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RESEARCH ARTICLE

Time-Critical Maritime UAV Mission Planning Using a Neural Network: An Operational View

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ABSTRACT An operational planning procedure for a time-critical maritime unmanned aerial vehicle (UAV) search mission is introduced and evaluated. The mission is the fast identification of a target vessel. The triggering report only contains information regarding the category and displacement of a vessel carrying out a prohibited activity, resembling operational situations. A neural network trained to classify vessels is combined with vessel clustering to reduce waypoints in the flight plan. The UAV's onboard sensors provide input for the neural network regarding each vessel in the search area, resulting in a prioritization of vessels to be visited. As the accuracy of the classification and the possibilities for clustering depend on several operational factors as well as on the UAV's sensor degradation, we investigate three methodologies to identify which planning procedure to use in various operational situations. The results show that our robust and agile approach can help a UAV find the unknown target vessel as soon as possible.

INDEX TERMS Artificial intelligence, optimization methods, unmanned aerial vehicles (UAV), decision support systems.

I. INTRODUCTION

The oceans are important to all nations due to maritime transport, oil exploration, fishing, and their influence on the environment and climate on land. Unfortunately, many clandestine activities occur in the oceans, like maritime piracy and trafficking of people, narcotics, and weapons. In addition, environmental crimes such as illegal fishing, pollution, and dumping waste are an increasing concern regarding ocean governance, maritime safety and law enforcement [1].

In the exclusive economic zone (EEZ), which corresponds to an area stretching from the end of the territorial sea, 12 nautical miles (22 km) from the coast, up to 200 nautical miles (370 km), the coastal state is primarily responsible for the preservation of natural resources. It has judicial and supervisory powers to combat the dumping of ship waste and pollution from offshore activities [2].

Many countries have a huge EEZ, making constant monitoring to inhibit and detect crimes at sea very difficult [3]. Some alternatives are emerging, such as monitoring illicit activities by satellites. However, this monitoring is restricted, as it can identify pollution at sea but cannot subsequently identify the responsible vessel. An even bigger problem happens with illicit fishing because it may be possible to detect an unusual movement of a vessel on the high seas without being able to prove an unauthorized fishing activity, let alone identify the specific vessel.

Many armed forces and coast guards have been improving their methods of planning and executing maritime patrols to inspect the oceans, mainly in the EEZ. In maritime patrols, aircraft are generally used for detection (location of something of interest); classification (boat, iceberg, oil slick, etc.); identification and inspection (name and nationality of the

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vessel and object activity); and execution (notice of issuance or collection of evidence) [4]. Any immediate action needed, such as the seizure of the vessel, is carried out by a patrol vessel in the search area, accompanying the aircraft.

Unmanned aerial vehicles (UAVs) have several advantages over manned aircraft [5]. In the case of maritime patrol, those advantages include greater autonomy, greater stealth, and a much lower operating cost. UAVs have been used very successfully for decades by countries like the United States, Japan, Pakistan, Spain, India, and China in different maritime missions, such as patrol and law enforcement, investigation and evidence collection, emergency action, maritime search and rescue, oil spill and ship discharge pollution monitoring, buoy patrol and examination, channel survey, and international maritime supervision or maritime patrol [6].

A. LITERATURE ON UAVS IN MARITIME MISSIONS

Several studies have presented applications of UAVs in maritime surveillance missions, mainly developing route optimization algorithms, one of the most important parts of planning. Dridi et al. [7] describe a multi-objective optimization approach to solve a maritime surveillance problem where a set of resources is assigned to a specific set of tasks: however, routing is not considered. Amaral et al. [8] seeks to optimize the detection and tracking of targets using a swarm of UAVs for maritime border surveillance.

Kumar and Vanualailai [9] present a Lagrangian swarm model that can cover large areas of the sea effectively. The controllers derived in this work generate a linear formation that, if applied to dynamic systems, will have the capacity to be a very good model for the effective surveillance of an EEZ and also for search and rescue. Monitoring the activities of trawlers in Kuala Keda is studied by Suteris et al. [10]. They create a route optimization method for UAVs for maritime surveillance. The goal is to find the fastest route, to cover all the locations at sea, either by boat or by boat and UAV.

Fauske et al. [11] describe a model for studying the movement of force elements (FEs, the vehicles used in surveillance) to keep a recognized maritime framework sufficiently up-to-date. The marine area of interest is divided into a grid of hexagonal cells, and the FEs move from cell to cell. Each cell must be observed a certain number of times during the planning horizon, and the time lag between successive observations must not exceed a certain threshold, which may vary for different cells.

Brown and Anderson [12] optimize the trajectory of a UAV for wide-area maritime radar surveillance. Considerations of the dynamics, propulsion, and mission requirements of a fixed-wing UAV and maritime surveillance radar provide a method for obtaining fuel consumption, detection probability, and revisit time for a given trajectory.

Suseno and Wardana [13] present a method to create a flight path for a maritime surveillance mission to identify vessels carrying out illegal fishing. The number of nodes in the route is significantly reduced using a point clustering technique to shorten the flight path. The route is plotted using the nearest neighbor algorithm from the takeoff location, then to all vulnerable points, and back to the landing location.

