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The Grey Wolf Optimizer Algorithm Modification for Enhanced Performance of Autonomous Underwater Vehicles in a Physical Field Survey

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***Abstract*—The purpose of the study is to modify the Grey Wolf Algorithm. It is aimed at increasing the speed of the mission execution in order to examine a physical field and detect anomalies. It should consider the limitations imposed by the physical model of the group of autonomous unmanned underwater vehicles operation. For this aim, the simulator is deigned in an integrated development environment NetBeans for Java programming language. To assess the algorithm efficiency, a computational experiment was performed using several types of real physical fields as the source data. The simulation outcomes were compared to those obtained by the tack survey method. The study shows that the proposed algorithm provides better management of a group of autonomous uninhabited underwater vehicles than the well-established tack method of examining the physical field. The modified Grey Wolf Algorithm used in applied problems within the physical field survey proved to be beneficial and reliable. In spite of satisfactory test results, it is necessary to confirm the usage of the algorithm by real autonomous unmanned underwater vehicles. It is required to continue investigating the operation of the Grey Wolf Algorithm in a dynamically changing environment and the influence of different control functions on it.**

Keywords—Grey Wolf Optimizer, swarm algorithms, autonomous unmanned underwater vehicles control, autonomous unmanned underwater vehicles, optimization algorithms component.

I. INTRODUCTION

A great number of autonomous underwater vehicles (AUV) have been designed in different countries all over the world in just past three decades. They solve a wide variety of specific problems concerning ocean exploration and development. These countries are considered to be advanced ones in the marine technology field. In a short period of time, AUV were able to show their efficacy in doing quite complicated deep water operations.

At present, AUV are used in commercial and research fields. They solve problems that had been previously esteemed expensive or difficult to perform. This multifunctionality is achieved by a wide range of equipment available for the vehicle to install. This ensures their ability to complete the following functions: seabed mapping, object search and identification, and a physical field survey.

The problem of the field trajectory measurement is the most common problem definition. It is also a general solution pattern for the survey of any fields with characteristic properties of a spatial pattern. They are variability, abnormal level, the correlation in the field geometry and others. When solving such problems, the input information on the control field is usually presented as a digital map, an image, or data array. The coordinate values are assigned to a certain scalar field parameter there.

The measurements of physical fields in the water column and at the bottom of a water body are based on developing a network of observations. It is bound to principal stations, a sea line or the bottom checking points according to the common practice. The network of depth and area measurements constitutes a system of layers (sections) featuring the spatial pattern of the field. The data obtained as a result of replacing a repeating field by a network of point measurements are used to generate a field map in the future. The reconstruction of the field map according to these measurement data is a routine problem, although it is very intensive. Today, methods of trajectory surveys using autonomous, remote-controlled and hauled vehicles are applied more often. In this regard, the use of AUV has several advantages. It occurs especially when performing complex measurements off soundings and under extreme environmental conditions [1, 2].

The tack method to explore the water area is still quite major, irrespective of the specific problem. In other words, the vehicles navigate along a zigzag path, turning around 180 when reaching the border of the surveyed area [3]. This method is universal. It fits all types of underwater research targets, including the solution of the problem referring the examination of the physical field. In this case, the frequency of measurements is broadcasted to the vehicles in addition to the tack map. Such an algorithm is highly accurate in finding

the maximum value of the physical field. It has some certain disadvantages, though. They include the following:

- Accuracy dependence both on the sampling frequency, and on the tack width, usually varied within the range from 1 to 10 meters;
- Execution time of a highest priority problem, depending on the size of the surveyed area and the number of vehicles in the research group;
- The necessity to store in memory the values of all taken measurements and the coordinates of the samples caused by the limited task of a physical field survey. According to it, the location of the extreme value cannot be determined clearly without the whole area survey.

Despite the obvious simplicity and effectiveness of the survey tack method, this one is not the best one for solving the problem in a physical field survey. Nowadays, swarm optimization algorithms have proven to be the most suitable for that [4]. These include the Grey Wolf Optimizer (GWO) [5] highlighted in this study. S. Zhang and Y. Zhou compared the speed of the swarm intelligence algorithms. They came to the conclusion that GWO is highly competitive with other algorithms [6] when solving multidimensional optimization problems. There are many descriptions of the well-known grey wolf algorithm modifications in academic books recently, when used in various applied problems: Parkinson's disease at a premature stage [7]; virtual network function placement [8]; a clustering method [9]; economic load dispatch problem [10]; image segmentation [11]. It should be focused that the choice of modification algorithm type depends on the features of its application area.

