# Motion Planning for an Autonomous Helicopter in a GPS-denied Environment

Svetlana Potyagaylo
Faculty of Aerospace Engineering
*svetapot@tx.technion.ac.il*

Omri Rand
Faculty of Aerospace Engineering
*omri@aerodyne.technion.ac.il*

Yaron Kanza
Faculty of Computer Science
*kanza@cs.technion.ac.il*

Technion, Israel Institute of Technology
Haifa, 32000, Israel

**The paper is focused on the development of algorithms for motion planning of an autonomous helicopter in a GPS-denied environment. Methods for determining the location of the helicopter, during the flight, are presented. The methodology is based on a lightweight laser range finder as a sole onboard sensor. The sensor reading interpretation are combined with various path planning algorithms according to the vehicle-environment size ratio. Two different environments are studied: a tight environment where travel distances and obstacle dimensions are in the order of the rotor diameter, and an open environment where obstacles are much larger than the rotor diameters. For each environment, two cases are considered: a case where the map of the environment is entirely known a priory, and a case where obstacles are discovered during the flight.**

## INTRODUCTION

Autonomous uninhabited rotary-wing aerial vehicles (UAVs) have maneuverability and hovering ability that make them suitable for various tasks such as surveillance, monitoring, payload delivering, etc. Commonly, while navigating, UAVs rely on accurate knowledge of their location, and most of them gain their location data using a Global Positioning System (GPS). However, a GPS may be unavailable in most indoor and in numerous outdoor scenarios, because large structures and buildings can obscure or reflect signals from the GPS satellites, leading to inaccuracy and errors in the position estimation of UAVs. Thus, relaying on a GPS reduces the overall usability of UAVs and limits the variety of their feasible tasks. An alternative approach, which is widely used for ground robots, utilizes vision-based techniques for navigation. Yet, vision equipment is relatively heavy, and generally speaking, their suitability to small aerial vehicles is limited.

The problem where a robot is positioned in an arbitrary environment, has to build a consistent map of the environment and should simultaneously determine its location within this map is known as Simultaneous Localization and Mapping (SLAM). SLAM has been studied for different scenarios such as indoor, outdoor and underwater navigation of robots (Ref. 1). Within this paper, a study of SLAM in the context of airborne uninhabited vehicles will be presented. Accordingly, we study the navigation of autonomous rotary-wing (RW) aerial vehicles by exploiting a lightweight laser range finder. At each point, the vehicle is supplied with reading of its distance from the nearest objects around it which is in line of sight and unshadowed by another obstacle.

Executing SLAM by UAVs is not a straightforward procedure because of several reasons. First, aerial vehicles, and helicopters in particular, have to deal with navigation in a three-dimensional space. Thus, the dynamics of flying vehicles, and especially of RW vehicles, is more complex than that of ground robots. In addition, navigation commands must be provided instantly, whereas onboard computing time is very limited. Although RW UAVs can interrupt the flight and hover (i.e. momentarily stop to allow onboard calculation to be completed), this is not desired because it will increase fuel costs, flight time and the vulnerability of the vehicle. Finally, UAVs for indoor applications must be small, and differently from ground robots, they have a considerably limited payload capability, so they lack the capacity to carry relatively heavy sensors.

The problem of autonomous flight and operation of RW UAVs in a GPS-denied environment is situated in the intersection of two fields – robotics and vehicle's aeromechanics. Motion planning for such vehicles is based on adaptation of planning techniques to sensing using merely lightweight sensors. There are two variations to this problem. The first, where the UAV has an accurate map of the area and of the obstacles in the mission area, and the second, where the UAV should plan its motion without having a complete knowledge of the obstacles prior to their detec-

Presented at the American Helicopter Society 66th Annual Forum, Phoenix, AZ, May 11-13, 2010. 

tion.

## PATH PLANNING TASK

We shall first review two methods for path planning that were presented in Ref. 2 and will be used in this paper. The first method is suitable for obstacle avoidance in the case when the vehicle is small relatively to a typical dimension of the workspace and the obstacles. This method is based on the *Potential Fields* approach, improved by employing an optimization procedure. The second one, namely *The Maneuvering Map method*, and is suitable to the case where the size of the UAV is comparable with the size of obstacles. In the first case, we simplify the vehicle's dynamics, while in the second case, detailed dynamics of the discussed vehicle is included.

To describe the above methods, we momentarily assume that the onboard sensor — a laser range finder — is capable of determining the distance to the closest obstacles, surrounding the vehicle, that are in the line of sight and within a prescribed (maximal) radius. This means that even if an obstacle is located in the range of the sensor, the shadowed parts of the obstacle or additional shadowed obstacles are "not visible". All detected obstacles along the path (or parts of them) are stored as a "virtual map" which allows the algorithm to avoid unsafe areas that are invisible at the current position of the UAV but were observed earlier. In addition, we momentarily assumed that the vehicle's path-planing algorithm is fully supplied with the vehicle's exact position and attitude, at all times.

### The Optimized Potential Fields Approach

The potential field method considers the UAV as a particle moving in a force (or vector) field produced by the repulsive and attractive forces from obstacles and goal, respectively. The idea of having obstacles that "induce" forces over a vehicle has been first suggested by Khatib (Ref. 3) with respect to manipulators.

Potential fields were originally developed as an online collision-avoidance approach, since this method is applicable when the vehicle does not have prior information of the obstacles, but senses them during its motion. The UAV moves in its configuration space as a point, under the influence of an artificial potential function produced by forces with respect to the goal and the obstacles. The goal generates an "attractive" potential which pulls the UAV toward the goal, and the obstacles produce "repulsive" potentials which push the vehicle away from them. The negative gradient of the total potential is treated as an artificial force applied to the UAV. The field function can be defined as the sum of an attractive and a repulsive potentials. The simplest motion scheme is obtained by neglecting all dynamic effects, and thus, the direction of movement is assumed to coincide with the force direction.