B. OPERATIONAL ISSUES AND OUR APPROACH

The maritime traffic environment near the coast can be very chaotic as there are many fishing boats on this strip and the maritime traffic near a port is very intense. Trespassing vessels or vessels carrying out some illegal activities are hard to locate. These vessels can use some subterfuge to mask their intention, such as staying close to other vessels and not turning on the automatic identification system (AIS) to hide information from search aircraft. In addition, weather conditions make the area to be patrolled full of uncertainties and very dynamic. These changing conditions make it hard to predict the minimum distance needed to identify and recognize a vessel with good resolution. Therefore, from an operational point of view, planning a fixed maritime patrol route before a flight is almost impractical.

Of course, there are ways to estimate at-sea vessels' data using internet pages [14] and satellite images. However, this information is not extracted in real-time. It also does not provide all information regarding medium and small vessels: the International Maritime Organization (IMO) requires that AIS be fitted only aboard ships of 300 gross tonnage and upwards engaged on international voyages, cargo ships of 500 gross tonnage and upwards not on international voyages, and all passenger ships irrespective of size [15]. Therefore, these data will only be partially useful in pre-planning. After takeoff, the aircraft must update these often incomplete data using its sensors and must acquire more information needed to accomplish its mission, such as documenting a vessel carrying out illicit activity using video or still photography.

Altogether, this implies that a maritime patrol must use the information that the aircraft obtains in flight from its own sensors. This becomes even more important if one considers the non-cooperative behavior of some vessels.

This work aims to present a planning methodology for maritime patrols in a time-critical scenario using onboard sensors. Coast guard or air force aircraft usually search for vessels committing illicit activities, knowing the type of vessel and its displacement area using information about illicit vessels acquired through intelligence reports. The aircraft typically search a large area due to the lack of knowledge of the direction and speed of the target vessel. In our study, the objective of the maritime patrol in this time-critical scenario is to find the target vessel as soon as possible.

A classification of vessels is an essential component of this effort. Many studies consider the classification of vessels by training convolutional neural networks with images of different types of vessels. Recent studies are Mishra et al. [16] and Liu et al. [17]. However, this type of classification does not use the information for route planning, as real-time image classification requires a high-resolution image that can only be acquired within a few miles of the vessel. To sidestep this limitation, we trained a neural network to pre-classify the vessels and thus prioritize them for investigation. This classification serves as input for the planning methodology. The data needed as input for the neural network can be acquired at a distance of several hundreds of kilometers (details provided in Section II. C). It uses onboard sensors, making its operational utilization by a patrol possible and enabling the patrol to find the target as quickly as possible. The traditional traveling salesman problem (TSP) looks for the fastest route to visit a set of predefined points. This work seeks to solve a different problem. There are predefined points to be visited, however, the journey ends as soon as a specific point (target) is found. In a real patrol mission, the target has some characteristics that can be used to prioritize the route towards it. In our methodology, these characteristics are collected by UAV onboard sensors and used in the neural network to prioritize the UAV route. Traditional TSP algorithms lack the sorting capability to prioritize the route.

The main contributions of this article are:

1) Using an artificial neural network to assist in planning the vessels to be visited;
2) Clustering vessels based on the range of the UAV's electro-optical sensor;
3) Optimizing the patrol route, considering variation in neural network accuracy and the range of the UAV's electro-optical sensor.

C. OVERVIEW OF THE PAPER

We aim to develop and evaluate an operational planning procedure for a time-critical search mission triggered by a report of illegal activity. The report only contains information regarding the type of the target vessel and its displacement area. The UAV has its onboard sensors at its disposal. In Section II, we introduce and evaluate three planning methodologies to find a target vessel as quickly as possible. We also introduce our maritime time-critical scenario that will compare the different methodologies. Their quality depends on several operational factors that we can consider, even though these are out of the control of the maritime patrol. In Section III, we consider uncertainty factors such as variation in our neural network accuracy (reduction of information that the aircraft can collect from vessels) and range variation of the electro-optical sensor (reduction of visibility due to weather conditions or sensor degradation). This way, our methodology has features related to robustness (predict uncertainties and plan for the worst-case scenario) and agility (easy and quick to adapt to changes due to scenario dynamics) [18] in finding the criminal vessel as quickly as possible. Our work is summarized in Section IV.

II. FASTEST ROUTE PLANNING METHODOLOGY

To search for a target vessel performing a criminal activity, this work uses an integer linear program (ILP) formulation of the TSP, with some operational adjustments that illustrate the use of information obtainable by onboard sensors:

1) The TSP algorithm serves as a baseline approach. It uses the ILP formulation (see hereafter) of the TSP, where the route aborts in case the UAV finds the target vessel.
2) The cluster algorithm also is based on the TSP, where the route finishes when the UAV finds the target vessel. In this case, the various vessels in the area have been clustered, depending on the range of the UAV's electro-optical sensor.
3) The pre-classification algorithm also clusters the targets. In addition, it uses information from a neural network that will be discussed hereafter. This network has been trained to classify the type of vessels. The neural network output is used to route the UAV along clusters of vessels that contain at least one instance of the reported type of vessel. If the UAV, due to misclassification of the target by the neural network, did not find the target in any of these clusters, it must continue its route using the TSP to visit the other clusters until it finds the target.

The UAV uses a synthetic-aperture radar (SAR) to search for vessels. The SAR provides information about the speed, size, and heading variation of each vessel. It may also use electronic support measures (ESM) equipment to analyze the information from the vessels' radars. The UAV has an electro-optical sensor for vessel identification. It is also assumed that the UAV performs the patrol at an altitude of 8,100 meters, which allows the location of all vessels considered important up to a distance of 370 km. Note that the UAV can only identify the target vessel after visiting it or visiting the corresponding cluster. The UAV updates the route in flight to include the displacement of the ships and, depending on the range of the radar, the appearance of new vessels.

