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Landmarks based path planning for UAVs in GPS-denied areas

Shreya Singh * **P.B. Sujit** **

* *IIIT-Delhi, New Delhi 110020, India (e-mail: shreya12160@iiitd.ac.in).*
** *IIIT-Delhi, New Delhi 110020, India and FEUP – Portugal (e-mail: sujit@iiitd.ac.in, sujit@fe.up.pt).*

Abstract: In this paper, we propose a UAV path planner travelling from a given source to goal location in GPS-denied areas. The environment consists of a set of cellular towers which are treated as landmarks having finite communication range. The vehicle has to perform dead reckoning in regions where landmarks are not available. Therefore, the objective is to determine a time optimal path taking the presence of landmarks into account while ensuring the covariance due to dead-reckoning is within a given bound. Solving the stochastic optimal control problem to determine a path in the continuous domain is very difficult and hence we discrete the path as a set of way points and optimize the location of these way points to obtain a time optimal path satisfying the covariance bounds. We use a particle swarm optimization technique coupled with a rabbit-carrot based path following technique to determine a near-optimal path. Numerical results are presented to show that our approach produces feasible paths that are near-optimal and satisfy the covariance bounds.

Keywords: Path planning, UAV, GPS-denied areas, navigation

1. INTRODUCTION

Unmanned aerial vehicle (UAV) applications are growing rapidly with the availability of low cost UAVs and cheap sensors and computational units in the market. A recent application being anytime delivery of essential supplies like medicines from one location to another [Agha-mohammadi et al. (2014); Mathew et al. (2015)]. In order to perform this task, the UAV needs to navigate from a source location (S) to a goal (G). For navigation, usually GPS with inertial measurement is used. However, there are many situations where GPS may not available- primarily due to interference [Trinkle and Gray (2001)] or lack of required number of available satellites at the desired location/region. Although a high precision inertial measurement unit (IMU) [Hanse (2004)] can be used, it costs several tens of thousands of dollars which is not a viable option for these applications. Under such circumstances, the UAV needs to navigate using an affordable IMU with the help of other external aids for localization.

Over recent years, several advances have been made in developing path planning algorithms that localize with the help of camera/lidar [Kim and Sukkarieh (2004); Blosch et al. (2010); Bryson and Sukkarieh (2014); Yun et al. (2013)] and existing communication systems [Stachura and Frew (2011); Suo et al. (2012); Kurth et al. (2003)] that estimate the range and bearing of the vehicle with respect to a feature or landmark. Most of the effort has been dedicated towards developing path planners that minimize pose errors using different types of Kalman filters. Since this requires features or landmarks to localize, thus placement of landmarks or feature selection becomes an essential problem for navigation. There have seen several efforts in this direction to determine optimal placement of landmarks/features for localization [Peter Lommel and Roy (2000); Vitus and Tomlin (2010); Rathinam and Sharma (2015)].

In this paper, we consider an emergency scenario at night where a UAV located at S needs to travel to G for delivering some emergency material. In addition, we assume that sufficient amount of GPS satellites are not available to carry out a GPS based navigation. As the operation is at night, several SLAM based techniques that depend on vision cannot be utilized. However, there may be several cellular towers available along the way from S to G. For example, S and G can be two distant towns and the supplies must be delivered from one town to another. There may exist several villages along the way that have cellular towers providing finite coverage area in the villages but the area between the villages may not have any coverage. This implies that the available localization areas are sparse. This scenario is relevant and quite common in most developing countries like India which is depicted in Figure 1. Under this scenario, the UAV may need to use range and bearing information within the cellular tower coverage area for localization. The above algorithms that depend on the availability of a landmark to move from one location to another are not directly applicable, as most of them focus on determining accurate estimate of the vehicle pose using several types of Kalman filters for a given path.

In this context, we develop a multi-objective path planner that determines a path from S to G while minimizing the time to reach G as well as the coviarance of the estimator for the complete path. A similar problem was addressed in [Bopardikar et al. (2014)], where the authors are interested in generating a path that minimizes the path length while keeping the covariance within bounds. However, their approach uses nodes and they create a graph with costs as a combination of path length and covariance. It is well known that the discretized path gives lower performance than the continuous path. Also they

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assume the vehicle is holonomic. In this paper, we determine a continuous path for a UAV which is non-holonomic.

The rest of the paper is organized as follows: in Section 2, we state the mathematical optimization problem statement and solve this using particle swarm optimizer in Section 3. Numerical results of this approach are presented in Section 4 and we conclude in Section 5

2. PROBLEM FORMULATION

In this section, we describe how we model the vehicle motion, the environment and present the problem formulation.

2.1 Motion and Sensing Model

We consider a general model of an agent whose state evolves as per a non-linear discreet time dynamical system

$$\mathbf{x}(t+1) = \mathbf{f}(\mathbf{x}(t), \eta(t)), \tag{1}$$

where $x \in \mathbb{R}^n$ is the state at time $t, \mathbf{f} : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}^n$ describes the state transition map of the system and $\eta \in \mathbb{R}^n$ is the process noise. The agent is equipped with range and bearing sensors in order to estimate the state x. We assume that the vehicle will be flying at constant altitude and can be modelled as a Dubin's car with kinematics as,

$$\begin{aligned} \dot{x}_a &= v \cos \psi, \\ \dot{y}_a &= v \sin \psi, \\ \dot{\psi} &= u, \end{aligned} \tag{2}$$

where (x_a, y_a) is the vehicle geographical local coordinates and ψ is the vehicle heading angle. The control u is determined using any path following algorithms described in [Sujit et al. (2014)]. In this paper, we use the basic path following algorithm – the rabbit-carrot based path following.

