorporated. For example, [34] developed an improved genetic algorithm, where an obstacle avoidance algorithm and the distinguish algorithm are combined with a GA algorithm to select only the feasible paths and to improve the path planning efficiency. The distinguish algorithm is designed for distinguishing whether the path is feasible or not.

In this paper we present a hybrid GA-based method developed to optimize path planning and navigation using pollutant maps generated from RS imagery. The power of the global GA search is combined with the speed of the local optimizer. Both optimizers work cooperatively to find the optimal solution, where GA determines the optimal region, and then the local optimizer takes over to find the best position for acquiring water samples [13]. In order to deal effectively with the large-scale environment, the following modifications to the state-of-the-art approaches were introduced. In the first place, this paper implements an improved combination of a GA with an obstacle avoidance algorithm and the distinguish algorithm proposed initially in [34]. This algorithm puts a feasible path in the feasible group and deletes an infeasible path or keeps it in the infeasible group, which markedly improves the efficiency of the path planning. The big family pool was adopted in our system, which consists of all old-generation solutions and current-generation offsprings obtained after mutation and crossover operations combined with different meta-heuristic solutions. Based on the Cooperative Genetic Optimization Algorithm [14], it offers a greater search selection diversity and gives the system the ability to save the elite searching experience from one population to the next one.

Multi-layered maps were employed to generate spatial and functional properties of the environment. Those maps enable the planning system to perceive and interpret environments according to different environment features. ROI maps can be extracted from the multi-layer map as additional layers. The ROI approach facilitates the planning system in directing the search toward desirable patches by paying additional attention to desired regions, and assuring at the same time the generation of feasible solutions [11]easily adaptable to different control strategies that ensure the collection of data of the greatest value. This paper proposes a hybrid Genetic Algorithm (GA.

In general, each optimization problem to be solved by a GA method requires a unique fitness function that represents a performance criterion used in the evaluation of the performance of all chromosomes in the population. Many functions, such as travelling distance, time window and the sample values (weights) should be optimized simultaneously. This may involve a combination of maximization and minimization criteria [5]. Individual objective functions are usually combined into a single composite function by weighting the objectives with a weight vector. The result of the optimization should reach a reasonable solution that compromises multiple objectives [23]. For mission planning of an unmanned aerial vehicle (UAV), [29] used the distance, the hazard, and the maneuvering of the route as components of their cost function. Each component has a weight factor assigned according to the objectives of the mission. The hazard is related to the existence of obstacles near the path, and the maneuvering refers to the maneuvers required to perform target tracking. For efficient determination and search of the best flight (UAV) routes, an objective function was created in [27] which involves the timeliness and the smoothness of the path. The objective function discussed in [9] included several components: the cost of the motion from the start node to the current node, the heuristically estimated value of getting from the current node to the goal, the terrain traversability component, the direction change cost, and the cost of navigating in shadow areas. Each component has a corresponding coefficient factor used to weight the objective function components according to its importance to the mission. An optimized path planning for skid-steered mobile robots [16] uses a cost function which consists of the terrine properties, longitudinal motion and turning of the robot. In this work, an objective function proposed to deal with the experiment conditions comprises the following components: the samples value, the ROI award, the distance, and the sampling time.

The waypoint technique was used in the path planning process as an approach appropriate for large monitoring environments [30]. Waypoints are defined as abstract points [15] used to determine local positions [28] through which a mobile platform can navigate, reach its region-of-interest destination, and collect the water pollutant samples [22]. In the application discussed in this paper, waypoints correspond to sampling points. In order to deal with multiple sampling areas, multi-point crossover (MPC) was implemented. The MPC operator works to build the final solution which consists of valuable segments of local paths from many search strategies. The mutation operator improves the local search and helps the population to avoid local minima. The evolution process optimizes the path planning by designing new chromosomes which consist of best value samples from many global paths.

Experiments were conducted on data from Lake Winnipeg located in Manitoba, Canada. The adaptive search techniques presented in the paper were applied to optimize the location of the sampling points for different pollution indices and behaviours: the concentration of individual pollutants and their combinations, and the maximum gradient of pollutant concentration.

The structure of the paper is as follows. Section 2 addresses the sample acquisition problem using remote sensing data. A discussion of the proposed hybrid GA-based architecture for path planning and the optimisation of the multi-behaviour sample acquisition is presented in Section 3. Experimental results are discussed in Section 4.

2. Multi-Strategy Sample Acquisition Mission

2.1. Problem Statement

The problem addressed in this paper consists in planning a trajectory for precise acquisition of water pollutants by a mobile platform, when the planning process is guided by prior rudimentary information about the distribution of pollutants obtained from remote sensing data. The acquisition mission should incorporate different acquisition strategies.

The sample acquisition mission is performed within a more general procedure consisting of the following phases:

1) Determination of water regions and their types, sample location zones, and water pollutants to be sampled;
2) Identification of the pollutant detection indices, coverage methods (e.g., uniform coverage, maximum concentration gradient) and the number of samples;
3) Selection of the sources of remote sensing data and their calibration methods;
4) Selection of the ancillary data from *in situ* sensors (e.g. wind, temperature);
5) Determination of the acquisition mission parameters (e.g., total mission time).

Most of the above factors and conditions affect the strategies that have to be incorporated in the planning procedure. Mission strategies can be classified in two categories:

(1) Water pollutant concentration strategies

In this type of strategies the aquatic acquisition platform collects the most valuable samples from different pollutant classes and their combinations, such as

- Chl-a,
- Chl-a & (TSS),
- Chl-a & Dissolved Organic Carbon (DOC),
- Chl-a & TSS & DOC.

In this class of strategies, specific samples should be collected while neglecting other samples within a certain time window. Time windows can be imposed because of the deterioration of the quality of samples over a period of time. Time requirements for Chl-a concentration sampling are discussed in [12].

With respect to the types of pollutants, the RS data have to be pre-classified. The final path maximizes the value of the collected samples along a trajectory that traverses regions of different distributions of the pollutant concentration. As a result, the planning algorithm works on many maps created to represent different concentration levels for different water pollutant classes. The optimal strategy directs the path to the best Region of Interest (ROI) zone. The samples values (weights) vary depending on the mission objective.

(2) Local coverage strategies:

In this mode the platform executes a specific navigation and collection behaviour depending on the shape of the sample spatial distribution. We distinguish here such sampling strategies as the uniform coverage of high-concentration areas, sampling at local concentration maxima, and sampling along maximum gradient lines, which is of interest in many environment monitoring applications [36]. The sampling process can be different in each patch to comply with the general and local mission goals.

Both types of strategies execute under some specific constraints. Time window constraints can be imposed on certain pollutant patches, and travel distance constraints on other patches. Also, a certain number of samples have to be collected in a specific patch before heading to another one.