A. TSP ALGORITHM

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 c_{ij}. We will investigate the TSP on the graph $G = (N, A)$. The objective is to find a route that visits each vertex at least once, starting and ending at 0, with a minimum total cost. The formulation of TSP is as follows, where we introduce a binary variable x_{ij}, which is equal to 1 if the arc ij is included in the tour, and 0 otherwise:

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

$$\text{Subject to}: \sum_{i \in N} x_{0i} = \sum_{i \in N} x_{i0} = 1 \tag{2}$$

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

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

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

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

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

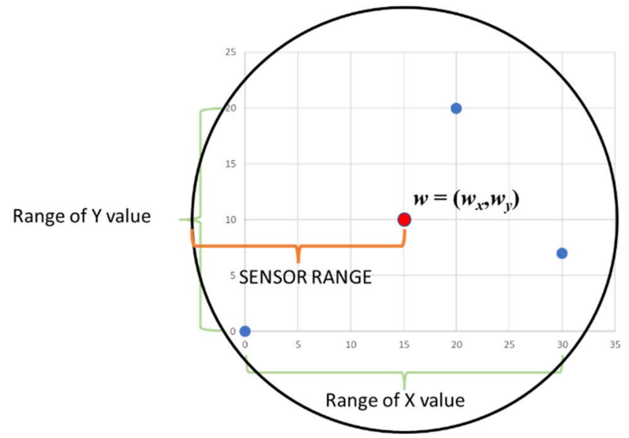

FIGURE 1. **Cluster example. NOTE: Blue dots = vessels; Red dot: centroid and new waypoint.**

sub-tours, and Constraints (5) and (6) are boundary and integrality constraints on the decision variables.

In this work, the vessels are the points to be visited, and as the UAV speed is in the order of 10 times greater than the vessels, the points are considered static. The UAV route finishes when it finds the criminal vessel.

B. CLUSTER ALGORITHM

As mentioned before, the UAV is able to localize all vessels considered important up to a distance of 370 km. This enables a clustering of all vessels in a 370 × 370 km area. This clustering and choice of new waypoints, introduced hereafter, explicitly utilizes the range of the electro-optical sensor R (somewhere between 10 and 25 km, depending on operational conditions or the type of equipment) of the UAV used for vessel identification.

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. Figure 1 illustrates this particular choice of creating a waypoint.

Lima Filho et al. [19] state that a spatial characterization is necessary to know if the resolution of the equipment is adequate for a mission at the operational level. Spatial characterization is the procedure that determines with precision what the actual field of view is of each detector element or how detailed the target is at a certain distance and altitude. However, we will consider that it is possible to perform the vessel identification in this work up to the maximum UAV's electro-optical sensor range. Figure 1 shows that if the UAV blocks the new waypoint, it will be able to recognize all the vessels that are within the cluster.

As shown in Suseno and Wardana [13], the clustering technique reduces the points to be visited and thus minimizes the flight path. The difference with our approach is that in Suseno, the clustering is based on cumulative historical data from a satellite, and the centroids are places that are frequently visited by ships.

We also remark that we can not use variants of the TSP, like the cluster TSP (CTSP). In that approach the UAV would have to visit at least one (arbitrary) vessel from each cluster. Instead, we identify a new waypoint, possibly not the position of a vessel, that guarantees that all vessels are within sensor range R. Obviously, the position of an arbitrary vessel from a cluster does not necessarily satisfy this property.

C. PRE-CLASSIFICATION ALGORITHM

The pre-classification algorithm uses a neural network to pre-classify the vessels, resulting in three different categories or types of vessel: fishing boats, merchant ships, and military vessels. Our case study considers a search for a vessel that is fishing illegally. Therefore, this algorithm looks for a TSP route along clusters containing at least one vessel that has been pre-classified as a fishing boat. The target vessel might be misclassified as a merchant or military ship; if so, its cluster may not be visited. In that case, the UAV follows a TSP and visits the remaining clusters that did not contain a fishing boat. Note that the misclassification may only occur if we use the neural network for route planning. Once the vessel is within range of the UAV's electro-optical sensor, it is identified with 99.99% accuracy.

1) THE ARTIFICIAL NEURAL NETWORK (ANN)

To perform the pre-classification of vessels, a neural network was developed with the same methodology as applied by Lima Filho et al. [20]. Preliminary tests were carried out with other types of machine learning, such as decision tree, support vector machine, and random forest. The results of these tests showed that ANN performed better than the others with the training set of the present study.

Information on heading variation for all classes was extracted from [14]. Information on military vessels (speed, size, and radar characteristics) was collected from reference [21]; merchant and fishing vessels (speed, size, and radar characteristics) were taken from [14], [22], [23], and [24]. A neural network was trained to classify the vessels into three classes: merchant ships, military ships, and fishing boats.