Hence, the potential field method enables to produce trajectories that are relatively smooth. It should also be mentioned that this method may be extended, in the sense that various levels of vehicle's dynamics may be included. Nevertheless, the forces under discussion will remain fictitious. Extension of this method to the 3D case is straightforward.

In the optimized Potential-Fields Approach proposed in Ref. 2, two parameters of the obstacles — the intensity and the correction angle of each obstacle — are determined by an optimization procedure that is used at a certain point of the path. The optimization is applied for all the obstacles that are either visible or were already included in the "virtual map" and are located within a prescribed distance (i.e. the maximal-influence distance) from the vehicle. The criteria for the optimization are the length of the path and its clearance from obstacles. Therefore, at each time point, the algorithm chooses the intensities of all the obstacles assigned for optimization, and sets their correction angles, so that the length of the future path (from the current position of the vehicle to the goal) will be as short as possible, while the distance from the path to the obstacles will be as large as possible:

$$P = \frac{D/d}{L/l} \to \max,$$

where $D$ is the the minimal possible distance from the UAV to the obstacles, $d$ is the desired minimal distance from obstacles, $L$ is the length of the path from the current UAV position to the goal, and $l$ is the length of the straight line from the current UAV position to the goal.

### The Maneuvering-Map Method

The Maneuvering-Map Method is a path-planning algorithm that takes into account the dynamics of the UAV. In this method, it is assumed that the trajectory of the UAV consists of discrete segments. Each of these segments represents a possible short maneuver according to the flight abilities of the helicopter. The path planning is divided into two stages — *pre-mission* and *online execution*. During the pre-mission stage, a "virtual map" of possible maneuvers of the UAV, with prescribed time intervals, is built, see Fig. 1.

During execution, when the information about the start and the goal position is known and obstacles are (fully or partially) observed, the above virtual map is "put over" the real map. Note that in this case, all possible maneuvers for the UAV under discussion are known, independently of the locations of obstacles and the mission task. Since the number of points grows approximately as $n^3$ (where $n$ is the number of time intervals), special purpose techniques to reduce the size of this data structure were developed and presented in Ref. 2.

During the flight, a collision-free path that ends in the vicinity of the goal and satisfies the given criteria is chosen from the maneuvering map, and may be carried out. For

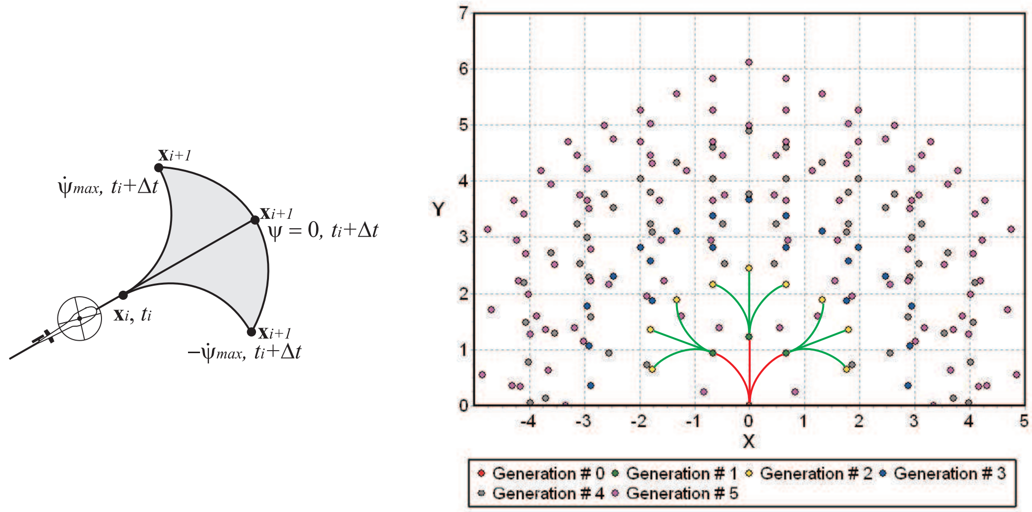



**Fig. 1. Possible maneuvers "tree map".**

a rotary-wing UAV, the use of such offline-calculated maneuver map might be flexible. If, for example, the UAV cannot find a collision-free path from the current state location to the goal, the map can be turned by some angle, and the process of path search can be repeated. For a fixed-wing UAV, such a sudden turn of the map is not feasible, however, a rotary-wing vehicle can execute a transition to the hover state, turn, while hovering, and resume the forward flight and the maneuvers. It is obvious that such a procedure is rather power-wasting and time-consuming, so a penalty must be included for it in the criteria.

## MOVING IN A GPS-DENIED ENVIRONMENT

To avoid collisions with the obstacles, typically the path planning algorithm is performed under a certain level of information about the obstacles. Generally speaking, the type, way and availability of these data define the planning methodology. In certain cases, one may assume that part of the information is known prior to the flight — for example, locations of buildings, electric mains or others dangerous regions that should be avoided. Yet, some information about the flight environment and about obstacles, in particular, may not be known a priori and could only be accessible by sensing. A relatively common method for acquiring these data is by using laser range finders and video sensors. Discussion of possible onboard sensing tools and there use for detecting obstacles is beyond the scope of this paper, and as already stated, in this study we have adopted the concept of working with a laser range finder.