2.2. GA-Based Planning System

Due to the complexity of the mission trajectory optimization problem, a hybrid GA/Adaptive Search system is proposed and investigated in this paper. The general architecture of the planning system is based on the deliberative architecture model [19]. As illustrated in Fig. 1, the deliberative level comprises the

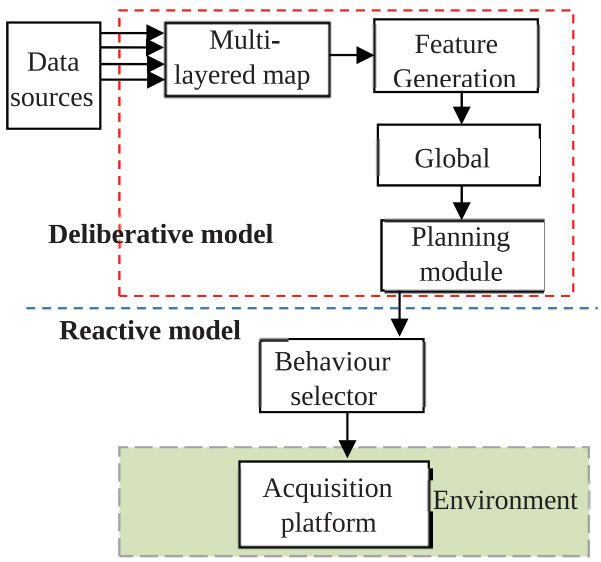

Fig. 1. General architecture of the GA- based planning system

environment modelling level, which operates on the remote sensing data and the ancillary information, and the adaptive GA-based trajectory generation level.

Water wave reflection can be exploited to determine the concentration of water pollutants. Examples of spectral signatures for different samples of chlorophyll pigment and TSS are shown in Fig. 2.

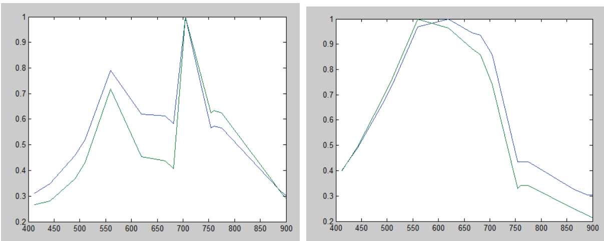

Fig. 2. Spectral signatures: a) Chl-a, b) TSS

The following two models were applied to measure the concentration of TSS [17] and Chl-a [10], [1] using different spectral bands of satellite images:

$$\mathrm{TSS} = 53.7\left[\frac{\mathrm{L}_{709}}{\mathrm{L}_{560}+\mathrm{L}_{665}}\right] - 17.0 \qquad (1)$$

where Lxxx is the radiance value of the band at wavelength xxx, and

$$\mathrm{MCI} = \mathrm{L709} - \mathrm{L681} - 0.389\,(\mathrm{L753} - \mathrm{L681}) \qquad (2)$$

The factor 0.389 is calculated as the wavelength ratio (709–681) / (753–681).

The input data structure used to generate the information required for multi-strategy path planning is implemented in the form of a multi-layer map (Fig. 3), which consists of a set of overlaying grid-based maps.

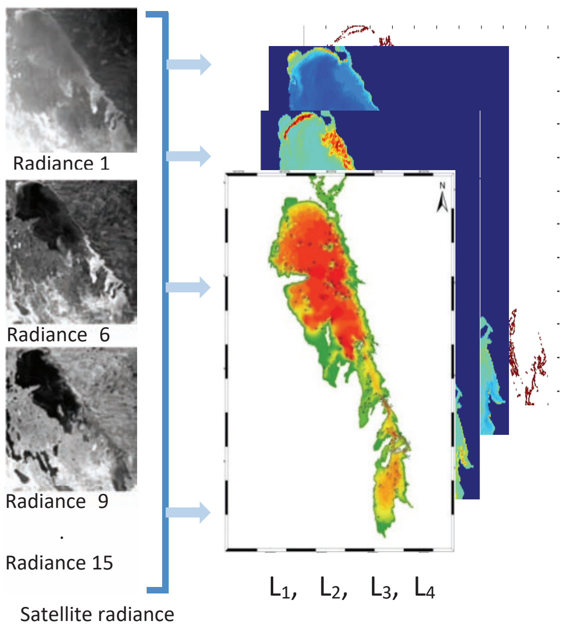

Fig. 3. Multi-layer map

The maps provide, for each spatial point (pixel), the numerical values NLi of the measured pollutants. The spatial resolution of the maps corresponds to the resolution of satellite images. Figure 3 shows the following layers: bathymetric map (L1), Chlorophyll-a (L2), TSS (L3), and the maximum gradient of chlorophyll-a (L4).

The overall goal of the acquisition mission is to maximize the quantity and the quality of the collected water pollutant samples V during the mission:

$$\max V = \max \sum_{j-1}^{M}\left[\sum_{i=1}^{N_j}\left(V_i^j(x,y)\right)\right] \qquad (3)$$

where V is the value of the sample, Nj is the number of the samples for each pollutant, and M is the number of water pollutant classes.

3. GA Method for Path Planning

3.1. Genetic Algorithm Architecture

The basic operation of the proposed GA-based path planning procedure can be summarized as follows (Fig. 4). The sampling points correspond to the

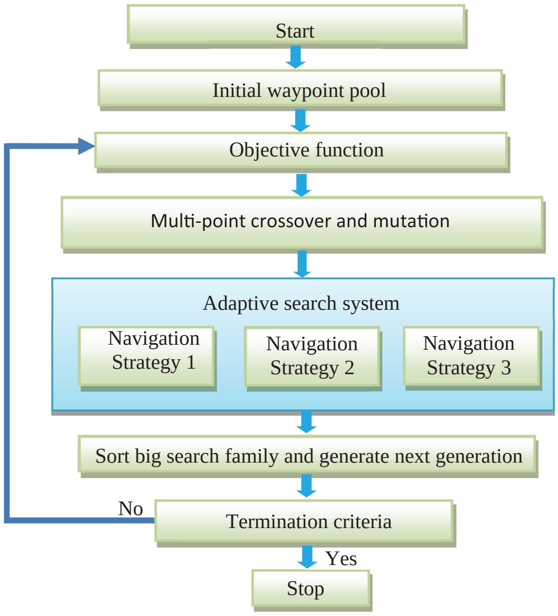

Fig. 4. Genetic Algorithm based path planning

waypoints of the global path of the mobile platform. Thus, the global path consists of several local paths, which are the arcs between two waypoints with a directed connection between them. The initial population of waypoints is pruned to generate collision free paths, subsequently stored in the initial chromosome pool population. Unfeasible solutions are deleted.

The adaptive search (AS) system improves the elite paths (the best 10 solutions) and returns efficient paths adapted to the local navigation behaviour. The big family pool consists of all old-generation solutions and current-generation offsprings obtained after the mutation and crossover operations combined with AS solutions. It gives the system the ability to save the elite search experience from one population to the next one [14]. The big family search results are sorted and pruned to form the next generation (Fig. 5).

A more detailed description of individual steps of the algorithm follows below.