The characteristics of the vessels used for the classification were speed, size, and variation of heading observed in 30 minutes in the "PAST TRACK" [14]; radar emission frequency

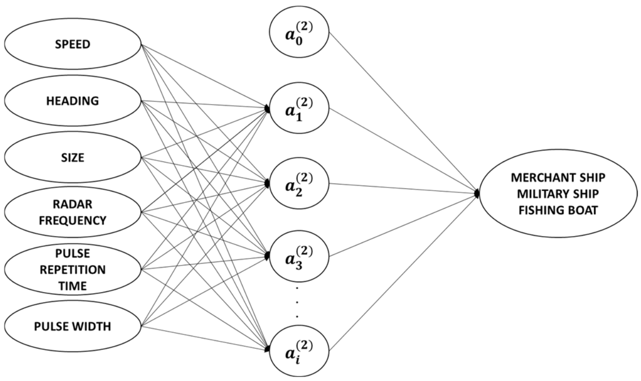

FIGURE 2. **Example of MLP with one hidden layer to classify vessels.**

TABLE 1. **ANN design of experiments.**

Parameters	Level 1	Level 2	Level 3
Solver	Adam optimizer [26]	SGD optimizer [27]	L-BFGS optimizer [28]
Hidden layers and hidden units	12	12, 24	12, 24, 48
Activation function	ReLu	Logistic sigmoid function	Hyperbolic tangent function

Note 1: 27 total runs.
Note 2: Default settings – Regularization = 1, Number of iterations = 200, Cross-validation number of folds = 10, Train test ratio = 0.7, Repeat train/test = 10.

(RF); radar pulse repetition time (PRT); and radar pulse width (PW). In this work, the type of ANN used is a multilayer perceptron (MLP), also often called a feed-forward neural network [25]. Figure 2 shows an example of an MLP with one hidden layer to classify vessels.

The training set was distributed as follows: 1000 merchant ships, 1000 military ships, and 1000 fishing boats. In the validation set, 350 samples of each class were used, totaling 1050 samples. The training set and validation set are available at https://github.com/GMLimaFilho/Time-Critical-Maritime-UAV-Mission-Planning.

To choose the parameters to be used in the MLP, a method similar to Lima Filho et al. [20] was utilized. Consequently, a design of experiment (DOE) of 3-level full factorial with three factors was applied, as shown in Table 1. The metric used to evaluate the results is accuracy. The following techniques were used to avoid overfitting: simplification of the model, early stopping, data augmentation, and the use of regularization [20], [25].

After the experiments documented in Table 1, a regularization tuning was performed with the values of $\alpha = 0.1, 0.5, 1,$ and 2.

D. THE MARITIME PATROL SCENARIO

This work aims to present a planning methodology for maritime patrols in a time-critical scenario using onboard sensors. We investigate which algorithm should be used, depending on the range of the sensor and the ANN accuracy. To this end, we created a realistic maritime scenario. To be precise:

1) Initially, 30 points are randomly generated and distributed in a 370×370 km area to represent the vessels in the search area.
2) Of the 30 points generated, 33% randomly received a tag designating them as fishing boats, mimicking the use of our ANN. Usually, the coast guard and armed forces are concerned about boats larger than 8.5 m fishing illegally. We found a mean of 32.6% of large fishing boats in the marine traffic on the Brazilian coast in March, April, and May [14]. We simulated different percentages of fishing boats (up to 60%) in our preliminary study and found that varying the percentage had a small impact on the results. The thirty vessels used in each simulation reproduce a typical scenario of the Brazilian coast, considering the area used and discarding vessels smaller than 8.5 meters. The different ranges of sensors used were based on the operational range of the sensors used in maritime patrol aircraft for vessel identification.
3) One of the points designated as fishing boats is randomly tagged as a criminal or target vessel.

Figure 3 shows an example of the performance of the three algorithms, where the sensor range used is 25 km (i.e., clusters 35.35 km in diameter). This example shows that the TSP algorithm flies vessel-to-vessel until it finds the target, and the cluster algorithm only flies over the centroids of all clusters in the route until it finds the target. The pre-classification algorithm only flies over the centroids of clusters that have at least one vessel classified as a fishing boat.

III. RESULTS AND DISCUSSION

In this section, we compare the three different algorithms for the time-critical scenario. To this end, we first derive the best ANN architecture for pre-classification. After that, we investigate the dependence on sensor range and ANN accuracy on the issue of selecting the best algorithm, using simulations of the maritime patrol scenario.

The *t-tests* and *p-values* with a 5% significance level were performed with all the average values of Figures 5, 6, 7, 8 and 10 to quantitatively support the results presented in this section.

A. THE BEST ANN ARCHITECTURE

This subsection aims to analyze which architecture is the best fit to train a data set of 3000 vessels with six features. For this, we selected the configuration of each solver in Table 1 that achieved the best accuracy, as shown in Table 2. A regularization tuning was performed with the values of $\alpha = 0.1$, 0.5, 1, and 2, as in previous ANN architectures. The best architecture found was the L-BFGS optimizer with one hidden layer with 12 hidden units, with a hyperbolic tangent function and $\alpha = 0.5$. This configuration reached an accuracy of 99.86% for the training set and 99.5% for the test validation. This ANN architecture will be used in the following discussion.