The aim of the survey is to modify the Grey Wolf Algorithm. It can increase speed of the mission execution. Thus, it will examine a physical field and detect anomalies. It will consider the limitations imposed by the physical model of the group of autonomous unmanned underwater vehicles operation.

II. METHODS

A number of functional requirements were put forward for the software being developed. They are based on the requirements of the subject area after reviewing the subject area and consulting the experts in this field:

- An AUV group begins to survey the field from one common area placed over the border of the investigated area;
- the measuring process of the field magnitude at a point, the calculation of AUV trajectory and the movement takes some time, which is determined by AUV characteristics;
- The main quality index of the problem solution are: accuracy (the ratio of the best solution found to the maximum field value in a given area) and speed (simulated time required in determining a solution);
- A problem must be solved in a finite amount of time;
- A measurement error of the extreme point - the reciprocal of accuracy - should not be more than 5%.

Developing a complete model of AUV behavior in solving the problem of examining a physical field is a very complicated task. At present, a similar simulation facility, considering all the aspects of underwater research, is being developed in the Institute for System Dynamics and Control Theory, the Siberian Branch of the Russian Academy of Sciences. However, the project is still to be completed. So it was decided to run a program. It is better include a number of suppositions that do not affect, either directly or indirectly, the process of examining the physical field. The following conditions are presented below:

- All AUV have the same features, for example, navigation speed, measurement accuracy and others, which influence the solution of the problem as well;
- The vehicles navigate proportionally. Moreover, there are no external interference units such as underflows;
- AUV are immaterial. Thus they cannot collide with each other when passing;
- The environment is static. As it was mentioned above, the physical field does not change during the whole mission time because there are no external interference units;
- There are no ground forms on the surveyed maps, which can restrict the navigation of vehicles or make some areas inaccessible;
- The time required for the vehicle to measure the magnitude of the field and then calculate the navigation path is taken per unit of simulated time.

These terms are temporary. As soon as the simulation facility is completed, the algorithms proposed in this paper are going to be retested including all the aspects of the underwater research field.

The authors decided to use Java programming language and NetBeans development environment to design a simulator.

For all the tests from this study, the authors used the same starting attributes to avoid contamination of experiments:

- The project group consists of 10 AUV;
- The speed of each vehicle is 20 meters per unit of simulated time;
- The group starts observation from the area with the center in the coordinates (50; 50) and a radius of 50 meters;
- All surveyed maps are sized 400 meters × 400 meters;
- The number of successive approximations is finite and equals to 100 for the conventional GWO and its modifications.

5 areas (digital maps) defined by elevation maps were selected as the original data for the computational experiment in this study. The areas are divided into 3 groups, specifying various possible options of the physical field being explored:

- Gradient distribution, when many closely placed points can have the same magnitude of a physical field, but with only 1 extreme point (Figure 1);

- Several local extreme points, among which there is only 1, having the maximum value of the physical field in a given area (Figures 2 and 3);
- A physical field with zeros, having one or several areas where the physical field is completely absent (the value is 0) (Figures 4 and 5).

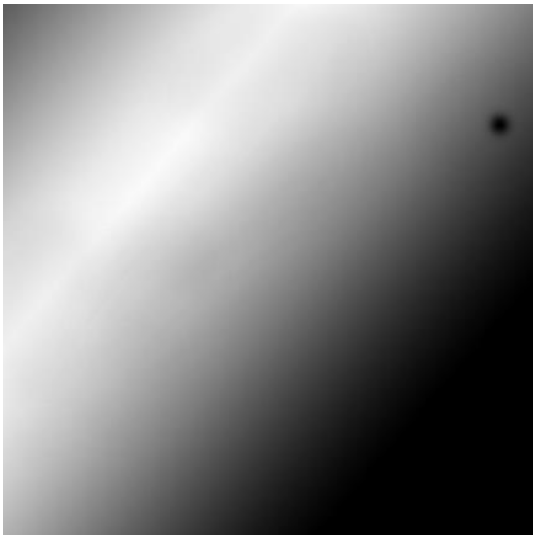

Fig. 1. Map with gradient distribution (map 1)