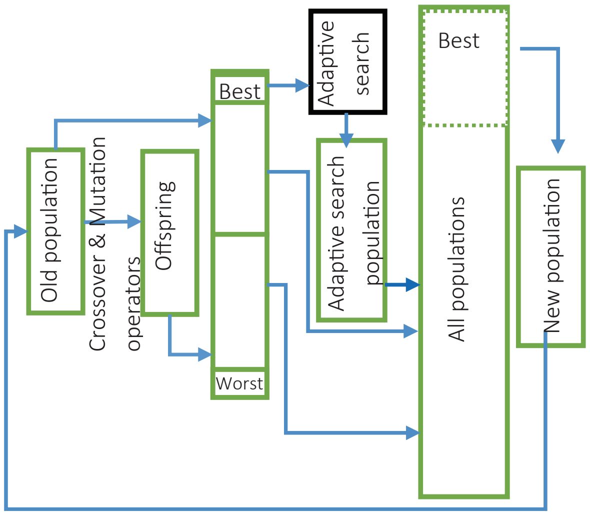

Fig. 5. Big family search [14]

3.2. Path Planning and Initial Waypoint Population

In the GA-based path planning procedure the population is represented, as in the Vehicle Routing Problem, by ordered sets of waypoints. Each feasible set is considered to be an individual in the population. Each waypoint, which is a sample candidate, represents a location in the environment (x,y). The initial genotype can be represented by a cell array, where each pair of cells represents the local path length and the heading angle towards the subsequent waypoint.

The path planning generator works as follows:

1) Determine the first waypoint in the path, i.e., the starting point, with the initial angle equals to zero.
2) While the path planning doesn't reach the desired target, generate a random number of *L,* the path length, between L_{min} and L_{max}, and a random heading angle β between β_{min} and β_{max} obtaining the next waypoints[31]. A maximum number of waypoints is given for each search strategy.
3) Different strategies are applied to water pollutant patches by adjusting *L* and β. Each path planning strategy handles different number of samples depending on the search path.

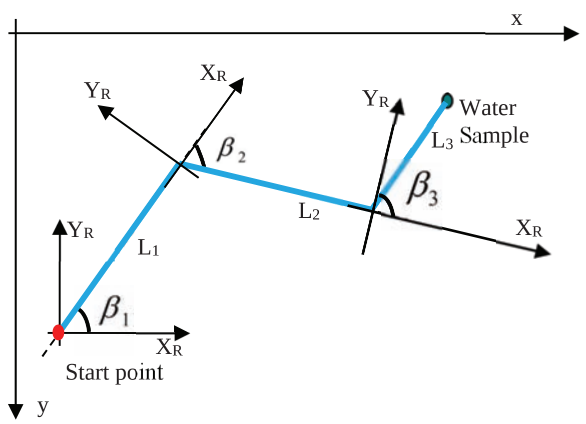

Fig. 6. Waypoint generation scheme

4) Continue with another patch or return to the starting point, depending on constraints, such as the maximum travel distance or the maximum number of water samples.

Figure 6 illustrates the path planning generator.

The chromosomes are encoded as an integer string. Each gene consists of two variables, the local path length and the heading angle as shown in Fig. 7a. Depending on the start point and the chromosome, the waypoint generation produces records as in Fig. 7b. The path planning waypoints are represented in the form of a long array as depicted in Fig. 7c. The GA search finds the waypoints between the starting point of the mission and the destination point.

a)

Heading angle	Travel distance	Heading angle	travel distance	..	Heading angle	travel distance

b)

heading	travel distance	previous waypoint (start point)	waypoint$_1$ x coordinate (Latitude)	Waypoint$_1$ y coordinate (Longitude)

c)

Starting point	Node 1	Node 2	.	……..	Node n	Destination point

Fig. 7. Chromosome and waypoint array. a) GA chromosome; b) Waypoint representation; c) Waypoint array

An obstacle free path planning algorithm [35] was adopted to deal with spatial constraints. It produces a feasible path that satisfies the conditions that the waypoints should be located outside the obstacles, in the sampling space, and the local path should not intersect with the obstacles.

In order to comply with the feasibility constraints and to enhance the efficiency of the path, a certain number of the waypoints in the elite solutions can be modified for each generation by applying three possible operations: waypoint deletion, insertion, or replacement [2] a tabu search system model is designed and a tabu search planner algorithm for solving the path planning problem is proposed. A comprehensive simulation study is conducted using the proposed model and algorithm, in terms of solution quality and execution time. A comparison between our results with those of A* and genetic algorithms (GA. Waypoint deletion eliminates all waypoints in the clear water body. The waypoint insertion operation explores the neighbourhood and inserts a new waypoint, according to a predefined behaviour for each water pollutant type. After deleting and inserting the waypoints the algorithm evaluates the path, conducts a neighbourhood search to replace the lowest waypoint value with a new one, and builds another feasible path Pn that satisfies the mission constraints.

3.3. Fitness Function

The fitness function is a particular type of the objective function that quantifies the optimality of a solution and evaluates the suitability of a solution with respect to the overall goal. In our navigation problem, it maximizes the collected information, directs the robot towards the ROI, and incorporates distance and time penalties.

The proposed fitness function F consists of 4 components, calculated for each candidate sample

$$F = SV + ROI + DIS + ST \tag{4}$$

where:

SV – data set value, which determines the value of acquired samples according to Eq. 5;

$$SV \left[\frac{\sum_{i=1}^{t} samples\ values}{Maximume\ number\ of\ collected\ samples}\right] \tag{5}$$

where sample values are calculated as the values of *V* in Eq. 3.

ROI – the region of interest award, introduced in order to optimize the convergence of the search for quality samples (Eq. 6):

$$ROI \left[\frac{\sum_{i=1}^{t} ROI\_samples}{Maximume\ number\ of\ collected\ samples}\right] \tag{6}$$

where: *DIS* – distance factor; *ST* – sampling time factor.

Two objective functions with different forms of *DIS* and *ST* factors were tested to assess their impact on the effectiveness of the sample acquisition mission:

Objective function 1 linearly maximizes the sample value and the ROI award and exponentially minimizes the sampling time and the mission travel distance. The distance and the time become, as the sample acquisition mission progresses, quadratically more expensive.

Objective function 2 linearly maximizes the sample value as well as the sampling time and the ROI award, and linearly minimises the mission travel distance.

Objective function 1
$DIS = 1 - \left[\frac{\sum_{i=1}^{t} \sqrt{(y_t - y_{t-1}) + (x_t - x_{t-1})}}{Maximume\ allowable\ distance}\right]$
$ST = 1 - \left[\frac{\sum_{i=1}^{t} sampling\ time}{Maximume\ allowable\ sampling\ time}\right]$
Objective function 2
$DIS = 1 - \left[\frac{\sum_{i=1}^{t} \sqrt{(y_t - y_{t-1}) + (x_t - x_{t-1})}}{Maximume\ allowable\ distance}\right]$
$ST = \left[\frac{\sum_{i=1}^{t} sampling\ time}{Maximume\ allowable\ sampling\ time}\right]$

Fig. 8. Linear and nonlinear DIS and ST components of the fitness function

3.4. Multi-Behaviour Operation

The basic idea of the multi-strategy GA-based path planning is that the acquisition platform explores water pollutant patches using different behavioural characteristics depending on the sampling requirements in each patch. The behaviours affect the local search optimization where the best evaluated neighbour is selected according to the adopted behaviour. The following behaviours represent different sampling strategies.