As already indicated, in certain scenarios, such as when operating inside buildings, autonomous vehicles cannot rely on GPS for identifying their location, due to poor reception, or no reception at all, of the GPS signal. Thus, an important task for an autonomous vehicle, in a GPS-denied environment, is to be able to identify its location merely based on its surrounding. When autonomous helicopters are under discussion, there are two additional difficulties. First, the vehicle cannot be "stopped" or "located" at a given precise point — even in a hover state, all the measurements are being taken while the vehicle is slightly moving and in the presence of perturbations. In addition, it should be noted that the payload carrying capacity of a typical small-size autonomous helicopter is quite limited.

Hence, the first goal of the present study was the development of a feasible method for *self-location estimation* for small autonomous helicopters in a GPS-denied environment. Clearly, once the system identifies its location, the vehicle should move towards its target. Thus, the second goal of this study is to develop algorithms and methods for computing the movement of the autonomous helicopter so that it will accomplish a given task of reaching a certain destination, while considering environmental constraints (such as walls and other indoor or outdoor obstacles), and the limitations of the vehicle (such as flight range, the ability to accelerate or slow down, the ability to turn, etc.).

For an autonomous flight of a UAV in a GPS-denied environment, the following ingredients are essential:

- A method of distinctive object recognition, for sensing of the environment: In this study, a laser range finder is used for detecting obstacles. The laser range finder determines the distances to the obstacles that are in line of sight with the UAV and within a prescribed radius from it. Based on this data, a virtual map of the environment is built during the mission. Hence, all the detected obstacles along the path are stored and they are taken into account when planning the continuation of the path, even when they are already out of sight.

- A method for estimating the position of the vehicle: In this paper, the position of the UAV is calculated based merely on signals from the above described laser range-finder. The method allows identifying distinctive objects in the environment (in the presence of noise, e.g. due to perturbations of the vehicle) and using them as *anchors* for position estimation and for planning the flight path towards the target. An important challenge when estimating the location of the vehicle is to maintain accuracy at all times and to avoid accumulation of errors, of various types, which can cause the vehicle to drift.

- A method for path planning: As already indicated, in this study we employ either the *Potential Fields* approach or the *The Maneuvering-Map Method*, see Ref. 2. For indoor applications, the main advantage of the second method is in computing the path according to the maneuvering abilities of the vehicle. Other methods that neglect the dynamics of the vehicle are suitable only for highly agile UAVs, but not for actual vehicles, and certainly not for RW UAVs in a relatively tight environment.

- A method for computing control commands that allow navigating the UAV to go by the planned path: In our approached, an inverse-simulation technique is proposed for computing control commands that make the UAV fly along the planned path, see Ref. 2.

### Data Association

As explained earlier, accurate estimation of the location of the UAV based on previously detected items is one of the most important challenges this paper addresses. The main goal is estimating the location based merely on scans of the environments by the laser range finder. Our location estimation technique is based on *data association*.

Data Association is the process of matching two range scans, obtained from a laser range finder, in order to determine the position and the orientation of the vehicle. Data Association approaches can be categorized based on their association method, such as: feature to feature, point to feature and point to point approaches. In a feature-based approach (Refs. 4, 5), features such as line segments, corners or wall boundaries are extracted from laser scans and then matched to extracted features from a previous scan. In a point-to-feature approach (Ref. 6), the points of a scan are matched to features or to regions, for creating the map. Thus, arbitrary shapes in the environment can be represented in such maps, however, maps that are created this way require a lot of memory. Point-to-point matching approaches (Refs. 7, 8) do not require the environment to be structured at all, and maps are composed of a collection of full sensor readings, including raw data and the location and orientation of the sensor. A disadvantage of this approach is that it can be memory demanding and computationally intensive if all the collected data is stored and processed.

**Algorithm 1** Find an estimated location of the UAV, using Data Correlation

```
Consider an initial location and heading: x = x_0, y = y_0 and ψ = ψ_0 (for Point P), which will be denoted by the vector (x_0, y_0, ψ_0).
Let M = ∅ be an empty virtual map.
Scan the environment using a laser range finder with respect to (x_0, y_0, ψ_0), and store the resulting data as a vector r(θ), for the scanned angles in the range −θ_max ≤ θ ≤ θ_max.
Convert the (r, θ) representation of the points achieved from the scan to a Cartesian representation where points are pairs of the form (x, y). Add the points to the virtual map M.
Once the vehicle has moved to a new "True" position (x^T, y^T) and orientation ψ^T, produce a new scan of the environment r^T(θ), for −θ_max ≤ θ ≤ θ_max.
Compute an initial guess for the location of the vehicle (x_g, y_g, ψ_g) according to the last known location and the movement parameters of the vehicle.
repeat
    Create a new virtual scan r_v(θ), based on the virtual map M and the initial guess (x_g, y_g, ψ_g).
    for each reading r_i^T in the vector r^T(θ) of readings from the True world do
        let r_i^1 = r_i^T cos(θ_i^T + ψ_g) + x_g
        let r_i^2 = r_i^T sin(θ_i^T + ψ_g) + y_g
    end for
    Convert the "true" laser data so that it would look as if it was measured from the guess position. At this step the following equations are used: r'_i^T = sqrt((r_i^1)^2 + (r_i^2)^2) and θ'_i^T = tan^{-1}(r_i^2 / r_i^1).
    Calculate a norm of the error that represents the discrepancy between r'_T(θ) and r_v(θ), only for the range covered by both.
    Use a nonlinear solver technique for computing a new guess vector (x_g, y_g, ψ_g).
until The guess vector minimizes the error norm.
return (x_g, y_g, ψ_g)
```

In this paper, we present a two-dimensional point-to-point scan-matching technique where the map extracted from the laser-scan data is stored in two forms, simultaneously: (1) as a feature-based map that serves as the basis for the path-planning procedure, and (2) as a point-based map that is used for determining the location of the vehicle.