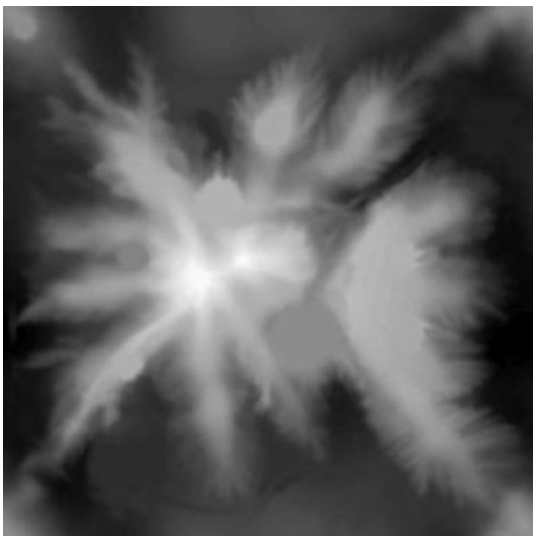

Fig. 2. Map with several local extremes (map 2)

Fig. 3. Map with several local extremes (map 3)

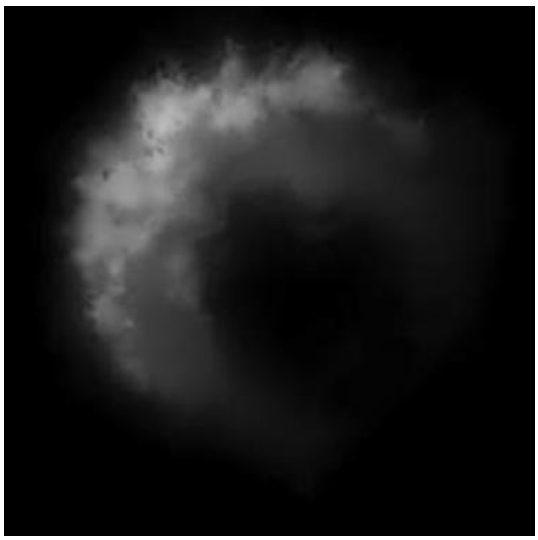

Fig. 4. Map with zero areas (map 4)

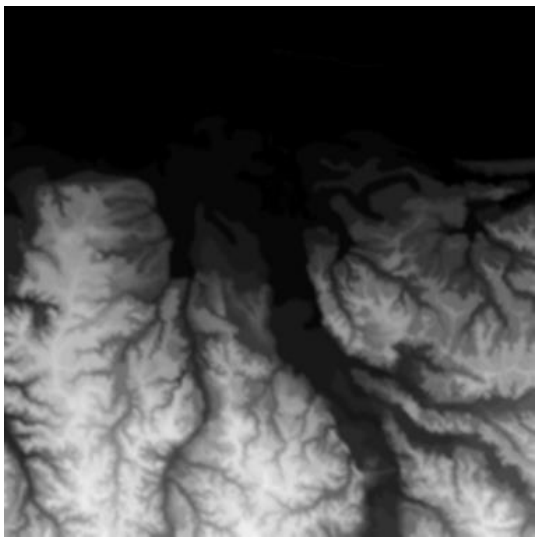

Fig. 5. Map with zero areas (map 5)

Since each Grey Wolf Algorithm to execute is unique through stochastic coefficients [5], 10 experiments were carried out on each map.

III. Results and Discussion

The specified results are the average values obtained from the test.

