A Review of the Informative Path Planning, Autonomous Exploration and Route Planning using UAV in Environment Monitoring

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***Abstract*—Unmanned Aerial Vehicles (UAVs) have been used in several applications for monitoring environments and mapping. To carry out the mapping of these environments, the UAV needs to decide which path to follow to collect as much information about the environment to maximize the search area. In the literature, these issues are being addressed within the area of Informative Path Planning (IPP), Route Planning (PR) and Autonomous Exploration of environments. As a way to clarify these problems and their objectives in robotics, this article aims to present a comprehensive review on these areas highlighting their of approaches. For this, a comprehensive review of the main existing methods to solve them was carried out and this study serves as a starting point and a guide for everyone interested in exploring the monitoring area for data acquisition in unknown environments.**

***Index Terms*—UAV, enviroment monitoring, informative path planning, route planning, autonomous exploration.**

I. Introduction

UAVs have resources related to flexibility, security, ease of operation and low cost of ownership. These characteristics have facilitated the adoption of these vehicles in several areas, being used successfully in applications of traffic monitoring [1], monitoring of diseases in eucalyptus [2], monitoring in agriculture [3], [4] search and rescue scenarios [5], industrial inspection [6], environmental disaster areas [7], [8] surveillance missions, among other applications [9]–[12].

The monitoring area for data acquisition in unknown environments has been the study of many researches in the field of robotics, in these applications, it is necessary that UAVs visit a certain area, analyze the environment and make a decision on which path it should following to maximize the search area in order to collect information and/or knowledge about the environment minimizing uncertainties or the location of certain patterns.

In the literature, we found that these problems have been addressed in three areas of robotics research: Informative Path Planning, Route Planning and Autonomous Environment Exploration. These researches, despite being different, solve the same problem by giving different approaches and focus.

The Informative Path Planning problem is autonomous decision-making to define which route the UAV should follow to collect information about the environment. This way, paths need to be planned to maximize the information gathered about an unknown environment while satisfying the given budget constraint [13].

In the IPP approach, the researches on monitoring unknown environments using UAV have adopted some methods, such as: Bayesian Optimization (BO) using Gaussian Processes (GP), to collect a set of information sequentially considering a set of specific constraints for a given problem. [14] and [15] consider the BO-POMDP (Partially Observable Markov Decision Process) formulation to perform sequential decision-making under uncertainty [14]–[16]. Other approaches are Covariance Matrix Evolution Strategy - CMA-ES, Interior Point - IP, Simulated Annealing - SA [13], [17], [18] among other methods has been adopted.

Route Planning using UAV can be considered a variant of the classic problem in the literature, which is the Vehicle Routing Problem (VRP) [19]. For decision-making regarding finding optimal routes in unknown environments, UAV Route Planning aims to monitor the environment in order to maximize the visited area, increasing knowledge about the environment or minimizing uncertainties [2]. Some methods used for route planning are BO using GP [20] [2], Rapidly-exploring Random Tree - RRT [21], SA [22], among others.

In Autonomous Exploration, the problem of path planning in unknown environments is to produce a consistent representation of the environment. Autonomous Exploration also involves decision-making, selecting the trajectories that a robot should follow to minimize the overall uncertainty in the model and maximize the gain of information about the environment. Essentially, exploration is a path optimization procedure for finding trajectories that efficiently learn the environment [23] [24].

Some of the adopted methods are algorithms based on Occupancy Grid Mapping: Octomap with Road Map [25] [26] and Graph Simultaneous Localization and Mapping - SLAM

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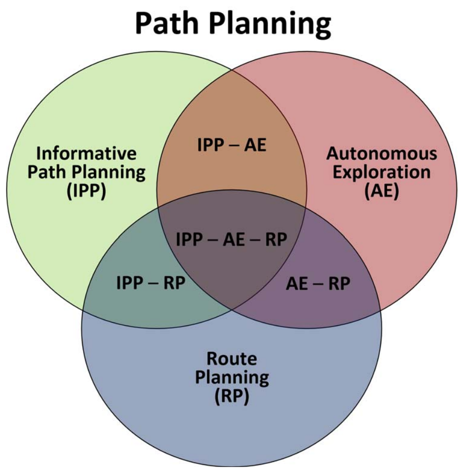

Fig. 1. The Informative Path Planning, Autonomous Exploration and Route Plannig Problem's.

