Towards Obstacle Avoidance and Autonomous UAV Operation

Chen Friedman [*], Inderjit Chopra [†]
Alfred Gessow Rotorcraft Center, Department of Aerospace Engineering
University of Maryland, College Park, MD 20740

Svetlana Potyagaylo [‡], Omri Rand [§]
Faculty of Aerospace Engineering
Yaron Kanza [¶]*Department of Computer Science*
Technion- Israel Institute of Technology
Haifa, Israel, 32000.

ABSTRACT

This paper presents the status and progress of the ongoing work directed towards the development and implementation of autonomous navigation algorithms for Micro Aerial Vehicles (MAV). The method proposed is founded on a mapping methodology, which is supported by a laser scan matching algorithm and virtual occupancy grid method. Navigation and path planning is performed by means of an extended and optimized version of the potential field approach. This paper contains a description of the methodology along with initial results from both simulations and experiments that demonstrate the ability to navigate around corners from start to goal positions as well as mapping realistic corridor environments using a ground platform. A notable advantage of the current methodology is the separation between the MAV's model and the navigation algorithm, which makes them suitable for various rotary wing (and other) platforms.

INTRODUCTION

This paper describes an ongoing effort towards enabling autonomous navigation of a rotary wing MAV. The operation of MAVs can be imperative for a variety of mission scenarios including surveillance, search and rescue, and biological chemical agent detection . The need of an out-of-sight autonomous vehicle in a GPS-denied area that are limited in communications (*e.g.* underground areas) or the need to maintain radio silence in hostile environments is important but enormously challenging. One major difficulty for operation in confined areas is obstacle avoidance. Unlike ground vehicles, any contact between a flying vehicle and other objects can easily results in a mission abort. In particular, exposed rotors are very sensitive to collision of any magnitude with other objects. A review of static obstacle avoidance can be found in the work by Kunchev et al. [1].

The present work focuses on safe 2D navigation of an MAV from an initial known position and orientation to a definite final goal, while the main assumptions are: (a) an unknown map/terrain and (b) no external positioning aid (*e.g.* GPS). This enables the vehicle to be completely autonomous once the user defines the goal-position. Within the present approach, the vehicle generates a map of its surroundings as it moves through the initially unknown space. Problems of this type are generally solved using Simultaneous Localization and Mapping (SLAM) algorithms. The SLAM problem is the combined estimation of both position and the evolving map at the same time. The main difficulty in SLAM is the coupling between maps and position estimation. For example, in a known map scenario, one can per-

---

[*] Graduate Research Assistant, chenfr@umd.edu
[†] Alfred Gessow Professor and Director, chopra@umd.edu
[‡] Graduate Research Assistant, svetapot@techunix.technion.ac.il
[§] Professor, omri@aerodyne.technion.ac.il
[¶] Professor, kanza@cs.technion.ac.il
Presented at the Specialists' Meeting on Unmanned Rotorcraft and Network Centric Operations, Tempe, AZ, January 25-27, 2011.

form scan matching of an acquired laser scan against the known map and determine the vehicle position. On the other hand, if the position is known, then the registration of new laser scans can be carried out accurately and the resulting map would be accurate and coherent.

Previous work on the SLAM-type problems shows that with the use of estimation theory techniques (such as Extended Kalman Filters and Particle Filters), it is possible to solve the SLAM problem for ground vehicles as well as some aerial platforms [2–4]. A notable contribution is that of Achtelik et al [5] enabling a particle filter based SLAM algorithm to autonomously guide a quadrotor.