After choosing the best parameters for the MLP, an ANN feature withdrawal study was performed. The DOE is shown

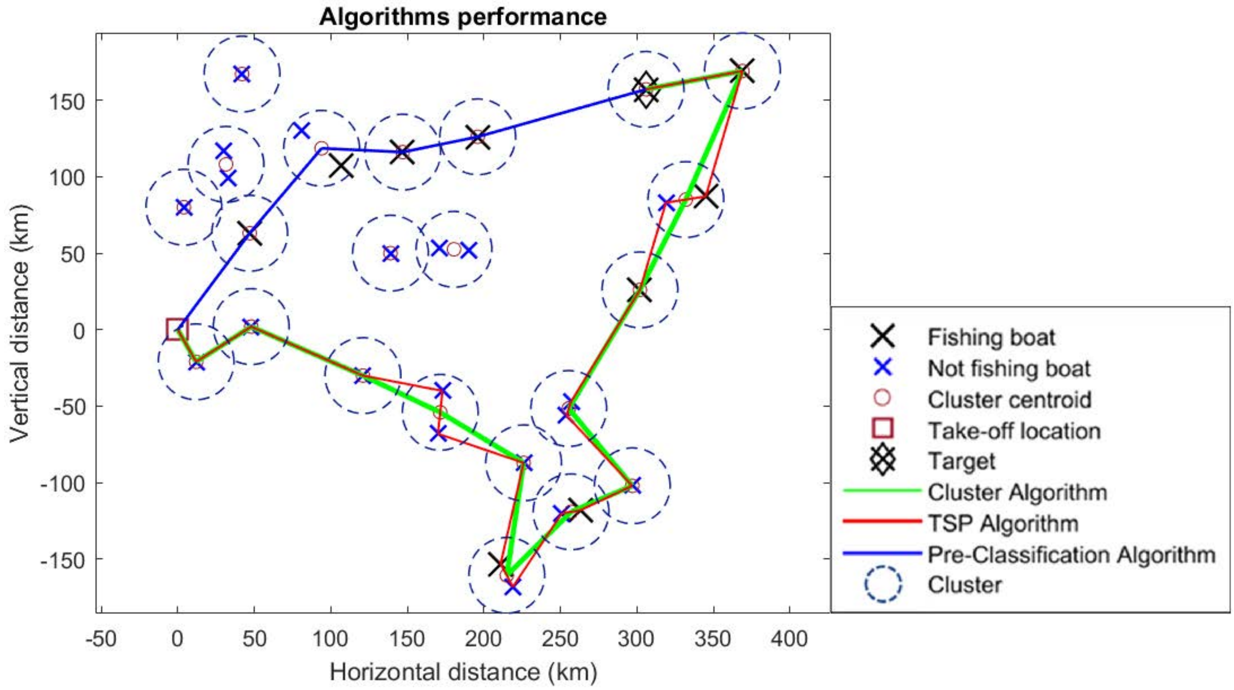

FIGURE 3. Algorithms performance. Note 1: The first three legs of the TSP algorithm route overlap with the first three legs of the cluster algorithm route. Note 2: The last leg of the TSP algorithm route overlaps with the last leg of the cluster algorithm route.

TABLE 2. The best ANN architectures.

Solver	Hidden layers and hidden units	Activation function	Accuracy
Adam	12, 24, 48	ReLu	99.5 %
SGD	12, 24, 48	ReLu	99.3 %
L-BFGS	12	Hyperbolic tangent function	99.8 %

in Table 3. This procedure simulates operational situations in which the UAV sensor does not receive a certain characteristic from the vessels. This will degrade the accuracy of the ANN.

TABLE 3. ANN feature withdrawal study.

	SPEED	HEADING	SIZE	RADAR SIGNAL (RF, PRT, PW)
CASE 1	YES	YES	YES	NO
CASE 2	NO	NO	YES	YES
CASE 3	YES	YES	NO	NO
CASE 4	NO	YES	NO	YES
CASE 5	NO	YES	YES	NO
CASE 6	YES	NO	YES	NO
CASE 7	YES	NO	NO	YES
CASE 8	NO	NO	NO	YES

Note 1: ANN needs at least two characteristics to work correctly.
Note 2: : YES = feature available, NO = feature withdrawn.

Figure 4 shows the variation in ANN accuracy due to feature removal.

Notice that cases 3, 4, 7, and 8, which have small accuracies, correspond to the cases in which the vessel size is unavailable.

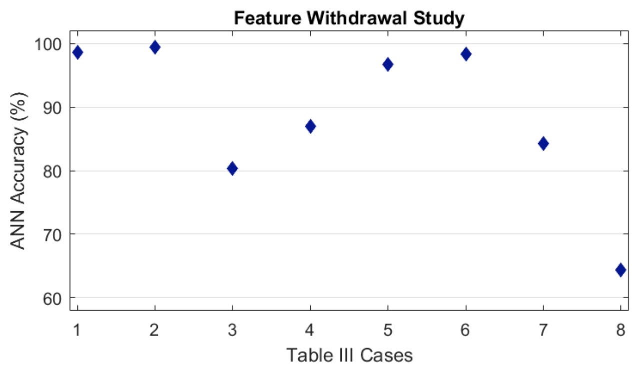

FIGURE 4. Variation in ANN accuracy due to feature removal.

B. VARYING SENSOR RANGE AND ANN ACCURACY

This subsection presents the experiments using the TSP, cluster, and pre-classification algorithms. The goal in the time-critical scenario is to find the target vessel as quickly as possible. This means that the measure of performance is the distance traveled to the target vessel (distance to target). This vessel can only be identified after visiting it or the corresponding cluster centroid. The three algorithms are run at each simulation. To investigate the dependence on sensor range and ANN accuracy, the maritime patrol simulations were performed using the experiments presented in Table 4.

Figures 5, 6, 7 and 8 show the distance to target as a function of the ANN accuracy for different sensor ranges given in Table 4. Note that the variation will only occur in the pre-classification algorithm, as it is the only one that uses the

TABLE 4. Description of experiments (EXP) performed.