For determining its location, the vehicle scans its environment and compares the result of the scan to previous scans in memory. In the matching process, the last scan is moved and oriented to best fit the in-memory map. This association procedure returns the location and orientation which provide the best match. The data association process is typically called *scan matching*. For conducting it, several iterative techniques have been proposed. These iterative methods often converge to a good solution quickly, however, using them effectively requires providing a relatively accurate initial guess of location and orientation.

We employ Algorithm 1 for computing the location estimation of the UAV, using the scan matching method. The algorithm maintains a virtual map $M$ of data collected in the scans. After a movement, the location estimation is being done by a converging iterative process. In each iteration, the algorithm "guesses" the location of the vehicle, computes a virtual scan using the guessed location and the virtual map $M$, and compares the computed virtual scan to the actual true scan in the real world. Using a non-linear solver, a new guess location is computed. The process terminates when a location that minimizes the error between the actual scan and the virtual scan is discovered and this location is returned as the estimated location of the vehicle.

The computation of a virtual scan from a guess location $(x_g, y_g, \psi_g)$ and a virtual map $M$ is being done as follows. For each point in $M$ that is visible from $(x_g, y_g, \psi_g)$, according to the scan range and the known obstacles, the distance from $(x_g, y_g)$ to that point is added to the scan vector. Then, the vector is sorted according to the angles of the points with respect to $\psi_g$.

In order to illustrate the scan matching method developed in this study, we will use the "deadlock" environment scheme shown in Fig. 2(a). In this environment, there are blocking walls in three directions and the vehicle must go in the fourth direction for "escaping". Assuming that a vehicle is located at Point $P$, with an initial orientation toward the upper wall ($\psi = \psi_0$), the laser scan reading that is shown in Fig. 2(b) is obtained. From this scan, the virtual map depicted in Fig. 2(c) is created. Suppose now that the vehicle moves to a new location $P_T$ and it is now heading to a north-west direction, with orientation $\psi = \psi_T$, as shown in Fig. 2(d). The resulting scanner reading of the environment will take now the shape that is presented in Fig. 2(e). At this step, the "virtual" scan uses the expected location and orientation of the vehicle (computed based on the movement parameters of the vehicle and the last known location) as the initial guess of position and orientation. Then, the two scans are matched, as shown in Fig. 2(f). Note that the matching is conducted only for the relevant range, which is the overlap of the two scans. The transformation of the virtual scan to match the true scan is being applied on the location that is calculated based on the movement of the vehicle, for achieving the corrected estimated location.

## RESULTS

### The case of an a priori known map

In some cases of indoor flight missions, and of other missions in a GPS-denied environment, the "environment map" is a priori known. When the map is known, the location of the vehicle can be found by scanning the environment and correlating the sensed information with the known map. This task can be simplified by defining distinctive *anchors* in the map and looking for them during the mission. Such anchors can be corners, edges of doors or windows, etc. In order for this approach of defining anchors or landmarks to be useful in a GPS-denied environment, the path of the vehicle must be plan so that at any point in time, at least one anchor will be within the laser detection range (and not shadowed by an obstacle). The use of anchors for location discovery may also be applicable for routine flights in a predetermined flight routes of air vehicles, in different types of missions.

For the case where the map is known and anchors are being used, we employ the maneuvering-map method, which was discussed previously. The tree-shaped maneuvering map (such as the one illustrated in Fig. 1) is put on the map of the environment, and a path the avoids the obstacles is chosen (see an illustration of that in Fig. 3). The selected path as the one in Fig. 3 is the shortest path among the paths in the map that lead to the desired destination without any collision with an obstacle. Note that executing a flight along the chosen path is feasible since the path is composed of movement steps that comply with the maneuvering capabilities of the vehicle.

To demonstrate the proposed algorithms for a GPS-denied environment in the case where information about the obstacles is known, the example shown in Fig. 3 will be discussed. The task in this example is of an autonomous flight from a start location to a target location. During the flight, the algorithm identifies distinctive objects in the environment (for example, corners and ends of the walls, as illustrated in Fig. 4) based on the obtained scan produced by the laser range finder (see details about distinctive objects in Ref. 9). These objects serve as the anchors for estimating the coordinates of the vehicle. Note that the flight is restricted by the requirement that at each point the UAV must sense at least one anchor that was determined in a previous step of its flight path.

Continuing our example, Fig. 5 presents the recognition and detection of anchors in a scan produced by a laser range finder. The anchor-detection procedure is an iterative process of checking the scan point by point in a search for two kinds of the anchors: corners and wall edges. A corner can be distinguished as a change in the derivative of the scan signal. A wall edge takes the form of a significant change in the signal value (a "jump" in the value) or as a point where the signal reaches the maximal possible value — the wall is detected at a range that is not maximal and at the point where the wall ends, the range "jumps" to the maximal range since no obstacle is detected.