When doing the research using the Grey Wolf Algorithm and a standard tack search algorithm, a number of features were identified:

- Using the original Grey Wolf Algorithm rather than the tack method can reduce the mission time more by augmenting the margins of error.
- Maps with several local maxima and with zero areas in the physical field are the most difficult to explore.
- The results of the Grey Wolf Algorithm operation depend on the agents' initialization technique. In the original GWO, the agents are distributed evenly across the area. But the restriction is imposed on AUV. So the group should begin the survey from one common area at the edge of the surveyed area. In the latter case, it can cause an error in the algorithm operation. It will result in the less square search than the surveyed area. Thus, AUV may not find a point with the maximum value of the physical field. A high error values were put on the map with several local extremes because of this drawback.
- The original algorithm does not consider the time required to move the agent from the current point to the next. GWO assumes that agents move immediately. But that does not correspond to AUV operation mode for good reasons.

Taking into account the mentioned features of the GWO algorithm, the authors proposed some modifications that can improve the algorithm efficiency.

As mentioned above, the study of GWO proved the dependence of the seeking area size on the AUV initial construction density. It deals with the search area in each iteration. It depends on the group leaders' coordinates. It decreases during the iterations only. So, if there is a close spacing of vehicles in the first iteration, the search area may not cover the area being surveyed. It will make the results incorrect.

To solve this problem, it is proposed to use dummy-based measurements - points on the map. They have a dynamically changing weighting coefficient. Such points are not part of a research group. They do not have a physical realization or move, but participate in the selection of group leaders. Therefore, they affect the calculation of AUV coordinates for the next iteration. Dummy-based measurements are distributed along the perimeter of the surveyed area. And the startup value is a random generated number [150; 250].

The weighting coefficient of a dummy-based measurement is used when choosing alpha, beta and delta instead of the measured field value. Also, dummy-based measurement has a certain radius. It is set by the user to recalculate the weighting coefficient.

Thus, this method is developed to solve two problems:

1) To increase the n-dimensional search cube. There is an area where agents are distributed at initial iterations (in this study, the authors mean a two-dimensional area)

2) To involve AUV in areas for one reason or another were not examined during the whole mission.

The following formulae were used to recalculate the weighting coefficient:

$$E = \sum V_i \tag{1}$$

$$E = \frac{E_0 + \sum V_i}{n+1} \tag{2}$$

where V_i are the real measurements that run into the area bounded by the given radius of the dummy-based measurement coverage; n is the number of measurements that run into in this area; E_0 is the initial value of the weighting coefficient.

However, the complexity of calculating the formulae grows in a linear direction and depends on the number of measurements taken. To eliminate this dependency, the authors proposed to use a recursion function:

$$E_i = \frac{E_{i-1} + E}{2} \tag{3}$$

where E_i is the current value of the dummy-based measurement; E_{i-1} is the value in the previous iteration; E is the real measurement made by the vehicle in a given radius from the dummy-based measurement. In formula (3), it is required to check only n measurements made in this iteration, where n is the number of AUV used while recalculating the weighting coefficient of each dummy-based measurement.

Making allowance for the fact that the described method should be called up with each dummy-based measurement in each iteration, one can calculate the complexity of this algorithm. It is equal to O (n×k), where n is the number of measurements made in this iteration and directly dependent on the number of AUV in the research group. K is the number of dummy-based measurements. The parameters are set before the start and do not change while operating. Thus, the algorithm is quite fast and does not demand any special resources.

For each test run, 50 dummy-based measurements were generated and distributed around the perimeter of the area. The coverage radius was equal to 50 meters. The test results in comparison with the standard tack method and the original GWO are presented in Figures 6 and 7.

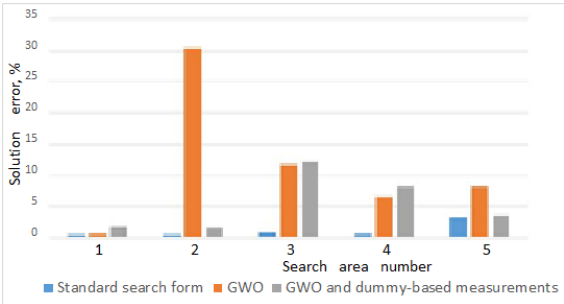

Fig. 6. The impact of modification on the solution error

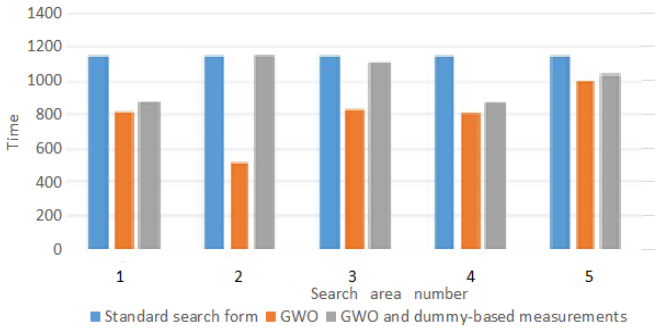

Fig. 7. The impact of modifications on the search time

According to the test series results, the authors came to the following conclusions:

1. The use of dummy-based measurements debugs incomplete coverage of the surveyed area.

2. The error in determining the largest value of the physical field. It is independent of this modification or is reduced mostly (maps 2 and 5 in Figure 6).

3. The average time to complete the mission is faster than using the standard GWO, but slower than examining by tacks.

In the original Grey Wolf Algorithm, each agent calculates the next waypoint with no respect to the others. When GWO is transferred to AUV subject area, it leads to a great time loss caused by phase traction. When testing the original algorithm, it was noted that the group had to wait for one or several AUV. They got the farthest waypoints from them. Such down time not only increases the entire mission completion. But it also complicates the apparatus way of operation at the physical level. Though, preserving coordinates for a long time is quite a difficult task for real AUV.

Since all AUV used have the same characteristics, any robot can arrive at any waypoint. It will not affect the algorithm operation, though. In view of this, the authors proposed to generate a common package of waypoints for all AUV, and distribute the vehicles over them, minimizing the following function:

$$F = \max\{x_{ij}\} \to \min \tag{4}$$

where x_{ij} is the distance from i– AUV to j-waypoint, and $\{x_{ij}\}$ is a great many of all distances between the vehicles and waypoints.

With the restriction context, only one AUV can arrive at each waypoint. One has to solve a problem of allocation (maximum-weight matching) with an irregular objective function.

The assignment problem [12] is a particular case of a linear programming transportation model. The offer and demand limits are set rigidly and do not differ from unity. In the conventional formulation the solution of this problem is matching of the minimum weight of all available in the assignment matrix of a given dimension (n × n).

To sum up, the objective function has the following form:

$$F = \sum_{i,j=1}^{n} x_{ij} \to \min \tag{5}$$

The assignment problem in the setting is considered when problems are distributed in parallel computing systems. Today, there are some ways to obtain an exact solution of this problem [13]. However, in this study it was decided to find an approximate solution only. So it was proposed to use one of three algorithms:

- The Hungarian algorithm [14]. It is an original algorithm for solving the assignment problem in the standard formulation with the low complexity;
- Swapping is a fast algorithm used for improving any valid development scheme drawn by the authors;
- A Hybrid algorithm assumes the development scheme obtained through the Hungarian algorithm for the development scheme by the Swapping algorithm.

A gradual improvement of the objective function of any starting matching through the replacement of its largest element implies the basis of the Swapping-algorithm developed by the authors. The algorithm looks for an opportunity to make a valid exchange of waypoints between AUV to reduce the down time of vehicles. They have the maximum distance in the developed scheme and other robots. Exchange is valid when the objective function decreases. The verification of the exchange validity is performed for AUV first. It has a minimum distance in the scheme, and then in ascending this value.

