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RESEARCH ARTICLE

A Novel Bias-TSP Algorithm for Maritime Patrol

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ABSTRACT This work aims to develop a search planning strategy to be used by a drone equipped with an inverse synthetic-aperture radar (ISAR) and an electro-optical sensor. After describing the specifics of our maritime scenario, we discuss four methodologies that can be used to find vessels involved in illegal fishing activities as quickly as possible. In addition to the clustering of the vessels, determined by the drone's electro-optical sensor range, we introduce a novel technique to bias a traveling salesman problem (TSP) tour. This bias is based on deliberately increasing distances to vessels that are classified as probable fishing vessels. This increase in distance is meant to prioritize visits to probable fishing vessels. Vessels are classified based on their length. The classification result and the vessel clustering are available before the actual planning of the tour. Simulations of scenarios in which we have a few vessels fishing illegally show that the novel technique, the bias-TSP, combined with a tour orientation based on operational considerations, outperforms the classic TSP: the mean distance traveled to find all the vessels involved in illegal fishing activities is reduced by at least 35–50%. We also show that different drone take-off locations significantly impact the results.

INDEX TERMS Optimization methods, design of experiments, traveling salesman problem (TSP), decision support systems, drones.

I. INTRODUCTION

In many communities, fishing is an essential component of the economy and ecosystem in the daily lives of citizens [1]. In a study carried out in West Africa, Merem et al. [1] show that the losses from unauthorized fishing reached close to two billion dollars in 2015 in that region. In addition, the associated impacts on the loss of ecosystem services and the destruction of habitats are devastating. Conventional valuation of lost potential and the price of stock recovery for preferred species from 1980 onwards show prices in the hundreds of billions of dollars for West Africa.

Illegal fishing is a serious problem that profoundly affects the economic sector of a country and the ecosystem of an entire region. As a result, several countries have been improving their methods of deterring and searching for these illicit acts and improving their methods of planning and executing maritime patrols to inspect the oceans [2].

Unmanned aerial vehicles (UAVs) have been increasingly used in different types of missions, as they have many advantages over manned aircraft [3]. Regarding maritime patrol missions, we can highlight greater autonomy, lower radar cross section (RCS), and a much lower operating cost.

The objective of this work is to develop a maritime patrol planning methodology to find vessels carrying out illegal fishing as quickly as possible in a realistic maritime scenario without a trigger report. The data used for route planning come from the MarineTraffic site [4], from the inverse synthetic-aperture radar (ISAR) that locates the vessels and measures their size, and from the drone's electro-optical sensor. Integer linear programming (ILP) is used, and a weighting technique is applied at the points (fishing boats) to be

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visited to bias the route and prioritize the visitation of this type of vessel.

The Brazilian coast extends for about 8,000 km from Cabo Orange (4°N) to Chuí (34°S) [5]. The exclusive economic zone (EEZ) extends 200 nautical miles (370 km) from the coast and corresponds to an area of 3,539,919 km^2. The Continental Shelf extends up to 350 nautical miles from the coast and corresponds to an additional 960,000 km^2. Together, these zones cover almost 4.5 million km^2 [6]. With an immense diversity of marine fauna, this is an area of Brazilian jurisdiction in which the state can exercise sovereign rights over the exploration, conservation, and management of resources and other economic activities. The state also has judicial and supervisory powers in its EEZ to combat the dumping of ship waste and pollution from offshore activities and is primarily responsible for the preservation of living resources [7].

Designating the means to constantly monitor this immense maritime area, which is a responsibility of the Brazilian state, is a complicated task. With this in mind, a methodology was developed to optimize the means of surveillance of illegal fishing in this area, carrying out scheduled maritime patrols in random areas in the Brazilian EEZ, using only drone sensors and MarineTraffic data.

One finds several other applications of UAVs in surveillance and maritime search missions in the literature. Dridi et al. [8] develop a multi-objective optimization to solve a maritime surveillance problem where a set of resources is assigned to a specific set of tasks. Amaral et al. [9] optimize target detection and tracking using a swarm of UAVs for maritime border surveillance. Kumar and Vanualailai [10] present a Lagrangian swarm model that can cover large areas of the sea effectively and could be a very good model for effective surveillance of an exclusive economic zone (EEZ) and search and rescue. Suteris et al. [11] create a route optimization method for UAVs for maritime surveillance to find the fastest route to cover all locations at sea.