Errors in the measures affect the anchor-detection procedure. Fig. 6 shows the actual flight path in the presence

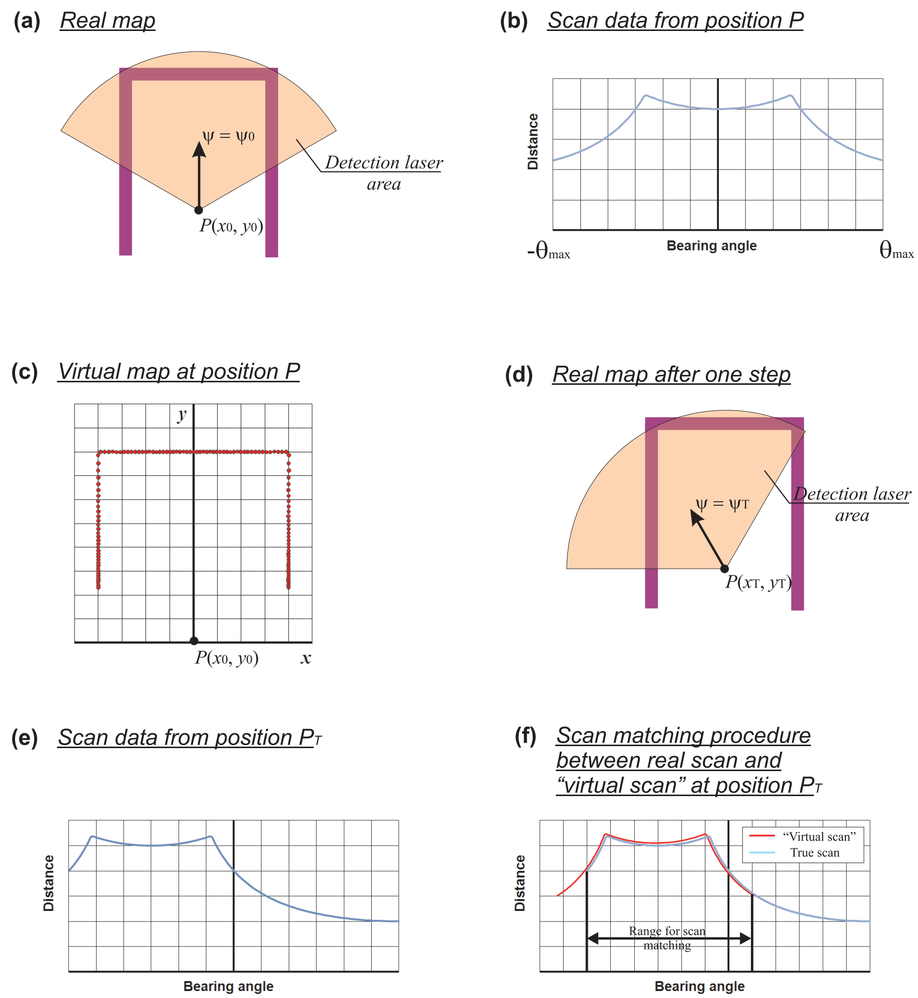



**Fig. 2. Data correlation notation.**

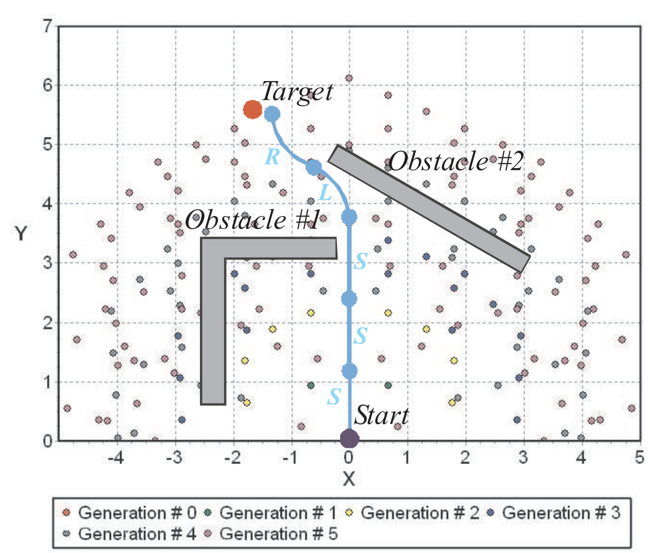



**Fig. 3. The flight path for the case of a known map.**

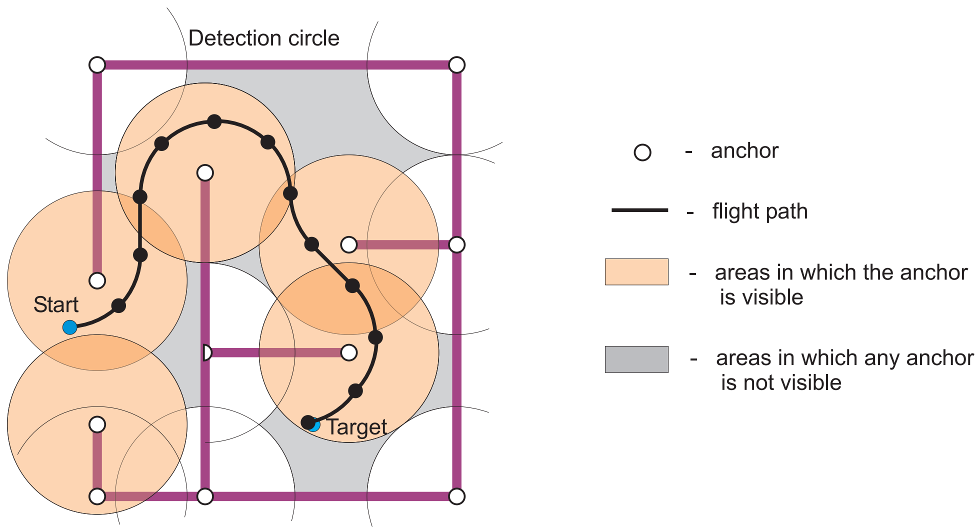



**Fig. 4. Indoor flight path with anchor-based planning.**

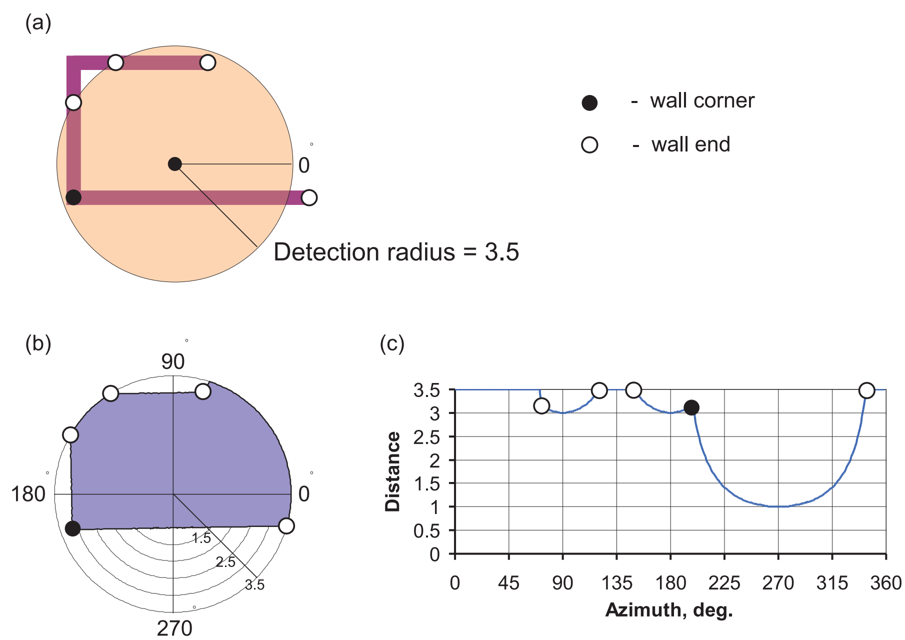
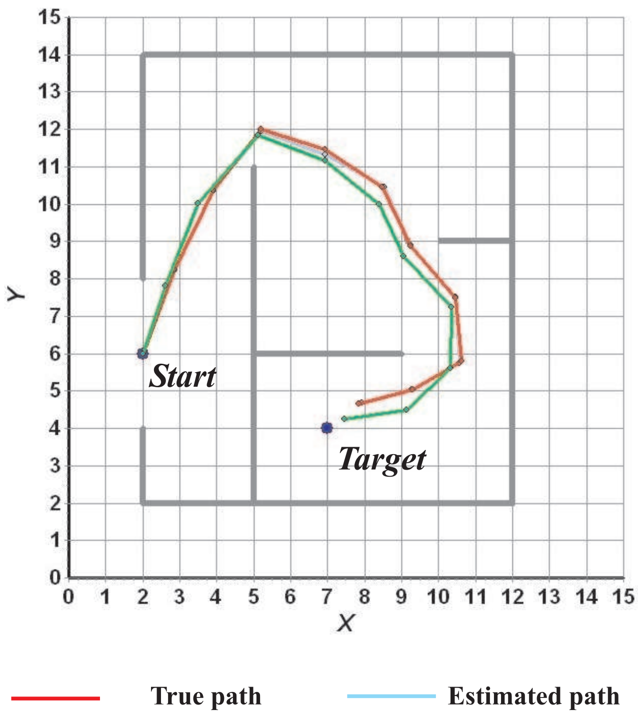



**Fig. 5. An example of anchor recognition by laser signal: (a) wall configuration; (b) azimuthal perspective; (c) signal versus azimuth angle.**

of errors, both in the scanner readings and in the execution of the control commands. One can observe three paths here: (1) the actual flight path of the vehicle where the line follows the true location of the vehicle, (2) the estimated path where at each point the location of the vehicle is the estimated location according to the anchor-detection procedure, and (3) the desired path that is calculated by the path-planning algorithm (the maneuvering-map method). At each step the scan is obtained, and the anchor-detection procedure is carried out. Based on the observed anchors and their known coordinates, the current position of the vehicle is estimated. Then, the path planning algorithm checks the planned path from the current location to the destination, taking into consideration the following three criteria: (1) collisions with known obstacles, (2) the length of the path, and (3) the availability of anchors along the planned path. If at least one of criterion is not satisfied, a new path is calculated. In Fig. 6, the case of replacing the planned