Behaviour 1– Short local path and high sample values. The sampling process selects the best sample according to equation

$$SV = \left[1 - \frac{local\ path_{i\,j}}{Max\ local\ path}\right] * V_{chlo\ j} \tag{7}$$

where *i* is the departure waypoint, *j* is the destination waypoint, and is the chlorophyll concentrations in cell (x,y) of the MCI layer.

Behaviour 2 – Maximum gradient (MG) sampling. Valuable samples (bigger than a given threshold number) are selected along a short local path according to the following equation:

$$SV = \left[1 - \frac{local\ path_{i\,j}}{Max\ local\ path}\right] * V_{MG} \tag{8}$$

The sampling behaviour for other samples maximizes the local path according to equation

$$SV = \left[\frac{local\ path_{i\,j}}{Max\ local\ path}\right] * V_{MG} \tag{9}$$

Behaviour 3 – Multiple pollutant patches. The AS procedure selects the best sample value (Eq. 10), with the maximum local path range distance and the highest sample weight.

$$SV = \beta \left[\frac{local\ path_{i\,j}}{Max\ local\ path}\right] * V_{chlo\ j} * V_{TSS\ j} \tag{10}$$

where and are Chl-a and TSS concentrations in cell (*x,y*) taken from the MCI and TSS maps.

Behaviour 4: Long local path and TSS sampling The AS procedure selects the best sample value as defined by equation (11), where the value sample corresponds to the maximum local path range distance and the highest sample weight;

$$SV = \left[\frac{local\ path_{i\,j}}{Max\ local\ path}\right] * V_{TSS\ j} \tag{11}$$

An example of water pollutant patches obtained for different behaviours from a 3-layer map (MCI, TSS and MG) is shown in Fig. 8.

3.5. Multi-point Crossover

Multi-point crossover is used to enhance the process of selecting valuable samples located in distant zones. The crossover procedure is explained in Fig. 10. Parent chromosomes, P1 and P2, are cut at multiple random locations, and the portions of the chromosomes between the cuts are swapped. The

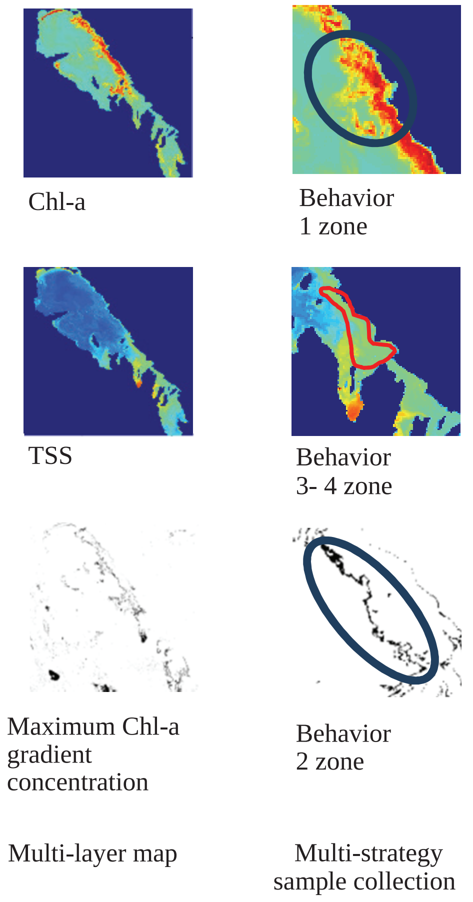

Fig. 9. Water pollutant zones for multi-behaviour navigation

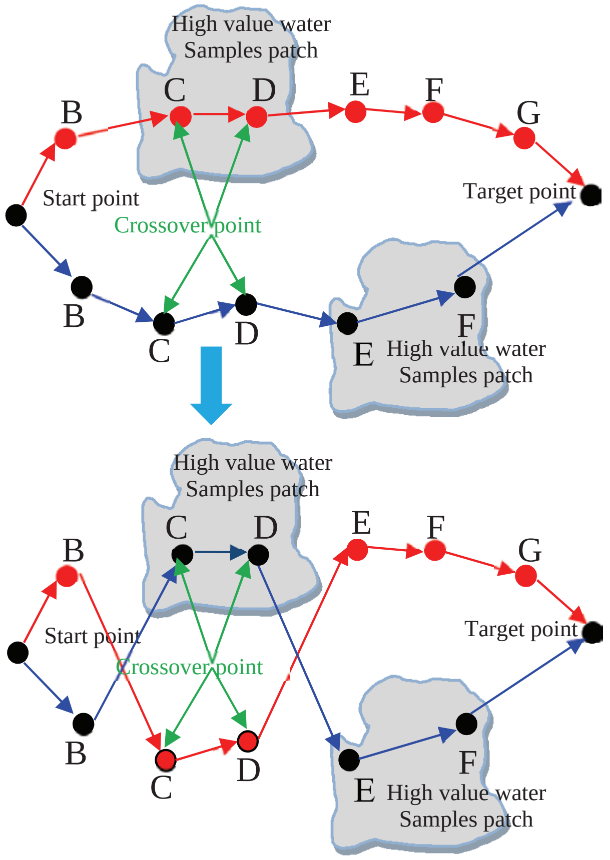

Fig. 10. Multi-point crossover. a) A two-chromosome and two-point crossover. b) Two offsprings

result is a pair of offsprings I1 and I2. The crossover is applied on the best-fitness chromosomes chosen from the pool. Due to the difference in the chromosome length, the crossover point should be applied to the shorter chromosome.

3.6. Planning Process

Figure 11 represents the overall architecture of the developed adaptive GA-based mission planning system. The mission objective is defined and accompanied with a strategy definition to achieve the mission goal. A multi-layer map is generated to interpret the global environment and to weight the importance of different water pollutants in the sampling strategy. A set of ROIs is generated to guide the search toward specific patches associated with their acquisition strategies.

An adaptive search algorithm improves the multi-strategy path planning in different patches employing local search optimising procedures. A suitable fitness function evaluates the chromosome in the search for maximizing the mission goal.

4. Experimental Results

4.1. Experimental Framework

The experiments were carried out using satellite data from the northern basin of Lake Winnipeg for a path starting at the point located at longitude (99°02’08”) W and latitude (55°35’18”) N and the destination point at longitude (96° 50’ 24”) W and latitude (51°55’51”) N. The direct distance between the start point and the target is around 236 km. The maps used in the experiments were in the form of a raster grid, where the dimensions of cells corresponded to the resolution of the MERIS satellite sensor, i.e., 260 m × 300 m. Each cell had an associated value $V_{x,y}$ obtained from the multi-layer map as discussed in Section 2.