Fauske et al. [12] present a model to study the movement of vehicles used in surveillance to maintain a recognized and updated maritime picture. Brown and Anderson [13] optimize the trajectory of a UAV for wide-area maritime radar surveillance and provide a method for obtaining the UAV's fuel consumption, detection probability, and revisit time for a given trajectory.

A method to create a flight path for a maritime surveillance mission to identify vessels carrying out illegal fishing is proposed by Suseno and Wardana [14]. The number of nodes in the route is significantly reduced using a point clustering technique based on the history of places frequently visited by fishing vessels (vulnerable points), thus shortening the flight path. The flight path of the UAVs is planned using the nearest neighbour algorithm from the take-off location to the vulnerable points and then back to the landing site.

Finally, Lima Filho et al. [2] present an operational planning procedure for a time-critical UAV search mission. The mission is the quickest possible identification of a target vessel based on a triggering report that contains only information about the category and displacement of a vessel carrying out a prohibited activity. A neural network trained to classify vessels is combined with vessel grouping to reduce waypoints in the flight plan. The UAV's onboard sensors provide input to this neural network for each vessel in the search area, resulting in a prioritization of the vessels to be visited.

II. OPERATIONAL CONTEXT AND PROBLEM FORMULATION

The traveling salesman problem (TSP) is a classic problem in the literature, with a well-known ILP formulation (see hereafter). Various approaches have been introduced to find an (approximately) optimal solution. For example, Gupta et al. [15] modify the genetic algorithm (GA) using the parent selection in the randomized bias (RBGA) method to compute an optimal solution. Nikfarjam et al. [16] introduces the biased 2-OPT mutation into Evolutionary Diversity Optimization for the TSP, which mainly focuses on more frequent components in the population and aims to decrease their frequency to increase diversity.

Bossek et al. [17] introduce a new variant called the node weight-dependent TSP (W-TSP), where nodes have weights that influence the cost of the tour, as the weights are collected during the route, and each distance is multiplied by the weight of the cities already visited. It captures aspects of other TSP variants, such as the time-dependent TSP or the traveling thief problem (TTP). In the TTP, the overall benefit is given by the profit of the collected items minus the cost of the tour. This cost increases with the weight of the collected items. Clearly, the weights impact the structure of the solution found.

In this paper, we present a maritime patrol TSP where, as we will explain later, we also use weights to alter the Euclidean distances. The goal is to find target vessels that are involved in some illegal activity as soon as possible. As illegal fishing is a serious problem that profoundly affects the economic sector of a country, we consider the case of fishing vessels that are fishing illegally. The sooner these specific fishing boats can be located, the better it is for successfully completing the mission. For example, if it takes too long to visit these boats, they can escape or cease their illegal activity. Our problem may be seen as a special case of the traveling repairman problem (TRP), where the goal is to minimize the sum of the waiting times of jobs; see Afrati et al. [18]. In our case, it is the total time until the drone reaches the last of a set of yet-unknown targets; see van Ee et al. [19].

Duca et al. [20] use a dataset of 600,000 ships to show that the length of a fishing vessel usually has a maximum of 50 meters. As the coast guard and the armed forces are only concerned with boats larger than 8.5 meters fishing illegally [2], vessels that are between 8.5 and 50 meters in length should therefore be *prioritized* (or *classified* as *probable fishing boats*) in the maritime patrol. This prioritization is based on the MarineTraffic [4] and information from the inverse synthetic-aperture radar (ISAR) of the drone. The ISAR is capable of locating and measuring the size of vessels (larger than 8 m) up to its maximum range (400 km). Although the result of this prioritization is available before the actual planning of the route, there is no information about the number and location of fishing boats that are committing illegal actions. As there are real cases (less than 5%) in which the fishing vessel is longer than 50 meters, and there are possible measurement errors, the actual route of the drone must eventually visit all vessels. The planned tour will therefore be one route visiting all vessels, where we must find the illegal fishing boats as soon as possible. (The range of the drone is not large enough to make a tour along the probable fishing boats (the prioritized vessels) and then also make a tour of the remaining vessels). To this end, we introduce a special variant of the classic TSP, where we use weights to deliberately increase the Euclidian distance toward vessels that are prioritized. As we will show, increasing the distances to any of these probable fishing boats is a simple and successful way to make sure that a computed tour visits the target vessels as soon as possible, even though, in the end, the complete TSP tour may not be the fastest route along all vessels.