path can been observed, as described in Subsection "The Maneuvering Map Method": after three steps (the Right, Left and Right turns) the map of maneuvers is turned and a new path is extracted. This requires a maneuver comprised of a transition to a hover state, a turn while hovering and continuing the flight.




Obtained path: RLR-RSLSRRS

| True position x / y | Estimated position x / y |
|---|---|
| 2,857/8,249 | 2,856/8,230 |
| 3,920/10,363 | 3,921/10,352 |
| 5,188/12,015 | 5,195/11,946 |
| 6,932/11,464 | 6,936/11,317 |
| 8,465/10,444 | 8,538/10,443 |
| 9,252/8,879 | 9,258/8,900 |
| 10,464/7,499 | 10,463/7,506 |
| 10,619/5,805 | 10,574/5,736 |
| 9,293/5,032 | 9,281/5,035 |
| 7,842/4,667 | 7,917/4,670 |

**Fig. 6. The actual flight path. All the turns are represented as straight lines.**

**The case of unknown map**

The case where the map is completely unknown prior to the flight is handled using the Potential-Fields Method. It is assumed that the initial location of the vehicle is known. At each step, the laser scan data is obtained and a data-correlation procedure, as described in Subsection "Data Association", is applied in order to determine the current vehicle position. Then the scan data are used for creating a "virtual" map, in memory. This map is stored in two forms — as an unordered data set of points using a global coordinate system, and as a set of straight lines representing the detected obstacles. The set of lines is used by the Potential-Fields method as the obstacle representation for calculating the repulsive forces on the vehicle. The algorithm for detecting the obstacles from the scans and creating the map of straight lines is presented next.