Despite the significant advancements in this field, these techniques have a major requirement, which limits their generality: the vehicle's mathematical model must be relatively accurate (low covariance output). Otherwise, estimation methods may fail. Thus, it appears that, all previous work on SLAM has been carried out with quadcopters (*i.e.* rotary wing aircraft composed of four rotors mounted on an "X-shaped" structure). The rotors in these configurations are fixed pitch and thus thrust is controlled by varying each rotor RPM individually. Using today's motors, servos, and speed controllers, the response of a rotor's thrust to a change in RPM is quite fast and therefore vehicle dynamics depends almost entirely on it's orientation. This leads to a dynamical model that is mostly governed by the quadcopter's rigid body longitudinal and lateral tilt angles, subjected to four known thrust values, that are directly controlled by four RPM command inputs. These type of vehicles have a fairly linear and accurate aerodynamic response model with relatively small output covariances. Modeling a conventional single-rotor MAV configuration yields a much higher output covariance model as the aerodynamics of that configuration is more complex and cannot be easily modeled with sufficient accuracy.

While quadrotors are quite stable platforms and have large control margins (large flight envelope), the proposed method is generic and can be applied to other types of vehicles (conventional tail rotor, coaxial, tandem etc.) as it does not require the vehicle model at all.

The current effort presents an algorithm for vehicle navigation combined with an obstacle avoidance scheme that does not require any knowledge of the vehicle dynamics characteristics (that may be nonlinear in the general case) which make it suitable for a wide range of currently available MAVs. The major assumptions are:

i. Two dimensional motion.

ii. Relatively small pitch and roll attitudes ensuring a 2D environment.

iii. Vehicle's motion is slow compared to laser scan speed.

iv. Unknown environment, no position information available.

METHODOLOGY AND ALGORITHMS

This section lists the necessary sub-algorithms to carry out the process of navigating an autonomous vehicle in an unknown environment from initial to goal position without the aid of external position data. The general process is described in Figure 1.

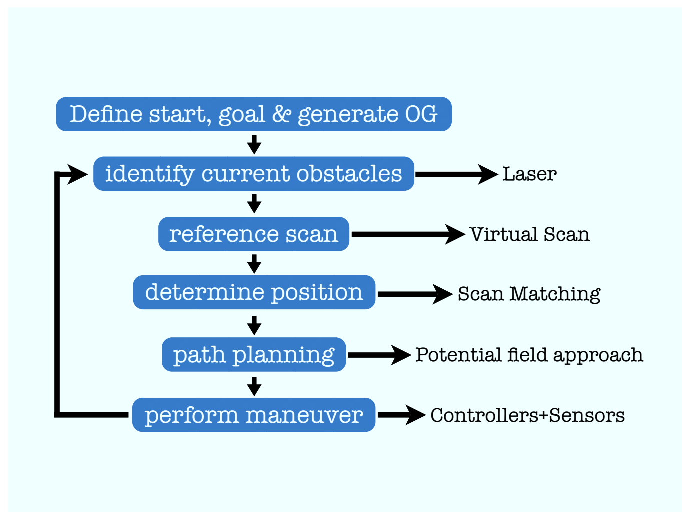


Figure 1: Continuous motion algorithm for general MAV navigation in an unknown environment with no position information

Laser Scan

The work presented here makes use of a single laser range finder for both position estimation and map generation. The main reasons for choosing the laser scanner were accuracy, response speed, and beam width. The main disadvantage of the laser sensor is its weight, approximately 200 gr, although sufficiently light enough to be mounted on a typical small scale MAV. Sonar sensors were not chosen due to their relatively wide beam, and therefore, difficulties in measuring sharp changes in the environment such as corners were expected. In addition, despite being a significantly lighter alternative, optic flow sensors can only measure distance relative to the vehicle's speed.

This research makes use of a 2D laser scanner made by Hokuyo [6], with a maximum range of approximately

$5m$ and a field of view of 240°. Angular resolution is approximately 0.35°, which produces approximately 700 laser measurements per scan with a scan time of 0.1 *sec*. A range of tests were carried out to establish the capabilities of the Hokuyo laser sensor, including distance-accuracy across the detection range, effects of surface inclination, and the types of outliers that may appear (mixed pixels, maximum and minimum range readings). Distance accuracy was found to be of the order of 3% of the measured distance, at the worst case, with the addition of a gaussian distributed noise with a standard deviation of the order of 1.5% of the measured distance. The laser had no problem detecting surfaces at inclination angles of up to 60° relative to the measuring beam.