ROI maps guide the multi-strategy sampling to orient the acquisition platform toward the valuable samples in the ROI zones using the penalty/award mechanism. Figures 12 a) b) and c) show regions of interest for MCI, TSS and the maximum gradient of the chlorophyll concentration. The regions are defined as the concentration of TSS bigger than 0.3 from the normalised TSS model, and the concentration of chlorophyll-a bigger than 0.5 from the MCI normalised model. Figure 12d represents the overall ROI formed from the MCI and TSS zones. Figure 12e illustrates three ROI zones, which are MCI, TSS and maximum gradient chlorophyll concentration, used in the experiments.

Matlab Genetic Algorithm Optimization Toolbox (GAOT) was used to program the proposed hybrid system. Table 1 shows the Genetic Algorithm parameters chosen for the optimization process.

Four experiments were conducted with two objective functions (Fig. 8) tested. Objective function 2 (linear optimization) was incorporated in the fitness function used in experiments 1 and 2, and objective function 1 (exponential optimization) in experiments 3 and 4. Hard distance and time constraints were implemented in the first two experiments. The mission

Table 1. Parameters of the Genetic Algorithm

Genetic Parameters	Magnitude
Number of generations	150
Population size	120
Crossover rate	60% randomly and the elite
Mutation rate	5% randomly and the elite
Type of crossover	Single-point and multi-point crossover
Type of mutation	4 point random & 4 maximum points
Selection type	Roulette Wheel

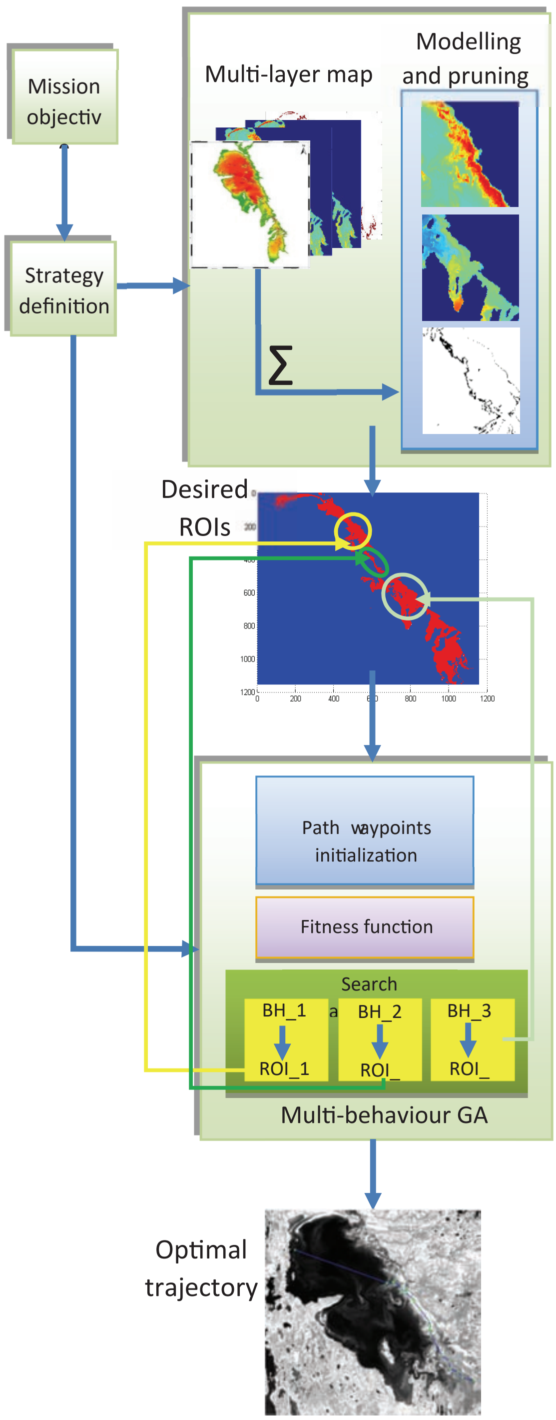

Fig. 11. Adaptive GA-Based Navigation System

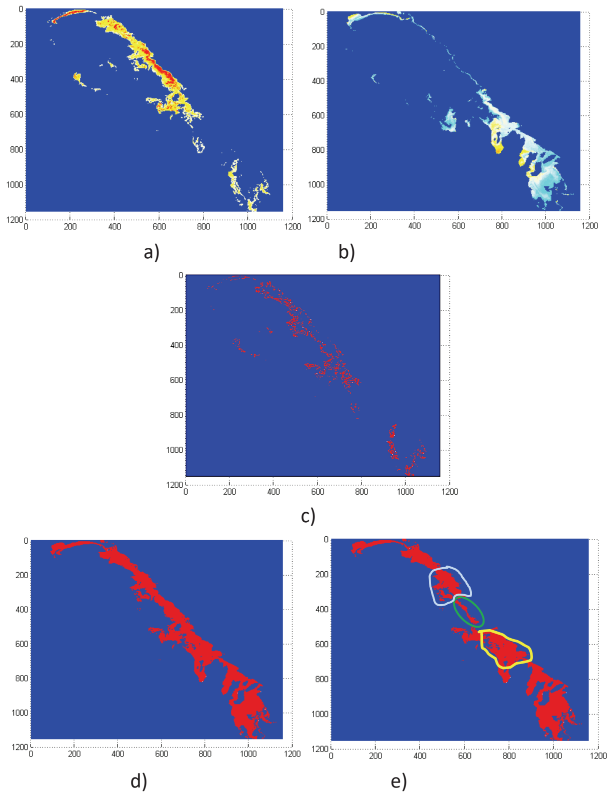

Fig. 12. a) Chl-a ROI (MCI > 0.5); b) TSS ROI (TSS > 0.3); c) Chl-a Max Gradient ROI; d) Combined Chl-a & TSS regions of interest, and e) Combined Chl-a & TSS & MG regions of interest

time was bounded by the value of 12 hours, and the travel distance was limited to 400 km. In experiments 3 and 4, the mission time had to be less than 9 hours, and the travel distance was limited to 330 km.

4.2. Path Planning Experiments

In the first experiment, the sample value (SV) was the sum of the TSS and Chl-a sample values. The results show that the path includes 10 samples from the clear water zone (outside the ROI zone), as shown in Fig. 13. The obtained results provide the rationale for hybridising the GA-based search for optimal samples.

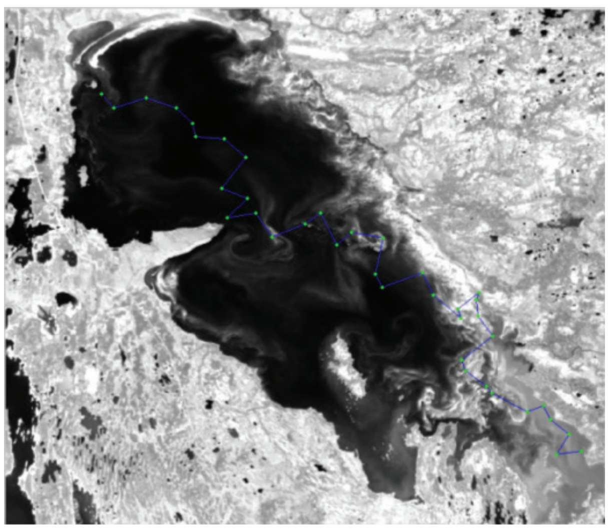

Fig. 13. Sample acquisition paths: Experiment 1

Experiment 2.