Sensor Range (km)	ANN Accuracy 55%	ANN Accuracy 65%	ANN Accuracy 75%	ANN Accuracy 85%	ANN Accuracy 93%	ANN Accuracy 99%
10	EXP 1	EXP 2	EXP 3	EXP 4	EXP 5	EXP 6
15	EXP 7	EXP 8	EXP 9	EXP 10	EXP 11	EXP 12
20	EXP 13	EXP 14	EXP 15	EXP 16	EXP 17	EXP 18
25	EXP 19	EXP 20	EXP 21	EXP 22	EXP 23	EXP 24

NOTE 1: 1000 simulations were performed for each EXP and with the three algorithms: TSP, cluster, and pre-classification. A total of 72,000 simulations were performed.
NOTE 2: The ANN accuracy variation was chosen based on generic values.

ANN. The variation of the other algorithms is a function of the randomness of the experiments.

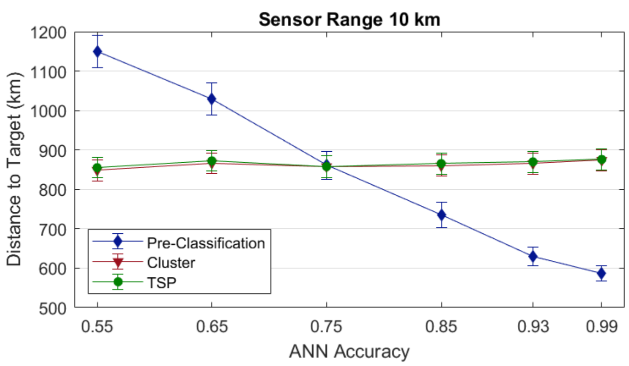

FIGURE 5. Experiments of three algorithms with a sensor range of 10 km. Note 1: Error bars represent 95% confidence intervals.

1) SENSOR RANGE 10 KM

Figure 5 shows no significant difference in the average distance to the target with the 10 km range sensor between the cluster and the TSP algorithms.

For the pre-classification algorithm, the distance to target decreases as the ANN accuracy increases. The other two algorithms perform better when the ANN has an accuracy lower than 75%. With an accuracy of 75%, the three algorithms have practically the same mean performance. However, when the pre-classification algorithm is compared with the cluster algorithm, it finds the target sooner in 64% of the cases and at the same time in 1% of the cases. For the same accuracy, the pre-classification algorithm finds the target sooner than the TSP in 65% of the cases and at the same time in 2% of the cases. With accuracy above 75%, the pre-classification algorithm performs best.

2) SENSOR RANGE 15 KM

Figure 6 shows that the cluster algorithm decreases the distance to target on average by 1.8% compared to the TSP algorithm.

The two algorithms perform better than the pre-classification algorithm when the ANN has an accuracy lower than 75%, similar to the previous case. Although the pre-classification, cluster, and TSP algorithms have the same performance when the accuracy is 75%, the pre-classification

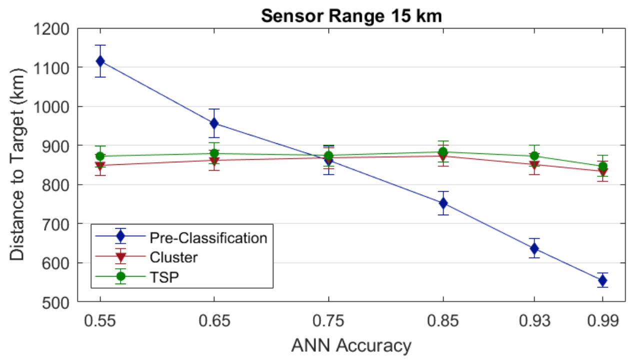

FIGURE 6. Experiments using three algorithms with a sensor range of 15 km. Note 1: Error bars represent 95% confidence intervals.

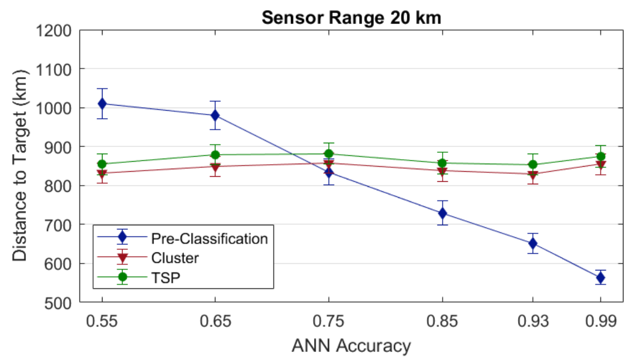

FIGURE 7. Experiments using three algorithms with a sensor range of 20 km. Note 1: Error bars represent 95% confidence intervals.

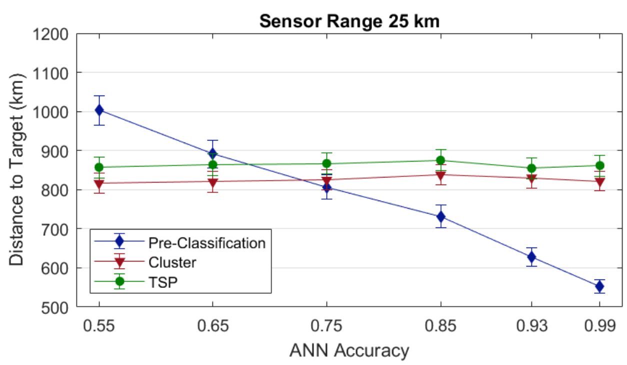

FIGURE 8. Experiments using three algorithms with a sensor range of 25 km. Note 1: Error bars represent 95% confidence intervals.

algorithm finds the target first in 65% of the cases when compared with the cluster algorithm, and 66% of the cases when compared with the TSP algorithm. With accuracy above 75%, the pre-classification algorithm performs much better than the other two algorithms.