In the TSP, one is given a set of N nodes with cardinality |N| = n. We denote a depot location by $0 \notin N$. Let $N+ = N \cup \{0\}$. To each arc $ij \in A \subset N+ \times N+$, we associate a cost cij representing the cost of using that arc in a tour. We introduce a binary variable x_{ij} for each arc ij. This variable is 1 if and only if the arc is used in the tour. An auxiliary variable u_i is introduced to denote the position of node i in the tour. We will investigate the TSP on the graph $G = (N, A)$. The objective is to find a tour that visits each vertex at least once, starting and ending at 0, with a minimum total cost.

$$\min \sum\nolimits_{ij\in A} c_{ij}x_{ij} \tag{1}$$

Subject to :

$$\sum_{i\in N} x_{0i} = \sum_{i\in N} x_{i0} = 1 \tag{2}$$

$$\sum\nolimits_{i\in N^+\setminus\{j\}} x_{ij} = \sum\nolimits_{i\in N^+\setminus\{j\}} x_{ji} = 1, \quad \forall j \in N \tag{3}$$

$$u_i - u_j + 1 \le \left(1 - x_{ij}\right)|N|, \quad \forall i, j \in N \tag{4}$$

$$1 \le u_i \le |N|, \quad \forall i \in N \tag{5}$$

$$x_{ij} \in \{0, 1\}, \quad \forall (i, j) \in A \tag{6}$$

The objective function is given by (1). Constraint (2) guarantees that the tour starts and ends at the depot. Constraint (3) is the flow conservation constraint and ensures that a node is visited exactly once. Constraint (4) prevents sub-tours, and Constraints (5) and (6) are boundary and integrality constraints on the decision variables. The cost in the objective function represents the (Euclidean) distances between nodes.

As mentioned before, in this present work, distances toward probable fishing boats will be increased. An intuitive explanation of how this might be effective in finding target vessels as soon as possible is the following. Increasing the real distance locates the fishing vessel in a "remote" area, forcing an optimal route most of the time to prioritize these fishing vessels over the vessels not classified as probable fishing vessels. If the optimization algorithm left this remote point to visit later, the cost would most often be higher. Increasing distance will, so to speak, tempt the solution to prioritize the visit to these vessels, as can be seen in Fig. 3, which shows the TSP versus the bias-TSP. The effectiveness of our scenario will be shown in a later section by means of simulations.

The main goals of this article are to:

1) Demonstrate the usefulness of increasing the distances to probable fishing boats to find vessels fishing illegally as quickly as possible.
2) Propose a preferred direction of the tour (clockwise or counterclockwise) based on the prioritization of vessels and operational practice.
3) Analyze the impact of the drone taking off from different locations along the coast in our scenario.

III. THE MARITIME SCENARIO

Usually, maritime scenarios are complex, as the maritime traffic environment near the coast can be very chaotic: there are many fishing boats in this strip, and the maritime traffic close to a port is very intense [2]. In addition, it is very difficult to predict the speed and displacement of fishing vessels, as they generally do not have a route as regular as a merchant ship. On the positive side, MarineTraffic [4] is used to eliminate vessels with an automatic identification system (AIS) that are not fishing boats.

To generate maritime scenarios for our simulations, we used information from the MarineTraffic website [4], complemented with information from maritime traffic reports from the Brazilian Air Force and Brazilian Navy. It was used to generate the distribution of vessels in an area of 370 × 370 km off the Brazilian coast.

As a result, the following assumptions, reflecting real-life maritime scenarios, were made:

1) Vessels with AIS and that were identified in MarineTraffic as non-fishing boats were ignored;
2) The scenario comprises 30 vessels in an area of 370 × 370 km;
3) Only fishing boats longer than 8.5 m are considered in this work.
4) Of all vessels, 36% are fishing boats;
5) Most (83%) fishing boats are located up to 60 km from the coast;
6) Some (17%) fishing vessels are located between 60 and 370 km from the coast;
7) 64% of the total number of vessels are non-fishing boats randomly distributed within an area of 370 × 370 km.
8) One (or more) of the points designated as fishing boats is (are) randomly tagged as a criminal or target boat. For this study, a maximum number of four targets was considered, assuming that in a real situation, it is very unlikely to find more than four boats fishing illegally in the area considered.