[27] to perform the environment mapping.

Algorithms based on Occupancy Continuos Mapping are also considered, such as Hilbert maps together with BO and Stochastic Gradient Descent [28] [29] that also perform the environment mapping. However, the representation of the occupation states is continuous.

It can be noticed that the IPP, RP and AE problems have in common the search for decision-making involving UAVs to obtain optimal routes in unknown environments. However, they consider different restrictions and different approaches as a solution.

Therefore, as a way to analyze these approaches and provide a review for robotics, this article contributes to the understanding of Informative Path Planning, Autonomous Exploration and Route Planning using UAVs in unknown environments. The concepts and differences between these problems, as well as the main methods adopted to solve them will be presented.

The article is divided as follows. In Section II the description of the problems: Informative Path Planning, Autonomous Exploration and Route Planning. In Section III, an overview of the literature highlighting the main methods to solve the problems. And finally, in Section IV, the conclusion of this comprehensive review.

II. Problem Descriptions

This section presents the description of the Informative Path Planning, Autonomous Exploration and Route Planning problems based on the definitions given by the work carried out in the area of robotics research.

As shown in Figure 1, the Informative Path Planing, Route Planning and Autonomous Exploration problems are highlighted. The intersection between them form subcategories such as: IPP - AE [12], IPP - RP [2], AE - RP [25] and IPP - AE - RP. These subcategories are the union of the IPP, AE and RP problem's.

A. Informative Path Planning - IPP

Based on the works in the literature [14], [17], [30]–[32], IPP is characterized by the lack of knowledge about the environment a priori. In this case, it is necessary to obtain a map of the environment or get a graph.

According to [30], if the scientist manually specifies the robot's exact trajectory while collecting sensor measurements, the problem will be relatively simple. Thus, the robot autonomously decides which path to follow during the collection of measurements, based on a probabilistic model of a dataset to be studied is known as IPP. Another definition is that the task of choosing trajectories to maximize information gain is known as informative path planning and is a fundamental monitoring concept [15]. In the same sense as the previous work [32] [32] is defined the IPP.

Another definition of IPP is designing the route of a vehicle, which must follow in such a way that a certain goal is maximized and a goal is achieved. The IPP maximizes the information collected from targets in a region of interest (ROI) [9].

So, IPP is an NP-hard optimization problem and has a trade-off between map completeness and practical efficiency. This trade-off is related to the time to exhaustively monitor a large area to get as much information about the environment and search for an optimal global solution [18], [31], [32].

To carry out IPP, it is necessary to calculate the route to obtain the maximum of gain information about the environment, not being concerned at first with the movement that the UAV will make to carry out the trajectory, but with which route will be taken to collect the information about the environment. This must be done by monitoring as much area as possible and thus maximizing the information gains collected from the environment.

B. Autonomous Exploration - AE

In the same way the IPP, the AE is characterized by a lack of knowledge about the environment.

Thus, according to the works in the literature, they treat the problem of trajectory planning in unknown environments as an AE that aims to produce a consistent representation of the environment. AE also involves making complex decisions, selecting the trajectories that a robot will follow to maximize the information collected about the environment and also minimize the overall uncertainty of model the [24], [33].

Other authors emphasize that AE is a major precondition for building a map of an unknown environment with a robot to provide the data of interest. However, achieving this task efficiently in large-scale or high-dimensional environments is still challenging. [25], [26].

According to [24] Autonomous exploration can be seen as active learning that aims to minimize uncertainty and produce high-fidelity maps [34], [35], where exploration requires the simultaneous solution of mapping, path planning and location.