3) SENSOR RANGE 20 KM

Figure 7 shows that the cluster algorithm outperforms the TSP by (on average) 2.8%. The two algorithms perform better than the pre-classification algorithm when the ANN has an accuracy lower than 75%, like the previous results. With an ANN accuracy of 75%, although the pre-classification and

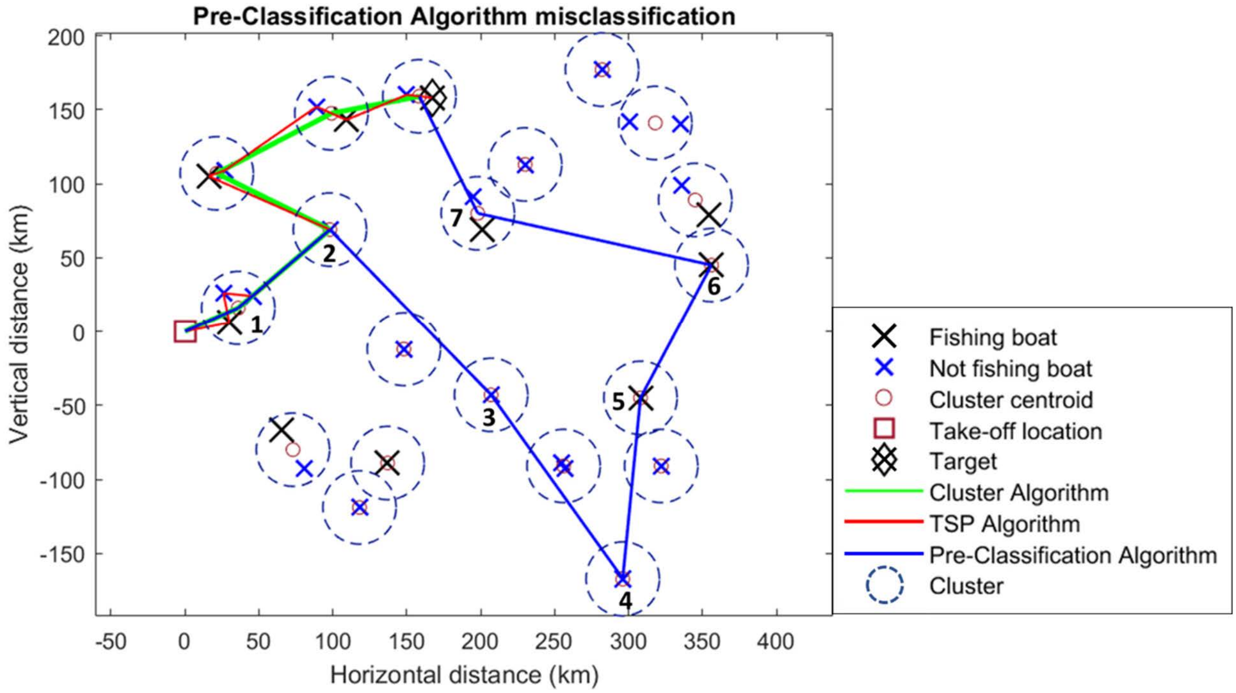

FIGURE 9. Pre-classification algorithm performance with low accuracy (65%) and misclassification. The sensor range is 25 km. Note 1: Centroid clusters of the pre-classification algorithm route were numbered to facilitate understanding. Note 2: The first two legs of the pre-classification algorithm route overlap with the first two legs of the cluster algorithm route, and overlap with the fourth leg of the TSP algorithm route.

cluster algorithms have practically the same mean, the pre-classification algorithm finds the target first in 65% of the cases and at the same time in 2% of the cases. With accuracy above 75%, the pre-classification algorithm is significantly better than the other two algorithms.

4) SENSOR RANGE 25 KM

Figure 8 shows that the cluster algorithm outperforms the TSP by (on average) 4.4%. Both of these algorithms perform better than the pre-classification algorithm when the ANN has an accuracy of 55%. With 65% accuracy, the pre-classification and TSP algorithms have statistically the same mean (*p-value* = 0.18), but the pre-classification algorithm finds the target first in 61.5% of the cases. With an accuracy of 75%, the pre-classification and Cluster algorithms have the same mean (*p-value* = 0.33), but the pre-classification algorithm finds the target first in 65% of the cases. With ANN accuracy equal to or greater than 85%, the pre-classification algorithm has a much higher performance than the other two algorithms.

If the accuracy is low, say 65%, we may encounter extreme instances of a maritime patrol mission for which the pre-classification algorithm performs worse than the other two. We present one in Figure 9. Using the pre-classification algorithm, the UAV is routed towards the nearest cluster centroid (1) that has been classified correctly as a fishing boat by the ANN. It then continues to cluster centroids 2, 3 and 4, but the three boats in these clusters have been misclassified by the ANN as fishing boats. The UAV continues its route until cluster centroid 7. After that, it finds the target indicated by the diamond. Figure 9 shows that both the TSP and the cluster algorithm find the target much sooner in this specific instance.