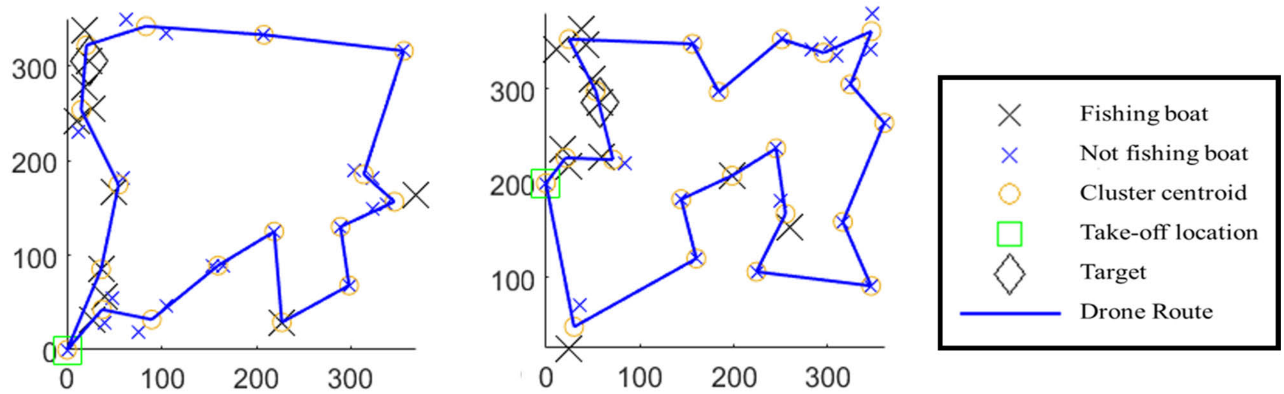

FIGURE 1. Scenario 1 on the left and Scenario 2 on the right.

Considerations regarding the drone:

1) It has an ISAR capable of locating and measuring the size of vessels (longer than 8 m) up to its maximum range (400 km). Note: The ISAR measurement accuracy considered in this work is 95%;
2) It carries out a maritime patrol at an altitude of 8100 m, which allows the location of all vessels considered important up to a distance of 370 km.
3) It has an electro-optical sensor capable of identifying any vessel greater than 8 m at a distance of 35 km at an altitude of 8100 m.
4) The flight range of the drone is 2,000 km.

We created two different scenarios that differ only in the take-off location in the search area; see Fig. 1. In Scenario I, the drone takes off from the lower (or upper) corner of the search area. In Scenario II, the drone takes off from the middle of the search area. The two scenarios were created to verify if the take-off position influences the optimization. In Fig. 1, the land is to the left of the y-axis.

IV. METHODOLOGY

This work uses an ILP formulation of the TSP with some adjustments to find vessels fishing illegally as quickly as possible. To this end, we introduce four algorithms which will be compared regarding the mean distance traveled before they find all targets:

1) The *TSP algorithm* serves as a baseline approach. It uses the ILP formulation of the TSP, the same algorithm used in Lima Filho et al. [2]. The tour direction criterion used in this algorithm is as follows: the drone flies from its start to the closest vessel. This determines the orientation of the tour (clockwise or counterclockwise).
2) The *cluster algorithm*. In this case, the various vessels in the area are clustered, depending on the range of the UAV's electro-optical sensor, and then the process proceeds as in the *TSP algorithm*. The clustering technique employed is a hierarchical clustering of the vessels. First, the (Euclidean) distance between every pair of vessels is calculated. Then, from the set of pairs of vessels that are within a pre-chosen distance L, the two closest vessels are paired in a cluster. The cluster replaces the vessels inside and new pairwise distances are calculated. This adjusted distance from one cluster to another, or to a vessel outside any cluster, is calculated as the largest distance between vessels in the two clusters, or from the vessels in the cluster to the vessel outside. Based on the new distances a new pairing is performed and then the process repeats until the minimal distance is larger than L. For each cluster, we create a new waypoint, replacing the vessels inside the cluster. To assure that all vessels of a cluster are within range of the electro-optical sensor when the UAV visits the new waypoint $w = (w_x, w_y)$, we take $L = R\sqrt{2}$ in the hierarchical clustering described above. Then, taking w_x to be exactly halfway between the minimum and maximum value of the vessel's x-coordinates, and likewise, for the y-coordinate of w, we may use Pythagoras' theorem to prove that all vessels are within range R. We refer to Lima Filho et al. [2] for more details. In this work, the clustering process uses the distance L = 50 km, which means that the drone must have an electro-optical sensor capable of identifying vessels at 35 km. The tour and tour direction criteria used in this algorithm are the same as in the *TSP algorithm*.
3) The *weight algorithm* is also based on the TSP. However, before applying the ILP, the real segment distances between points to visit are multiplied by a weight Z if any point of a given segment is a probable fishing boat and by Z^2 if both points are fishing boats. Here, we assume, as mentioned in Section II, that the drone can make a simple classification between fishing and non-fishing boats based on their size as measured by the ISAR. The tour is then generated based on the adjusted distances; however, the actual distances are used to determine the results. The direction of the tour used in this algorithm is determined as follows:

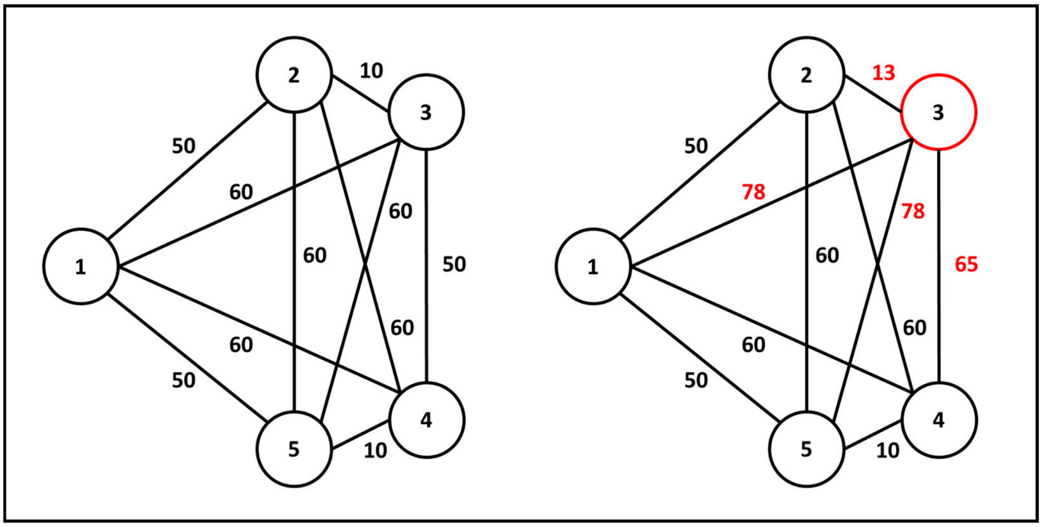

FIGURE 2. Traditional TSP on the left and BIAS-TSP on the right (multiplying 1.3 on the arcs leading to the fishing boat, node number 3). Note: The numbers on the arcs are distances in kilometers.

Calculate the number of probable fishing boats visited when, going clockwise, half the length (using real distances) of the total tour has been completed. Do the same for the counterclockwise case. Choose the direction that visits the most fishing boats. (Note that in Scenario I, this always will be parallel to the coast due to Assumption 5 in Section III).

4) The *bias-TSP algorithm* combines the *cluster algorithm* with the *weight algorithm*. The clustering procedure of Lima Filho et al. [2] is used. Then, comparable to the situation in the *weight algorithm*, the real distances to both the origin and destination of the segment are multiplied by Z^k, where k is the number of probable fishing boats within the cluster. The direction of the route used in this algorithm is the same as in the *weight algorithm*.

Note that the last two algorithms may have a different route orientation than the first two, as they are assumed to have equipment capable of classifying fishing boats. Hereafter, we will elaborate on the *weight algorithm*, and the *bias-TSP algorithm*.

A. THE WEIGHT ALGORITHM

In the traditional TSP, the points to be visited are equally important. However, in our maritime scenario, fishing vessels have a higher priority and must be visited as quickly as possible. Probable fishing vessels are identified by length due to a simple ISAR classification. However, the other vessels must also be visited due to fishing vessels that exceed 50 meters in length and possible measurement errors (5% error in the ISAR classification).

As mentioned before, the range of the drone is not large enough to make a tour along the probable fishing boats (the prioritized vessels) and also tour the remaining vessels. The planned tour will therefore be one route visiting all vessels. In addition, in a manned maritime patrol, a pilot often deviates from the ideal route to investigate a possible target and then returns to the route and visits all vessels. Therefore, we allow the visitation of all points, as in the classic TSP. To prioritize the visit of fishing boats, we use a weight to multiply the distances to these boats. After the algorithm plots the tour, the actual distances would be re-entered into the calculation of the true distance to the target.

Several weights between 0.8 and 1.4 were tested, as will be discussed in Section V. For the proposed scenario, weights between 1.1 and 1.25 obtained the best results. We will show that slightly increasing the real distances to probable fishing boats gives the best results and outperforms the TSP.

In the context of Fig. 2, the use of weights does not seem to make sense. However, in the context of Fig. 3, where there is a specific scenario, the use of weights leads to a desired prioritization of fishing vessels. Note that in the traditional TSP, the total route is shorter (307 km), and in the *weight algorithm*, although the total route is longer (334 km), the route prioritizes the fishing vessels and finds the target first (29 km before the traditional TSP). This 29 km of flight can be the difference between the target escaping the area or stopping illegal fishing activity and the drone not being able to register the fact.