So, the AE is a high-level task dedicated to building the model of an unknown environment in which the vehicle frequently makes decisions to select the trajectories that a

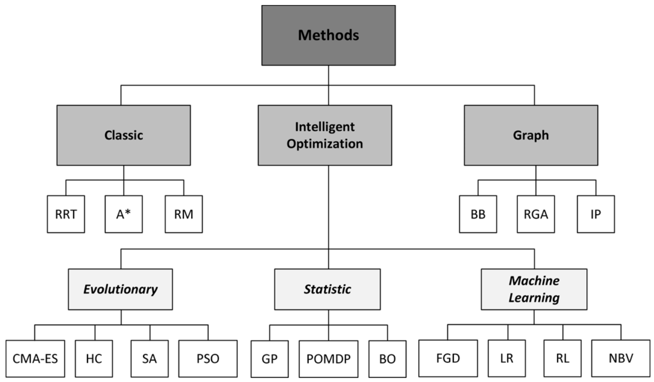

Fig. 2. The Taxonomy of analyzed methods for IPP, AE and RP in Monitoring Environment.

robot will follow to maximize the information collected about the environment and also minimize the uncertainty of model [25].

C. Route Planning - RP

When classifying routing literature, it can be segregated based on the problem type with an emphasis on the VRP, which has given the major research contributions in the domain of vehicle routing [36], [37] and is used as an input for all the routing problems in general [19]. So, when considering de UAV Route Planning monitoring the environment in order to maximize the visited area, increasing knowledge about the environment or minimizing uncertainties there is a similar problem with IPP.

In RP in unknown environments, the target is known, but the position of these targets is unknown. So an area must be tracked without knowing the location of the targets and therefore, it is necessary for the UAV to make a decision to identify these targets and plan its route, regardless of human support, this approach is known as route planning for an active classification. Thus, for decision making it is necessary to verify the information and extract the relevant data for the optimization of an efficient route planning according to each application [2].

Route planning is an important part of the unmanned aerial vehicle mission planning system [21]. There are many uncertain factors in the task environment of UAV, or the UAV is flying in a completely unknown environment [38]. At this time, the off-line route planning method is no longer applicable. The online route planning method can be used to generate a feasible route based on real-time detection of environmental information [39], [40].

III. Literature Review

This section presents a brief section on the challenges of planning missions for efficient data acquisition. A state-of-the-art overview highlighting the main methods developed to solve Informative Path Planning, Exploration and Route Planning problems.

As shown in the figure 2 was done the taxonomy of analyzed methods for IPP, AE and RP in the monitoring environment for the literature review. The methods were divided into classical, graph-based and intelligent optimization categories (Evolutionary, Statistic-based and Machine Learning).

A. Challenges

The monitoring area for efficient data acquisition in unknown environments has been the study of several researches in the field of robotics. According to the literature, it can be seen that the problems of Informative Path Planning, Route Planning and Autonomous Exploration address the same problem, but with different approaches.

So, there are still some challenges of how to plan missions to obtain efficient data in complex and unknown environments. To solve these problems in UAV path planning, it is necessary to make optimal decisions for various mission-critical operations performed by UAVs. These decisions require a map or graph of the mission environment so that UAVs are aware of their locations or close to their target/objective [41]. Keeping the focus on the aforementioned points, this reviews several UAV informative planning techniques used in recent years. The objective of the techniques is not only to find an ideal and shortest path but also to provide the environment map, as the environment is unknown in the cases of the informative path planning, autonomous exploration, and route planning problems discussed in this work.

B. Methods used for Informative Path Planning

In the search for solutions for IPP there are several methods proposed in the literature. Graph-based algorithms can be used to find trajectories to gain information about the environment [30], [42], [43]. Mixed Integer Linear Programming problems are generally solved using a linear-programming based branch-and-bound algorithm.

The key to Branch and Bound - BB [30] methods is finding an easily computable upper bound for the objective function. If the upper bound is loose (is often much higher than the actual objective), then a few branches of the search tree will be pruned. The goal is to find a function which is as tight as possible, while still being a valid upper bound.

The Branch and Bound was used by [30] to solve the IPP. The algorithm uses the objective function monotonicity to provide an acceleration dependent on the objective function versus the Brute Force Search. Results that suggest that by maximizing the reduction of variance in a Gaussian process model, the acceleration of the algorithm is significant were presented. To validate the algorithm, the execution time in different scenarios was analyzed.