At the start location, where the movement of the vehicle begins, the exact location of the vehicle is known. The environment is scanned for detecting obstacles. The result of the scan is a set of points representing the locations where the laser beam hit an obstacle. The points from the scan are sorted, in ascending order, according to the laser bearing angle. The algorithm connects by a line each set of adjacent points that the distance between them to the line does not exceed a prescribed residual error. When a point cannot be added to an existing line because the error exceeds the norm, a new line representing a new obstacle in the environment is created.

The lines are created based upon the points of the first scan. At the following scans, the detected points are added to existing lines. Each point is checked for belonging to an existing line (obstacle) in memory. If the test fails and the point cannot be added to any line, the point is added to a set of *singleton points*. After performing the test (of belonging to a line) for all the points of the scan, the procedure of drawing lines for connecting sets of points is applied to the set of singleton points. When a set of singleton points form a new obstacle, this obstacle is added to the features, i.e. to the lines of the map, and the points that form the obstacle are removed from the singleton set.

At the end of each scan, there are two maps in memory — one is in the form of an unordered data set of points (a point-based map, as explained in Subsection "Data Association"), and another map consists of straight lines (a featured-based map). The first map is used for the virtual-scan procedure required for determining the current vehicle position. The second map is used by the Optimized Potential-Fields method for determining the optimal path to the target position.

Fig. 7 shows an example of two scans: the "real" scan data from the laser finder and the "virtual" scan over the feature-based map in memory.

Fig. 8 depicts the actual flight path in the case of an unknown map without the presence of noise, neither in the laser scan nor in the execution of the control commands. In this example, the true and the estimated paths are shown. Also the estimated expected path, calculated by the Op-

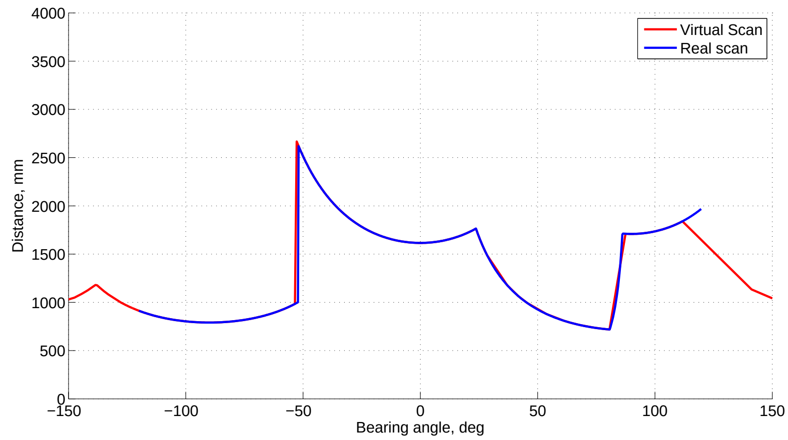



**Fig. 7. An example of two scans.**

timized Potential Fields method on the basis of the constructed map, is shown in red. Note that the expected path is changing whenever new obstacles are detected and added to the feature-based map.

## CONCLUSIONS

This paper investigates the problem of planning a flight of an autonomous helicopter in a GPS-denied environment. The problem is studied for a vehicle that senses the environment using merely a laser-range finder, which provides the distances to unhidden obstacles at a prescribed radius from the helicopter. The main challenges in such task are the following. (1) Location estimation — in the absence of a GPS, the location of the vehicle must be estimated according to its movement parameters and measures of the environment. (2) Obstacle avoidance — the motion planning should prevent collision of the helicopter with an obstacle. (3) Keeping the flight to be as short as possible — the planned path should not be much longer than what is necessary for completing the task. (4) Considering the dynamics of the vehicle — the control command for flying along the planned path should be according to the flight abilities of the helicopter.

The problem is studied for two environments — a tight environment where the obstacles are in the scale of the helicopter, such as in indoor flights, and an open environment where the obstacles and the flight path are much larger than the helicopter. Two methods of motion planning are presented and studied, for these two types of environments.

The Maneuvering-Map Method is being suggested for a tight environment. The method combines the path planning and motion planning tasks together and it conducts the flight planning while taking the maneuvering abilities of the helicopter into consideration. In a preprocessing step, a map of possible maneuvers is generated. By laying the map of possible maneuvers on a map of the environment, the helicopter can choose a path that leads to the target, without collisions and while performing only maneuvers that comply with the dynamics of the vehicle.

The Potential-Field Method is aimed at planning the motion in an open environment. In this method, path planning is separated from the planning of the control commands. For the planning of the control commands, an inverse-simulation technique is being employed.

The two proposed methods are geared to deal with the requirements of obstacle avoidance, considering the dynamics of the helicopter and providing a short trajectory toward the target. One of the main contributions of this paper is in showing how to adjust these methods to handle location estimation, which is required for coping with a GPS-denied environment. The problem of location estimation is studied for two cases — one where the obstacles are known a priori, and another where the map of the environment is not known prior to the mission, so that obstacles are discovered only during the flight.

For the Maneuvering-Map Method when the map is known, a method that is based on anchor discovery has been presented. By comparing detected anchors, from the laser scan, to recognized anchors in the map, the location of the vehicle is discovered. For an unknown map, a location estimation by employing a data association technique has been suggested. Essentially, the scanned data is collected during the flight and the collected data from each scan is matched to the stored data. The estimated location of the vehicle is the location that provides the best match between the scanned data and the data stored from previous scans.

The Potential-Fields Method has also been combined with the data association technique for location estimation of the vehicle during the flight. It has been shown that this approach can be used both when the map is known a priori and when the obstacles are only discovered during the flight. One of the novelties of the proposed approach is in using both a point-based map, of data collected from the laser scans, with a feature-based map, representing obstacles that were detected in the scans. The feature-based map is employed by the Potential-Fields Method for planning a path that avoids collisions with obstacles, while the point-based map represents a virtual map of the environment and is used in the location-estimation process.