The weights are used before computing the route; however, after optimization and tour orientation, the weights are replaced with the original distances. It is worth mentioning that to give the tour orientation, the algorithm checks which direction has more fishing boats, up to the radar limit (370 km in this work).

B. BIAS-TSP ALGORITHM

Bias-TSP uses the clustering process of Lima Filho et al. [2]. We create a new waypoint for each cluster,

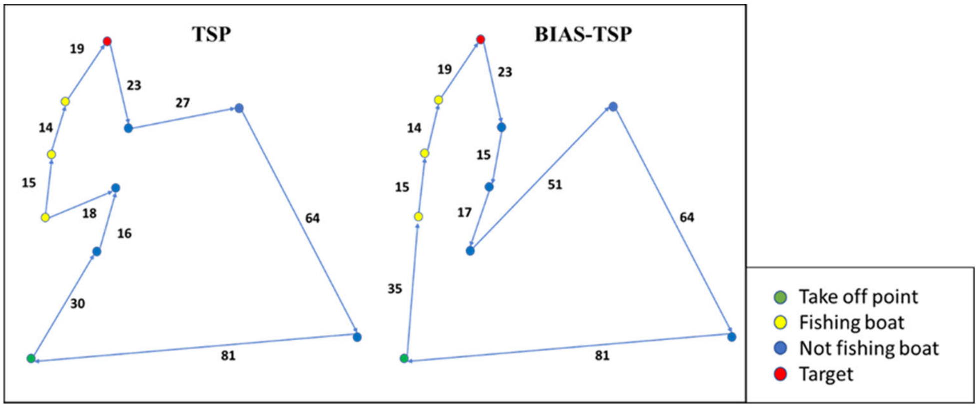

FIGURE 3. Examples of Traditional TSP and BIAS-TSP in an operational context. Note: The numbers on the arcs are distances in kilometers.

replacing the vessels within the cluster and thus decreasing the number of points.

After applying the weights, the ILP is used to find the shortest tour. Then, the true distances are used to calculate the total distance of the route to the targets. As in the *weight algorithm*, the direction of the route is given by the direction that contains more fishing boats, as explained before. The pseudo-code can be seen in Table 1

TABLE 1. Pseudo-code.

Bias-TSP Algorithm	
1.	Generate Initial Scenario according to Section III;
2.	Tag a maximum of four target fishing boats randomly;
3.	Apply the clustering process;
4.	Apply the weights Z^k;
5.	Solve the ILP;
6.	Find the route direction (the direction that contains more fishing vessels)
7.	**Output_1:** Best route found;
8.	Replace the true distance in the best route;
9.	Calculate the total distance to the last found target;
10.	**Output_2:** Distance to the target(s).

V. RESULTS AND ANALYSIS

This section presents the results obtained from the simulations and the analysis from a statistical and operational point of view.

A *t-test* was performed on the mean values presented in this section, and a *p-value* of 5% was determined to be significant.

A. CHOICE OF WEIGHTS

Several simulations were performed with different weights in the two proposed scenarios introduced in Section III to verify whether the weight algorithms proposed in the previous section are effective.

Preliminary tests of weights with values from 0.2 to 3 with a spacing of 0.1 were carried out. Only the most extreme values are shown in Figures 4 and 5. Note that a weight equal

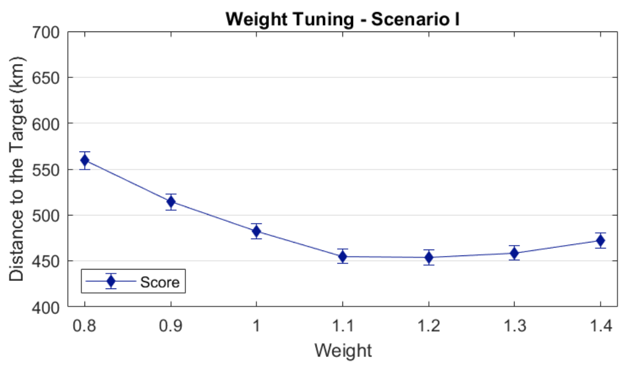

FIGURE 4. Weight tuning of Scenario I. Note 1: Error bars represent 95% confidence intervals.