A simple adaptive search, consisting in limiting the search to ROIs, was introduced in the second experiment. However, no specific behaviour guided the waypoint generation. Figure 14 presents the path generated by the modified system. The sampling area is located entirely in the ROI. Table 2 compares the performance of the two experiments.

Table 2. Results of experiments 1 and 2

	Experiment 1 (GA)	Experiment 2 (ROI-optimized GA)
Sampling time	0.475 @ 38 samples	0.475 @ 38 samples
path length (m)	3.9989e+005	3.4364e+005
Samples value	0.7004	0.8304
ROI award	0.3675	0.5550

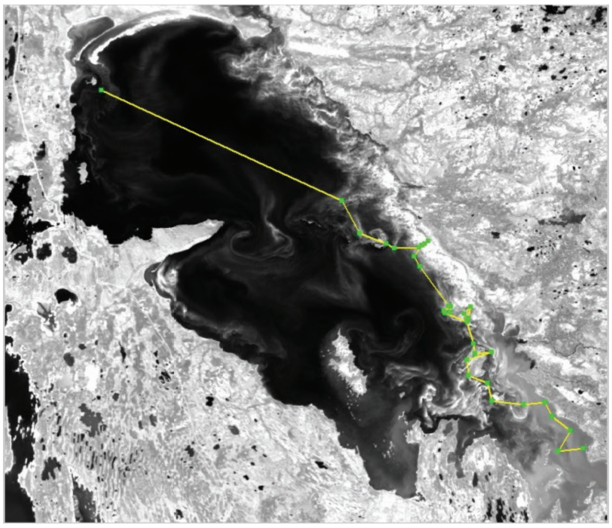

Fig. 14. Sample acquisition paths: Experiment 2

The path in the second experiment was approximately 56 km shorter and the value of the samples increased by about 13 percent, while keeping the number of samples at the same level.

4.3. Multi-Behaviour Navigation

In order to assess the multi-behaviour performance of the system and to further improve the path quality – in the context of the GA methodology – different behaviours were introduced to the local adaptive search the next two experiments. The third experiment explores the local behaviour optimization which performs two collection strategies depending on the types of the samples. Therefore, the ROI set consists of two zones, Chl-a and TSS. The search minimises the local path in the MCI patch according to Eq. 7, and maximises the local path in the TSS patch according to Eq. 11. The neighbourhood of a solution is explored, and the best neighbor is selected according to the adopted behaviour in each patch. Objective function 1 was used to optimise this experiment. The multi behaviour navigation shows good sampling performance in the two different patches, as shown in Fig. 15.

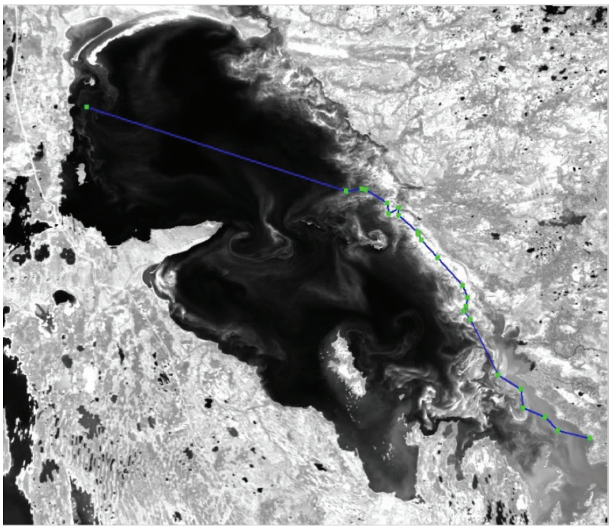

Fig. 15. Sample acquisition path from experiment 3

The mission collects 22 pure chl-a samples and 6 TSS samples along a 282 km long path. The samples value is 0.645, and ROI award equals to 0.6125. The distances between the chlorophyll samples are shorter than between the TSS samples, which is a consequence of applying the behaviour equation (Eq. 7) and high award for the Chl-a ROI. The longer local path between the six TSS samples results from the behaviour equation (Eq. 11). The total mission time is 8 hours and 54 minutes. The travel time is 7 hours and 14 minutes.

In the fourth experiment, the zone of the maximum gradient of chlorophyll concentration was introduced, which produced three separate patches with three different local search behaviours. Due to the behaviour conflict between the maximum gradient and the maximum value of the chlorophyll concentration, a new ROI zone was created. Thus, the three separate ROIs were generated as follows: the Chl-a zone, the maximum gradient of chlorophyll concentration, and the chlorophyll and TSS concentration zone. Figure 16 depicts the ROI map which was used in this experiment. The Chl-a samples were treated as the highest value samples with the shortest local path in the search algorithm (Eq. 7). In the maximum gradient zone, the search made the acquisition platform navi-

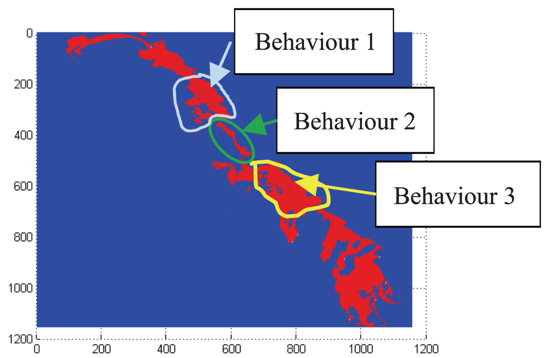

Fig. 16. Multi behaviour sampling for different patches

gate in adaptive way to follow the maximum gradient curve, using Eq. 8 and Eq. 9, and to maintain a proper distance between the samples. In the chlorophyll and

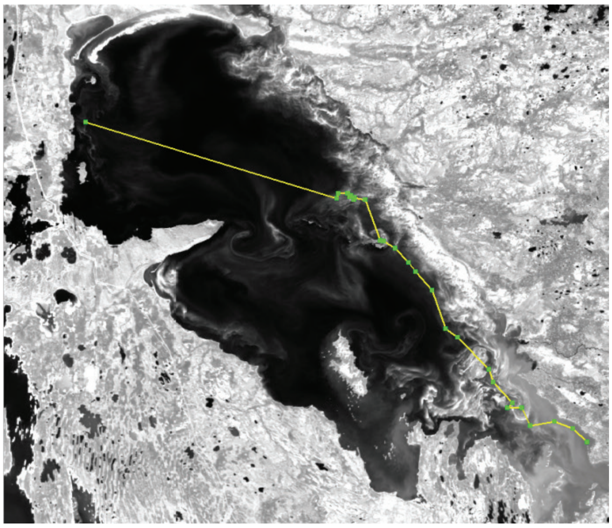

Fig. 17. Sample acquisition path from experiment 4

TSS zone, the behaviour model as in Eq. 10 was adopted. All behaviour optimization algorithms explored the neighbourhood and selected new waypoints in order to enhance the quality of the solution. Figure 17 shows an example of the planned path.