The following conclusions are drawn from our results.

1. The absence of an a priori known information, about the environment and about the obstacles in it, prevents the usage of the majority of the existing path planning algorithms and reduces the effectiveness of others. Thus, the algorithms proposed in this paper improve the ability for planning a path, for an autonomous helicopter, that reaches the target while traveling a relatively short distance, avoiding obstacles and taking into consideration the maneuvering limitations of the vehicle.

2. Accurate location estimation is a crucial, yet difficult, task for navigating an autonomous helicopter along a planned path, in a GPS-denied environment. The control of the vehicle and the planning of a path to the target require a relatively accurate knowledge of the location and orientation of the vehicle, at any time along the flight. Our results show that accurate location estimation can be conducted by using merely a laser range finder. When the map is a priori known, this can be done even in the presence of noise (in the measures and in the the control commands).

3. The proposed methods were tested over several different maps, which represent different types of environments and imitate real indoor and outdoor situations. The shown experimental results illustrate the potential of the algorithms and their viability for real-time implementation of path planning for autonomous helicopters in a GPS-denied environment.

We leave the issue of path planning in an unknown environment under the presence of noise to future work. This case is difficult because it requires handling carefully the problem of error accumulation where the estimated location of the vehicle becomes less and less accurate after each movement.

## References

[1] Durrant-Whyte H. and Bailey T. "Simultaneous localisation and mapping (SLAM): Part I. The essential algorithms". *Robotics and Automation Magazine*, 13, 2006.

[2] Potyagaylo S. and Rand O. "Planning and operational algorithms for autonomous helicopter". In *The American Helicopter Society 65th Annual Forum*, 2009.

[3] Khatib O. "Real-time obstacle avoidance for manipulators and mobile robots". *International Journal of Robotics Research*, 5(1), 1986.

[4] Lingemann K., Surmann H., and et al. "Indoor and outdoor localization for fast mobile robots". In *IROS'04. IEEE*, 2004.

[5] Neira J. and Tards J. "Data association in stochastic mapping using the joint compatibility test". In *IEEE Transactions on Robotics and Automation*, volume 17, 2001.

[6] Thrun S., Burgard W., and Fox D. "A real-time algorithm for mobile robot mapping with applications to multi-robot and 3D mapping". In *ICRA'00. IEEE*, 2000.

[7] Diosi A. and Kleeman L. "Laser scan matching in polar coordinates with application to SLAM". In *The IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2005.

[8] Bosse M. and Zlot R. "Map matching and data association for large-scale two-dimensional laser scan-based SLAM". *The International Journal of Robotics Research*, 27(6), 2008.

[9] Bailey T., Nebot E.M., Rosenblatt J.K., and Durrant-Whyte H.F. "Robust distinctive place recognition for topological maps". In *Proceedings of the International Conference on Field and Service Robotics*, 1999.

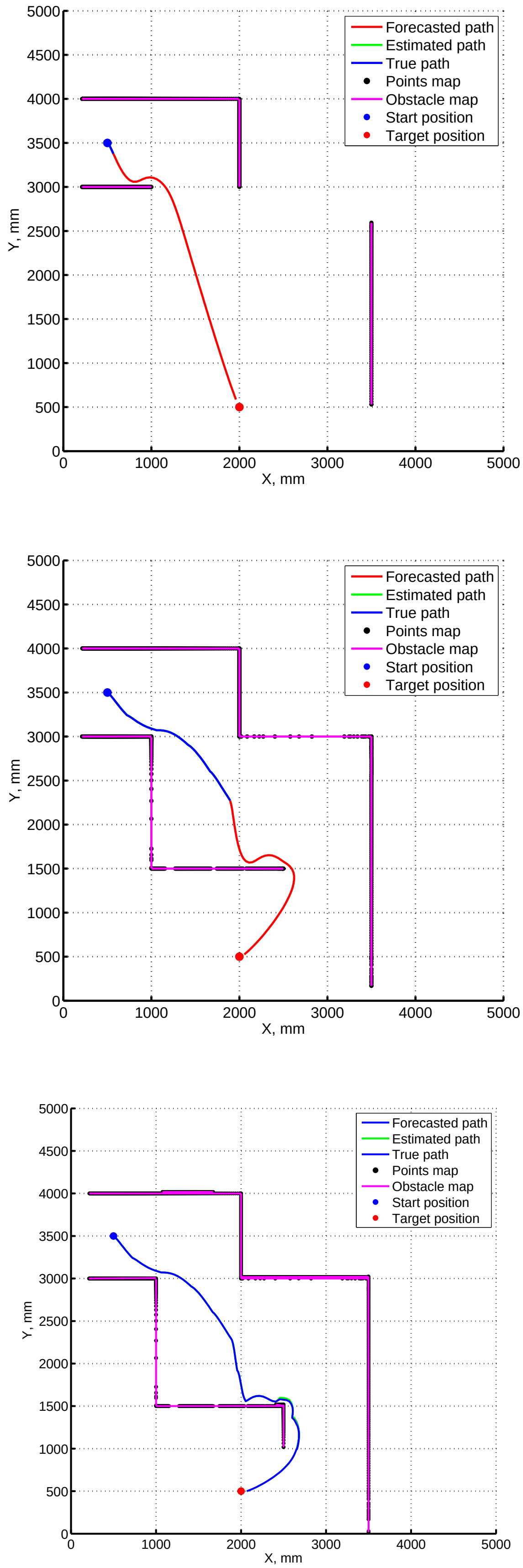



**Fig. 8. The created maps and flight paths.**