Interior Point - IP is a certain class of algorithms that solve linear and nonlinear optimization problems [44]. The IP was used to approximate gradient-based optimization [13].

It can be noticed that in situations where there is a large dataset, graph-based methods are limited in terms of problem-solving. In these situations, these methods have exponential growth, which makes it difficult to find a solution.

Recursive Greedy Algorithm - RGA [43] can also be used, however, they tend to converge to local optimal.

Another methods are Statistics-based BO is a global optimization technique that possesses major advantages when used to find the maximum of partially observed objective functions that are costly to evaluate, lack gradient information, and can only be inferred indirectly from noisy observations [45].

BO is robust to this setting because it builds a statistical model over the objective. More specifically, it places a prior over the space of functions and combines it with noisy samples to produce an incremental prediction for the unknown function. The prior usually takes the form of a Gaussian Process (GP) [46]. The key component for the effectiveness of BO is the use of an Acquisition Function (AF) that guides the search for the optimum by selecting the locations where samples are gathered based on the posterior in each iteration.

In this way, Path-planning algorithms for environment exploration come in two flavors. Approaches in which the UAV decides on its next move one step at a time are referred to as myopic [15], [47].

Myopic algorithms are suitable for most situations but lack a mechanism for anticipation, which may be problematic in cases where path-planning decisions may have negative long-term consequences.

The main tool for this is the partially observable Markov decision process, which assigns a reward to each admissible sequence of actions. Nonmyopic approaches are computationally complex and incredibly expensive, which is why myopic approaches are often preferred [12].

One approach that we can highlight is the one developed by [13], as they are adaptive and non-adaptive strategies using CMA-ES. Non-adaptive approaches explore an environment using a pre-determined sequence of actions to execute the route [48]. Adaptive approaches allow routes to change as information is collected, making them suitable for planning based on specific interests [13], [17], [31], [32].

The CMA-ES is a generic global optimization routine based on the concepts of evolutionary algorithms which has been successfully applied to high-dimensional, nonlinear, non-convex problems in the continuous domain. As an evolutionary strategy, the CMA-ES operates by iteratively sampling candidate solutions according to a multivariate Gaussian distribution in the search space

As shown in Table I some methods are used for IPP in environment monitoring and aplication.

TABLE I
THE METHODS USED FOR IPP IN ENVIRONMENT MONITORING.

Year	Author	Methods	Aplication
2014	Marchant and Ramos	BO-GP	Environment monitoring
2016	Lim, Hsu and Lee	RAId	Disaster region
2017	Hitz et al.	CMA–ES	Monitoring toxic cyanobacteria
2022	Blanchard and Sapsis	BO-POMDP	Anomaly detection in monitoring

TABLE II
THE METHODS USED FOR AE IN ENVIRONMENT MONITORING.

Year	Author	Methods	Aplication
2015	Rossi	HC	Monitoring for gas leakage localization
2019	Francis and Ramos	RL and FGD	Exploration
2020	Wang et al.	NBV	Exploration

C. Methods used for Autonomous Exploration

The BO method [24] is also was used in an approach for AE and for building maps. This method finds optimal continuous paths rather than discrete detection locations that satisfy UAV security and motion constraints. By balancing the reward function and the risk associated with each path, the optimizer minimizes the number of function evaluations that are computationally costly.

Another method can be used is the Functional Gradient Descent (FGD) to efficiently optimize the exploratory paths in continuous occupancy maps [23]. Stochastic FGD was adopted to overcome the limitations of standard FGD methods in order to ensure convergence. This process allows for the optimization of the entire path, resulting in continuous smooth paths that maximize the overall map quality, keeping the robot safe from collisions. In addition, the results were compared with exploration methods such as RRT planner [49] and Frontier [50].

A method based on evolutionary algorithm [51] is an approach for monitoring environment in a gas leak location. The profile of gas concentration measurements was modeled using a 2D Gaussian distribution model and the search was performed applying an exploration strategy based on the Hill-Climbing. The gas source location strategy optimizes the speed of the aerial robot while minimizing the monitoring system's energy consumption.