The path planning algorithm produced 28 samples as follows: 9 samples from the TSS & Chl-a zone; 5 samples from the MG zone; 14 samples from Chl-a zone including the start waypoint. The samples were collected along a path 285 km long. The normalized sample value was 0.5040 with the ROI award equal to 0.5650.

4.4. Convergence Analysis

To improve the convergence of the GA-based search, two crossover and two mutation operations were employed. The solutions to these operators were divided into two categories as follows: the first one consists of the elite solutions, and randomly selected solutions represent the second category.

The simulation results show that:

(1) The new procedure effectively enhanced the global search ability and improved the local searching ability;

(2) High convergence rate was obtained.

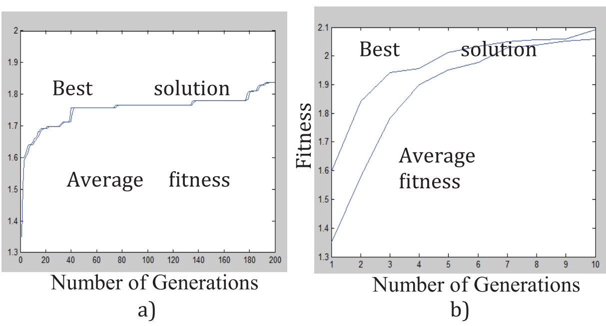

Fig. 18. Convergence in experiment 1 & 2

The results without the enhancement are shown in Fig. 18a. Both the quality of the solution and the speed of the optimization are enhanced by an order of magnitude by applying the improved operations (Fig. 18b).

The repeatability of the results is depicted, for experiments 3 and 4, in Figures 19a and 19b respectively. The convergence of both the best solution and the average solution is high.

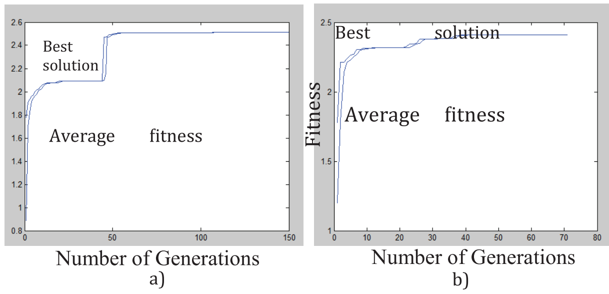

Fig. 19. Convergence in experiment 3 & 4

5. Conclusions

In this paper, hybrid genetic algorithms were proposed for navigation in a partly known environment, where the objective of the planning task is to find the optimal path for a mobile sample acquisition platform. The total quantity and quality of water samples is to be maximized according to navigation goals specified for each acquisition zone. Sampling in each patch may be guided by different patterns of behaviour for different purposes. Thus, the acquisition system is able to execute different behaviours along the global path. A hybrid genetic search was developed to deal with such a complex environment. The adaptive search algorithm models behaviours in different surrounding areas and executes them in each generation at the level of local path navigation. The locality of the navigation was defined in terms of regions of interest (ROI). In the process of generating the waypoints, the adaptive search deletes and inserts new waypoints in each solution depending on the ROI behaviour. This enhances the flexibility and the efficiency of path planning. The ROI component was introduces also in the fitness function, greatly speeding up the convergence of the planning process. Tests were conducted using medium-resolution satellite imagery. Multi-layered maps provided a rich context to the adaptive search system to perform flexible local search behaviours.

The experiments performed on large area environment show that the adaptive GA-based path planning method offers robust search capabilities and supports different sample acquisition strategies, ensuring the collection of meaningful data over multiple areas of interest.

ACKNOWLEDGEMENTS

The authors acknowledge funding from the International Science and Technology Partnership (ISTP – Canada) and the Natural Sciences and Engineering Research Council of Canada, grant 9227.

AUTHORS

Fadi Halal*, Marek B. Zaremba – Département d'informatique et d'ingénierie Université du Québec en Outaouais Gatineau, QC, J8X 3X7, Canada.
E-mail: half02@uqo.ca; zaremba@uqo.ca

*Corresponding author

REFERENCES

[1] K. Alikas, K. Kangro, A. Reinart, "Detecting cyanobacterial blooms in large North European lakes using the maximum chlorophyll index", *Oceanologia*, vol. 52, no. 2, 2010, 237–257. DOI: 10.5697/oc.52-2.237.

[2] I. Châari, A. Koubâa, H. Bennaceur, et al., "On the Adequacy of Tabu Search for Global Robot Path Planning Problem in Grid Environments". In: *5th Int. Conf. Ambient Syst. Networks Technol.* ((ANT-2014), Hasselt, Belgium, 2014, *Procedia Computer Science,* vol. 32, 2014, 604–613. DOI: 10.1016/j.procs.2014.05.466.

[3] I. Châari, A. Koubâa, H. Bennaceur, S. Trigui, K. Al-Shalfan, "SmartPATH: A hybrid ACO-GA algorithm for robot path planning". In: *2012 IEEE Congr. Evol. Comput.* (CEC 2012), Brisbane, Australia, 2012, 1–8. DOI: 10.1109/CEC.2012.6256142.

[4] C.T. Cheng, K. Fallahi, H. Leung, C.K. Tse, "A genetic algorithm-inspired UUV path planner based on dynamic programming", *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev*., vol. 42, no. 6, 2012, 1128–1134. DOI: 10.1109/TSMCC.2011.2180526.

[5] C.A. Coello Coello, "Evolutionary Multi-Objective Optimization: A Historical View of the Field", *IEEE Comput. Intell. Mag*., vol. 1, no. 1, 2006, 28–36. DOI: 10.1109/MCI.2006.1597059.

[6] G. Colmenares, F. Halal, M.B. Zaremba, "Ant Colony Optimization for Data Acquisition Mission Planning", *Manag. Prod. Eng. Rev.*, vol. 5, no. 2, 2014, 3–11. DOI: 10.2478/mper-2014-0011.

[7] H. Ergezer, K. Leblebicio, "3D Path Planning for-Multiple UAVs for Maximum Information Collection", *J. Intell. Robot. Syst.*, vol. 73, 2014, 737–762. DOI: 0.1007/s10846-013-9895-6.

[8] M. Gao, J. Tian, "Path Planning for Mobile Robot Based on Improved Simulated Annealing". In: *3rd Int. Conf. Nat. Comput.*, 2007, vol. 3, 8–12. DOI: 10.1109/ICNC.2007.547.

[9] A. García, A. Barrientos, "3D Path planning using a fuzzy logic navigational map for Planetary Surface Rovers". In: *ASTRA 2011 11th Symposium on Advanced Space Technologies in Robotics and Automation*, 12th–14th April 2011

[10] J. Gower, S. King, P. Goncalves, "Global monitoring of plankton blooms using MERIS MCI", *Int. J. Remote Sens*., vol. 29, no. 21, 2008, 6209–6216. DOI: 10.1080/01431160802178110.