The sensor output is modelled as

$$\mathbf{y}_j(t) = \mathbf{h}_j(\mathbf{x}(t), \nu(t)), \forall j \in \{1, ..., m\}, \tag{3}$$

where $\nu_j \in \mathbb{R}^n$ is the process noise of the jth sensor and $\mathbf{h} : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}^n$ describes the relation between state and

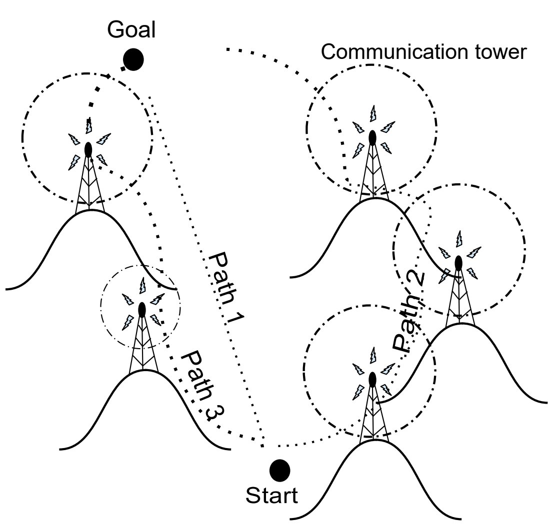

Fig. 1. Scenario showing the presence of communicating radio towers through which the UAV needs to fly to reach the goal from the start location. The vehicle localizes through the radio towers.

measurement. We assume that the noise vectors η and $\mathbf{v}$ are independently generated zero mean Gaussian random vectors.

Given the sensor and motion of the vehicle, we use Extended Kalman Filter (EKF) to predict the state of the vehicle when there are no measurements available from the cellular towers for localization. We assume that the EKF provides a consistent estimate $\hat{\mathbf{x}}_t$ and the estimation error covariance $\mathbf{P}_t$ of the filter. The EKF estimator of the state x is given as

$$\mathbf{P}_{t+1}^{-1} = (\mathbf{F}_t \mathbf{P}_t \mathbf{F}_t^{'} \mathbf{Q})^{-1} + \sum_{j=1}^{m} \gamma_{j,t+1} \mathbf{H}_j^{'} \mathbf{R}_j^{-1} \mathbf{H}_j \tag{4}$$

$$\begin{aligned} \hat{\mathbf{x}}_{t+1} = \mathbf{P}_{t+1}((\mathbf{F}_t \mathbf{P}_t \mathbf{F}_t^t + \mathbf{Q})^{-1} \mathbf{f}(\hat{\mathbf{x}}_t, \mathbf{0} + \\ \sum_{j=1}^{m} \beta_{j,t+1} \mathbf{H}_j^{'} \mathbf{R}_j^{-1} (\mathbf{y}_j(t+1) - \mathbf{h}_j(\mathbf{f}(\hat{\mathbf{x}}_t), 0))) \end{aligned} \tag{5}$$

where $\hat{\mathbf{x}}_t$ represents state estimator, $\mathbf{P}_t$ denotes the expected error covariance with respect to (η, ν), $\mathbf{F}_t$ is the linearisation of $\mathbf{f}$ around ($\hat{\mathbf{x}}_t$, 0) and $\mathbf{H}_j$ is the linearisation of $\mathbf{h}$ around ($\mathbf{f}(\hat{\mathbf{x}}$(t),0)). The matrix $\mathbf{Q}$ and $\mathbf{R}_j$ represent the process noise and the measurement noise covariance associated to the *j*-th sensor respectively. The variable $\beta_{j,t+1} \in \{0, 1\}$ is a binary variable that models the presence or absence of measurement update from the jth sensor.

In order to take the covariance error into account, we will consider the maximum eigenvalue of the error covariance matrix, $\hat{\Lambda}(\mathbf{P}_t)$ as the scalar metric for capturing state estimate uncertainty. We denote $\underline{\Gamma}(\cdot)$ and $\overline{\Gamma}(\cdot)$ the minimum and maximum eigenvalue of a matrix- which is a positive definite matrix or a positive semi-definite matrix.

2.2 Objectives

We want to find the shortest path from S to G that minimizes $\overline{\Gamma}(\cdot)$. If there was no constraint on $\overline{\Gamma}(\cdot)$ then, the objective function is

$$min \int_s \frac{ds}{\dot{s}} \tag{6}$$

$$\text{such that } \mathbf{x}(t_0) = (x_s, y_s) = S \tag{7}$$

$$\mathbf{x}(t_f) = B_r(G) \tag{8}$$

where $B_r(G)$ is a ball of radius r around the goal G. The constraints $\mathbf{x}(t_0)$ states that the vehicle are located at the start location (x_s, y_s) at time t_0. Since the vehicle carries out dead reckoning when there is no measurement updates, the vehicle may not accurately reach G at time $t_f(\mathbf{x}(t_f) \neq G)$ but it may reach r distance from G ($B_r(G)$) which is acceptable as it can get localized with respect to G and hence land at G. In this case, path 1 in Figure 1 will be selected.

On the other hand, if we are interested in optimizing the path with respect to the covariance error then,

$$min \int_s \frac{ds}{\dot{s}} \tag{9}$$

$$\text{subject to equation } (7,\ 8) \text{ and } \min \overline{\Gamma}(\mathbf{P}_t). \tag{10}$$

In this objective, we are interested in finding a path that has very low covariance. This system/metric is useful when the UAVs have too high gyro drift- that is, the IMU is of a cheaper version. Using a cheaper IMU implies that the drift can grow