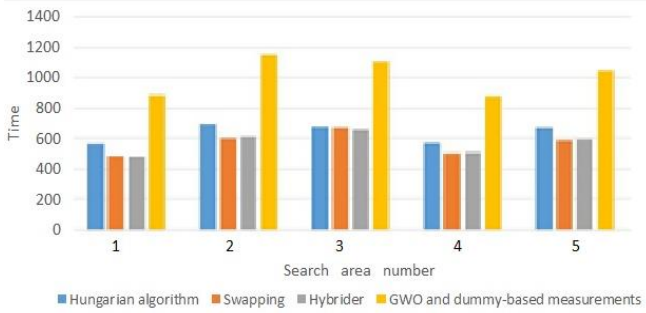

Fig. 8. Modification impact on the task time

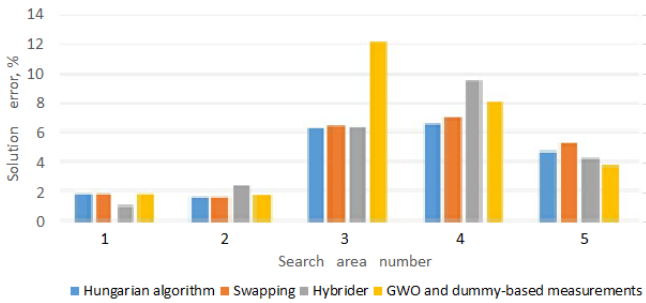

Fig. 9. Modification impact on the problem solution error

As can be seen in Figures 8 and 9, regardless of the time optimization type of the traction phase, the application of this modification has little effect on the error in determining the maximum field strength. An exception is Map 3 (Figure 9); the error has decreased by 2 times for it.

On the other hand, the total survey time compared with the modification using dummy-based measurements has decreased reasonably (from 30% to 50%). The most velocity enhancement of the survey is achieved when using both the Swapping-algorithm and the Hybrid algorithm. In these cases the average time of the mission performance does not differ much. Besides, it seems to be an indirect proof that Swapping does not depend on the choice of the initial feasible solution to the balanced assignment problem.

The standard Grey Wolf Algorithm is quite flexible. It accepts easily modifications related both to adaptation to the limitations of the subject area of underwater research, and to in-place changes in the algorithm operation logic.

According to the test results performed, it can be summarized that the following modifications of the standard Grey Wolf Algorithm should be used to achieve the best results:

- Using dummy-based measurements. It helps to avoid entering a local extreme point in the initial iterations;
- Using the Swapping algorithm reduces the time of the phase of traction. The hybrid algorithm shows the same quickening of the mission completion. However, it requires additional computational resources to make up a development scheme using the Hungarian algorithm.

To illustrate enhanced performance of the problem, the authors made a comparison of the survey using the tack method and the proposed GWO modification (Figures 10 and 11). Figure 10 shows that the solution error on all the maps is not greater than the certain threshold. Also, the execution time has decreased by more than 2 times (Figure 11).

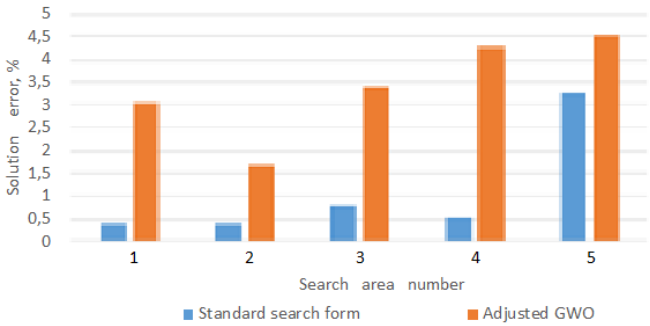

Fig. 10. Comparison of solution error

Fig. 11. Comparison of problem time

The proposed and tested modifications in this survey eliminate the disadvantages of the standard GWO completely. This allows supposing that the algorithm explained can be used by real AUV when performing underwater research problems.

IV. Conclusion

The modified Grey Wolfs Algorithm implemented by the authors differs greatly from the current tack search algorithm. It provides an essential time reduction in solving a physical field survey task with a solution error not exceeding 5%. The use of a modified algorithm has two main advantages:

First, the mission time is reduced much; it allows using the batteries of lower capacity and making more room for the payload;

Secondly, the tack method requires storing all the results of measurements taken in the memory of robots. But for GWO it is enough to store only the measurements made by the vehicles in the last iteration. Thus, it clears a large storage space during the long-time missions.

Both GWO standard and all presented modifications are not difficult to use and have O (n2) order of complexity. Thus, their performance does not demand AUV specific hardware. They can be applied to any most standard configuration.

In spite of satisfactory test results, to confirm the meaningful use of the algorithm with real AUV, it is required to carry out further research in different areas. They are the study of various control function. They influence the results of modified GWO when examining physical fields of various types. The research of GWO operation is in a dynamically changing environment. The performance and testing the algorithm based on a simulation complex. It implements all the features and limitations of the underwater research field and AUV operation. But some of them were not explained in this paper.

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