It is interesting to observe in the work of [51], that despite the authors considering the proposed algorithm as an exploratory strategy that aims to build a map of the environment for locating gas leaks. It could be presented as IPP since the information collected from the environment as its main mission is the detection of gas in an unknown environment and for this to happen autonomously, a map is built online so that the UAV can locate itself in the environment.

Another approach to efficient UAV exploration was proposed by [25], where a Road Map - RM was built incrementally along with the exploration process that explicitly displays the topological structure of the 3D environment. By simplifying the environment, a road map can efficiently provide the information gain and cost for a candidate region to be explored, which are two quantities for Next-Best-View (NBV) evaluation, suggesting thus the efficiency for determining the NBV. In addition, a local planner was made based on the Potential Fields method that drives the robot to the information-rich area during the navigation process.

As shown in Table III some methods used for Autonomous Exploration in environment monitoring

TABLE III
THE METHODS USED FOR RP IN ENVIRONMENT MONITORING.

Year	Author	Methods	Aplication
2016	Meng et al.	RRT	Environment monitoring
2019	Vivaldini et al.	BO-RRT	Classification of diseased trees
2021	Hari et al.	TSP	Persistent monitoring missions

D. Methods used for Route Planning

The methods classics can be used for RP like Rapidly-exploring Random Tree (RRT) algorithm is an efficient path planning method, which can quickly find the feasible solution in complex environment [21].

The RRT with GP-generated occupancy maps was used to explore unknown environments [52] developed an algorithm that combines Rolling. The method consists of a route planner that collects information about a search area, focusing on parts with greater uncertainty and following a disorganized geometry.

Another algorithm based on the RRT for the UAV route planning problem in an unknown environment [21]. According to the current information from the environment, the local route planning is carried out at the same time, the new information from the environment is detected and the next stage of the route is generated.

A route planning methodology with active classification for UAVs, in order to increase knowledge of the visited areas and minimize uncertainties in the classification of diseased trees [20]. Five different route planning algorithms were evaluated, continuous BO, discrete BO, Random points, pre-established trajectory and RRT. The main advantage of continuous BO is the combination of RP (building a route between the origin and objective points) and active classification (which allows you to choose objectives based on how they affect the uncertainty of the environment).

As an extension of [20], [2] developed a route planning framework for active classification using UAVs to maximize the information collected within a given distance, limited by flight range. The authors proposed BO+RRT, where BO chooses the destination points and the RRT suggests the trajectory between these points. The Logistic Regression classifier was used to classify the sick/healthy/soil trees and a GP was used to interpolate this information, producing a navigation map.

It is interesting to note that the work of [20] and [2] could be presented as IPP since, for decision making which route to take to collect information from the environment, it was done to cover as much area as possible to maximize the gains information collected about an environment.

As shown in Table III some methods used for Route Planning in environment monitoring.

IV. CONCLUSION

This article analyzed the state of the art in the monitoring area for efficient data acquisition in unknown environments, addressing its main challenges. Informative Path Planning, Route Planning and Autonomous Exploration were theoretically clarified and the main approaches in this area were presented.

According to the works analyzed in the literature, it can be seen that the IPP, PR, and AE problems presented, treat Informative Planning as an autonomous decision-making problem of the aerial robot to know which route to take to collect information about the unknown environment.

However, there are some differences in the approach given, IPP and RP in unknown environments have as main objectives the collection of information, such as temperature, and humidity, among others, using an onboard sensor. AE, on the other hand, focuses on the construction of the map, that is, producing a consistent representation of an unknown environment.

It can be noticed that the three problems consider that the trajectory that the UAV must take in order to the mission it should be done in such a way as to cover as much area as possible to maximize the gains of information collected about an unknown environment and minimize model uncertainties. For this, different restrictions are used, such as maximum monitoring time, battery, distance, collision avoidance, curve smoothing, among others.

Regarding the approaches presented, although they are presented in different ways, the methods used to solve the IPP, PR, and AE problems are solved in similar ways with similar methods.

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