[11] F. Halal, M.B. Zaremba, "Multi-strategy spatial data acquisition missions using genetic algorithms", IFAC-PapersOnLine, vol. 48, no. 3, 2015, 778–783. DOI: 10.1016/j.ifacol.2015.06.177.

[12] J. A. Hambrook Berkman, M.G. Canova, "Algal Biomass Indicators", *U.S. Geol. Surv. TWRI* book 9: Biol. Indic., 2007, chapter A.7, section 7.4.

[13] R.L. Haupt, S.E. Haupt, *Practical Genetic Algorithms*, John Wiley & Sons, Inc., Hoboken, New Jersey., 2004.

[14] C.-C. Hsu, Y.-C. Liu, "Path planning for robot navigation based on Cooperative Genetic Optimization". In: *Proc. 11th IEEE Int. Conf. Networking*, Sens. Control, 2014, 316–321. DOI: 10.1109/ICNSC.2014.6819645.

[15] M.T.S. Ibrahim, S.V. Ragavan, S.G. Ponnambalam, "Way point based deliberative path planner for navigation", *IEEE/ASME Int. Conf. Adv. Intell. Mechatronics* (AIM), 2009, 881–886. DOI: 10.1109/AIM.2009.5229900.

[16] P. Jaroszek, "Any-angle Global Path Planning for Skid-Steered Mobile Robots on Heterogeneous Terrain", *Journal of Automation, Mobile Robotics, and Intelligent Systems*, vol. 10, no. 2, 2016, 50–55. DOI: 10.14313/JAMRIS_2-2016/15.

[17] S. Koponen, J. Vepsäläinen, J. Pulliainen, et al., "Using meris data for the retrieval of CHL-A, CDOM and TSS values in the gulf of Finland and lake Lohjanjärvi", Eur. Sp. Agency, (Special Publ. ESA SP. 2004, 2005, 407–413.

[18] B. Li, R. Chiong, L. Gong, "Search-evasion path planning for submarines using the Artificial Bee Colony algorithm". In: *2014 IEEE Congr. Evol. Comput.*, July 2014, 528–535. DOI: 10.1109/CEC.2014.6900224.

[19] N.K. Lincoln, S.M. Veres, L.A. Dennis, M. Fisher, A. Lisitsa, "Autonomous asteroid exploration by rational agents", *IEEE Comput. Intell. Mag*., vol. 8, no. 4, 2013, 25–38. DOI: 10.1109/MCI.2013.2279559.

[20] C. Luo, S.X. Yang, M. Krishnan, M. Paulik, Y. Chen, "A hybrid system for multi-goal navigation and map building of an autonomous vehicle in unknown environments". In: *2013 IEEE Int. Conf. Robot. Biomimetics*, ROBIO 2013, 1228–1233.

[21] J.E. O'Reilly, S. Maritorena, B.G. Mitchell, et al., "Ocean color chlorophyll algorithms for SeaWiFS", *J. Geophys. Res*., 103, 1998, 24937–24953.

[22] S. Park, J. Cho, "ROI-based visualization of spatial information for a remote-controlled robot". In: *2013 10th Int. Conf. Ubiquitous Robot. Ambient Intell.*, 2013, 234–235.

[23] G.P. Rajappa, *Solving Combinatorial Optimization Problems Using Genetic Algorithms and Ant Colony Optimization*, University of Tennessee, 2012.

[24] F. Rothlauf, R*epresentations for Genetic and Evolutionary Algorithms*, Springer-Verlag Berlin, Heidelberg, 2006.

[25] M. Samadi, M.F. Othman, "Global Path Planning for Autonomous Mobile Robot Using Genetic Algorithm". In: *2013 Int. Conf. Signal-Image Technol. Internet-Based Syst.*, 726–730. DOI: 10.1109/SITIS.2013.118.

[26] A. Singh, A. Krause, C. Guestrin, W.J. Kaiser, "Efficient informative sensing using multiple robots", *J. Artif. Intell. Res.*, vol. 34, 2009, 707–755. DOI: 10.1613/jair.2674.

[27] T.Y. Sun, C.L. Huo, S.J. Tsai, Y.H. Yu, C.C. Liu, "Intelligent flight task algorithm for unmanned aerial vehicle", *Expert Syst. Appl.*, vol. 38, no. 8,2011, 10036–10048. DOI: 10.1016/j.eswa.2011.02.013.

[28] Tomasz Gawron, Maciej M. Michalek, "Planning the Waypoint-Following Task for A Unicycle-like robot in Cluttered Environments, *Journal of Automation, Mobile Robotics, and Intelligent Systems*, vol. 9, no. 1, 2015, 77–90. DOI: 10.14313/JAMRIS_1-2015/10.

[29] G. Vachtsevanos, L. Tang, G. Drozeski, L. Gutierrez, "From mission planning to flight control of unmanned aerial vehicles: Strategies and implementation tools", *Annu. Rev. Control.*, vol. 29, no. 1, 2005, 101–115. DOI: 10.1016/j.arcontrol.2004.11.002.

[30] S. Veera Ragavan, S.G. Ponnambalam, C. Sumero, "Waypoint-based path planner for mobile robot navigation using PSO and GA-AIS". In: *2011 IEEE Recent Adv. Intell. Comput. Syst.* (RAICS 2011), 756–760. DOI: 10.1109/RAICS.2011.6069411.

[31] J. Xiao-Ting, X. Hai-Bin, Z. Li, J. Sheng-De, "Flight Path Planning Based on an Improved Genetic Algorithm". In: *2013 Third Int. Conf. Intell. Syst. Des. Eng. Appl.*, 775–778.

[32] M. Yoshikawa, H. Terai, "Car Navigation System Based on Hybrid Genetic Algorithm". In: *World Congr. Comput. Sci. Inf. Eng.*, vol. 5, 2009, 60–64.

[33] L. Yu, Z. Cai, "Robot exploration mission planning based on heterogeneous interactive cultural hybrid algorithm". In: *5th Int. Conf. Nat. Comput. ICNC 2009*, 583–587.

[34] S.C. Yun, V. Ganapathy, L.O. Chong, "Improved Genetic Algorithms based Optimum Path Planning for Mobile Robot". In: *11th Int. Conf. Control. Autom. Robot. Vis.*, Singapore, 2010, 1565–1570. DOI: 10.1109/ICNC.2009.15.

[35] C. Zeng, Q. Zhang, X. Wei, "Robotic global path-planning based modified genetic algorithm and A* algorithm". In: *3rd Int. Conf. Meas. Technol. Mechatronics Autom. ICMTMA 2011*, 167–170. DOI: 10.1109/ICMTMA.2011.613.

[36] F. Zhang, N.E. Leonard, "Generating contour plots using multiple sensor platforms". In: *Proc. IEEE Swarm Intelligence Symposium*, 2005, 309–316.