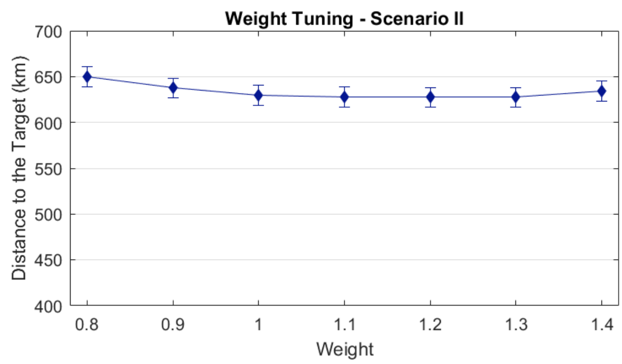

FIGURE 5. Weight tuning of Scenario 2. Note 1: Error bars represent 95% confidence intervals.

to 1 refers to the classic TSP, supplemented with the route orientation, as in the weight algorithm. Therefore, this part of the experiment sought to find a weight that was significantly better than weight 1.

Based on a statistical analysis with the t-test and defining a p-value of 5% as significant, we found that in Scenario I, the algorithm using a weight of 1.2 had the best performance, resulting in the smallest mean total distance traveled to the targets. Using the same tests in Scenario II it was verified that the algorithm with a weight of 1.2 also obtained the best performance; however, the difference was not significantly better. We can conclude that the application of weights in Scenario II did not significantly influence the result. Note: If we have a scenario that differs from the one described in Section III, probably the optimal weight may change.

B. EVALUATION OF THE FOUR ALGORITHMS

This subsection seeks to evaluate the algorithms described in Section IV to determine which one finds the targets in the shortest mean distance; that is, which one finds the targets as soon as possible.

Figs. 6 and 7 show the results of 16,000 simulations for each scenario. For this experiment, a random distribution of vessels and targets is generated as described in Section III, and the four algorithms are applied. Scenarios with one, two, three and four targets were created. Each time, the mean distance to the targets for each of the four algorithms is calculated.

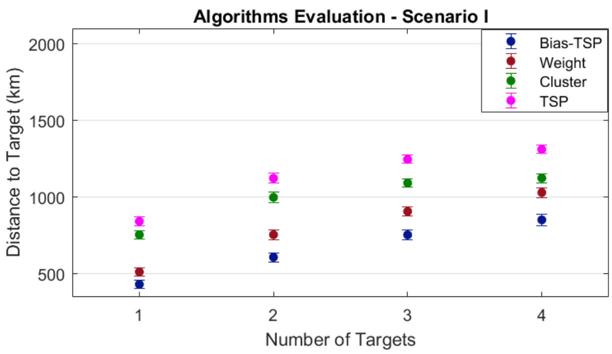

FIGURE 6. Algorithm evaluation in Scenario I. Note 1: Each colored dot in the figure above represents the mean of 1000 simulations with the respective algorithm. Note 2: Error bars represent 95% confidence intervals.

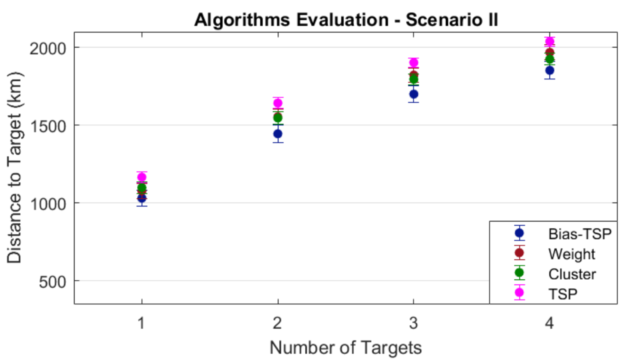

FIGURE 7. Algorithm evaluation in Scenario II. Note 1: Each colored dot in the figure above represents the mean of 1000 simulations with the respective algorithm. Note 2: Error bars represent 95% confidence intervals.

Using Fig. 6, we can see that for Scenario I, where the drone departs from the lower (or upper) corner of the search area, the algorithms that use the weight Z (*weight algorithm* and *bias-TSP algorithm*) obtain the best performance, even with the increase in the number of targets.

In Scenario II, the *bias-TSP algorithm* had a significantly better performance than the traditional TSP and the *cluster algorithm*. However, as shown in the previous subsection, the use of weights in Scenario II did not significantly influence the result; this performance improvement was due to the route direction criterion and not the weighting system.

Figs. 8 and 9 show the results of the same simulations in the form of percentage gains of the *bias-TSP algorithm* over the other algorithms.