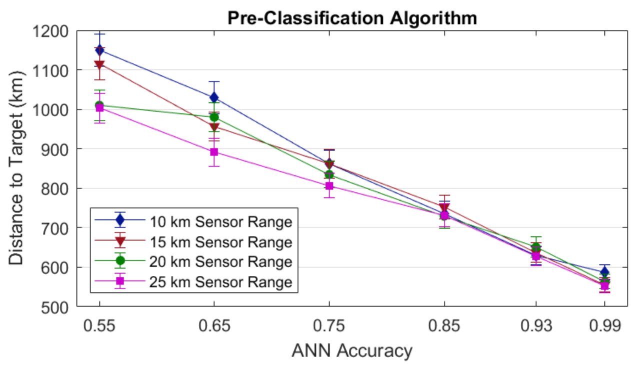

FIGURE 10. Experiments with the pre-classification algorithm with different sensor ranges. Note 1: Error bars represent 95% confidence intervals.

C. GENERAL ANALYSIS OF THE THREE ALGORITHMS

The performance of the cluster algorithm improves when the sensor range increases, as this increases the radius of the cluster, decreases the number of waypoints to be visited, and reduces the route. However, if the UAV has a sensor range of 10 km or less, the clusters contain so few vessels that the number of points to be visited is almost the same as the TSP algorithm. In that case, the cluster and TSP algorithms perform equally. The cluster algorithm is better than the TSP algorithm from an operational point of view at a 15 km sensor range and above. If the UAV's ESM is not working, it will lose the vessel's radar signal information (RF, PRT, and PW), and if the UAV's SAR is not working, it will lose the speed, heading, and size information from the vessels. Analyzing Table 3 and Figure 4, we can see that with the loss of information from the SAR, the ANN accuracy drops to 64%, and with the loss of the information from the ESM, the ANN accuracy drops to 98%.

The ANN only reaches an accuracy of less than 65% in CASE 8 in which the UAV only has the vessel's radar signal information as input into its neural network. In all other cases, the ANN has an accuracy greater than 75%. Analyzing the graphs in this section, regardless of the sensor range, shows that if the UAV has an ANN accuracy equal to or greater than 75%, the pre-classification algorithm will have superior performance. The pre-classification algorithm should not be used only if the UAV's SAR is not working.

D. PRE-CLASSIFICATION ALGORITHM ANALYSIS BY SENSOR RANGE

Figure 10 shows that for the ANN accuracy ranging from 55% to 75%, the sensor range makes a difference in the distance to target: it decreases if the range of the sensor increases. However, when the UAV has an ANN with accuracy equal to or above 85%, the sensor range has little influence on the distance to target, considering the analyzed range (from 10 to 25 km). Note that the UAV must have a sensor range of at least 10 km to perform target identification and record illicit activity. In the operational setting of a time-critical mission of finding a target vessel as quickly as possible, one may decide as follows: if the visibility is reduced to 10 km due to weather conditions, the pre-classification algorithm can be used without any performance loss as long as it has an ANN accuracy equal to or greater than 85%. So, if the UAV payload does not support a 25-km range sensor (which can be heavy), it can use a lighter 10-km range sensor as long as it has an ANN accuracy equal to or greater than 85%.

IV. CONCLUSION

This work developed a maritime patrol planning methodology for environmental protection to find a criminal vessel as quickly as possible.

A neural network was trained with data from 3000 vessels (information that can be obtained from a distance of hundreds of kilometers). It has been used to pre-classify the vessels and prioritize the vessels to be investigated. The ANN performed very well, even with few input features. Note that the information collected by the SAR increases the ANN accuracy more than the information collected by the ESM. If the ANN does not have any ESM information and has all SAR information (case 1), its accuracy is 98.57%, but if the ANN does not have any SAR information and has all ESM information (case 8), its accuracy is 64.38%.

Preliminary tests indicate that the best method for classifying vessels in this article is ANN. However, more robust tests were not performed with other standard machine learning algorithms. For future work, more detailed tests can be performed with different machine learning algorithms.

A cluster algorithm was developed to simulate the range of the UAV's electro-optical sensor, reducing the travel distance to the criminal vessel. The cluster algorithm performed better than the traditional TSP algorithm in all cases with the sensor range equal to or greater than 15 km.

An algorithm with a direct route to the pre-classified target vessels was also developed to optimize the patrol route, considering variation in neural network accuracy and the range of the UAV's electro-optical sensor. The pre-classification algorithm performed better than the other algorithms in all cases where the ANN accuracy was greater than or equal to 75%, regardless of the sensor range. If the ANN accuracy is greater than 85%, the sensor range has no impact on the vessel search.

We may summarize our findings for operational use as follows: if the UAV does not have SAR equipment, the cluster or the TSP algorithm must be used by a UAV with the electro-optical sensor range less than or equal to 10 km, and if the sensor range is equal to or greater than 15 km, only the cluster algorithm must be used. On the other hand, if the UAV has SAR equipment, the pre-classification algorithm must be used, regardless of whether the UAV's electro-optical sensor range is 10 or 25 km.

The pre-classification algorithm can be used to search any type of vessel (merchant ships, military ships, and fishing boats), as long as information about the class and the search area is available for planning.

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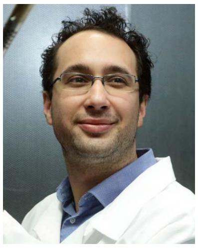

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