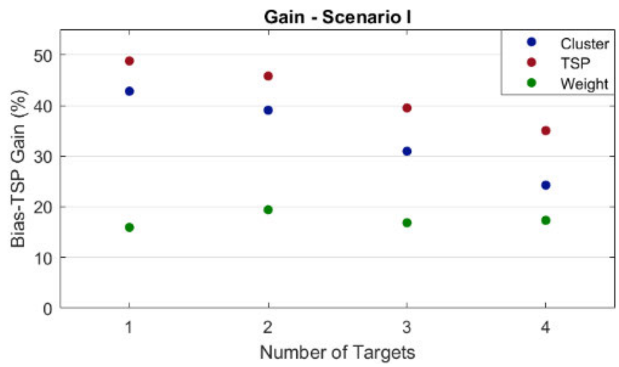

FIGURE 8. Gain of the bias-TSP algorithm in relation to the other algorithms in Scenario I.

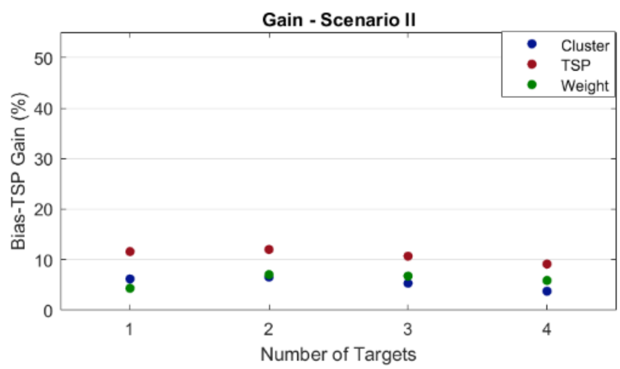

FIGURE 9. Gain of the bias-TSP algorithm in relation to the other algorithms in Scenario II.

In Scenario I, the gain of the *bias-TSP algorithm* decreases compared to the TSP and *cluster algorithm* in the cases where the number of targets is increased. The *bias-TSP algorithm* presented a gain of 49%, 46%, 40%, and 35% over the traditional *TSP algorithm* in the simulations with one, two, three and four targets, and a gain of 43%, 39%, 31%, and 24% over the about the *cluster algorithm* in the simulations with one, two, three and four targets. When the *bias-TSP* is compared with the *weight algorithm*, the gain stays approximately the same, between 16% and 19%, because the difference between the two algorithms is only the clustering process, which does not change with the increase in the number of targets.

In Scenario II, the gain of the *bias-TSP algorithm* over the others varied between 4% and 11% because, as already shown, there was no contribution from the weights; the contribution was made by the direction of the route combined with the clustering process.

When the mean distances to the target in Scenarios I and II were compared, it was found that all algorithms performed better by an average of 44% in Scenario I.

C. OPERATIONAL ANALYSIS

From an operational point of view for situations that resemble our maritime scenario, the *bias-TSP algorithm* should be used in any scenario that intends to identify illegal fishing vessels when there is no information beyond the search area. Analyzing the two scenarios using any of the algorithms presented in this work showed that beginning at the corners of the area is always better.

The algorithm proposed in this work is simple to implement and has a low computational cost. Regarding operational requirements, the drone only needs an ISAR to locate and measure the size of vessels and an electro-optical sensor capable of identifying large fishing vessels at a distance of 35 km.

The algorithms based on weights were also compared with the state-of-the-art algorithm for fast vessel identification, the *pre-classification algorithm* [2]. In this test, 10,000 simulations were carried out. However, the *pre-classification algorithm* did not have the flight range to fulfill 74% of the simulations because in this work's scenario, in addition to finding the targets, the drone must identify all the vessels since there is no information about the exact number of targets.

VI. CONCLUSION

Flying a drone to check for a vessel fishing illegally is a routine mission for many security agencies. Therefore, this work developed a methodology to search for illegal fishing vessels when there is no information about the vessels, and only the search area is known.

The application of weights in the algorithm showed good performances in Scenario I but was not found to be significantly different in Scenario II. The *bias-TSP algorithm* should be used in Scenario II, as it has characteristics, such as the direction of the route, that give it better performance than the other algorithms presented in this work.

Whenever possible, the drone should take off from the upper or lower corner of the search area. This improves the performance of the algorithms presented in this study. In our scenarios, the fishing boats are, in most cases, near the coast. This preference is easy to understand given the decision that must be made about the orientation of the tour.

The *bias-TSP algorithm* outperformed the other algorithms in all scenarios. It proved to be an effective algorithm, is easy to implement, and can be used in drones with basic maritime patrol equipment (ISAR and electro-optical sensor).

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