In the simulations presented in this paper, the laser scanner is replaced by a numerical scan model that performs ray casting to the simulated user-input obstacles and returns the distance plus the typical random normally distributed laser noise according to the tests results. Additional details can be found in the work of Okubo [7].

Occupancy Grid Representation

The surroundings of the vehicle are represented by an occupancy grid [8–10], where cells contain an integer value which equals the number of laser "hits" that each cell was associated with. Each occupied cell is treated as an obstacle all by itself in the navigation scheme. The occupied cells are also used to get a scan of the virtual world in order to estimate position.

Virtual Scan

The Virtual Scan is executed from the estimated vehicle position. It is achieved by performing a "simulated laser scan" produced by ray casting in each required angle and searching for occupied cells in the occupancy grid matrix. Starting from the assumed vehicle position, after carrying out the last command, the virtual scan produces a set of the closest occupied cells at a range of angles that matches the same field of view of the real laser. This is the essentially a picture of the environment as the MAV sees it had it been in that position. This serves as the reference scan from the map that was built thus far, and can be matched against the actual laser scan obtained from the true MAV position to get a corrected estimate. Note that an occupied cell is represented using its center coordinates.

In case that the ray encounters a "thick" wall which is made of several clustered occupied cells, the virtual scan logs the start and end of the cell cluster and then defines the wall location as the cell with maximum occupancy between these two cells. Assuming zero mean laser noise - the cell at the cluster's center would be the best candidate to represent the actual wall location.

Scan Matching

The process of scan-matching between two environment scans results in the appropriate roto-translation values required to match one scan on top of the other. Many types of scan matching algorithms exist [11–17]. However, since each algorithm has strengths and weaknesses and this work relies solely on scan matching for the position estimation and accurate map generation, the most promising way is to use brute force in finding the minimum of a cost function.

In this work, an adaptive direct algorithm was constructed, where the best rotation angle between the scans was found first, followed by the best pure translation. This was repeated in an iterative fashion while continuously narrowing the scope of the grid after each iteration (thus refining the search grid since the number of points was kept constant). In case the minimum is found on the search range boundaries those would be extended to cover additional area beyond the initially covered space.

Within the method described above, the best possible scan matching is guaranteed as long as the search range is large enough and fine enough to cover the real solution area. In the current work, we mostly used 20 points for the azimuthal grid, and the x-y grid was a 10 *mm* by 10 *mm* grid so each iteration required 120 function evaluations. It was found that while increasing the grid resolution is desired to obtain more optimal matches, for most cases the above grid is sufficient. Therefore, a mesh refinement scheme can be employed just for cases where the resulting cost function when using the coarse grid is too high.

The cost function used herein is a variant of that suggested by Diosi and Kleeman [18] and is constructed in the following steps:

i. Acquire the current laser scan.

ii. Perform a virtual scan of the environment (by ray casting over an occupancy grid).

iii. Roto-translate laser scan with proposed motion.

iv. For each virtual scan angle - find the linearly interpolated radius value in the roto-translated laser scan.

v. Calculate the square of the radii difference between the roto-translated laser and the virtual scan.

vi. Eliminate the contribution of points that are too close or too far from vehicle.

vii. Outlier filter: eliminate points that have large radius differences on both sides (mixed pixels).

viii. Occlusion filter: eliminate contribution of points that have a radius difference of more than a set threshold.

ix. Eliminate contribution of empty cells matches.

x. Sum all contributions to get final function value.

xi. Divide by the number on contributing points (to maintain fairness between all cases).

The minimization process is as follows:

i. Calculate cost function for a range of azimuth angles (while keeping x-y motion fixed)

ii. Find the minimum value and set its associated angle as the current best azimuth guess.

iii. Calculate cost function for a range of values within a circular area, using the best azimuth guess.

iv. Find minimum cost and declare corresponding x-y coordinates as the best matches for the next iteration.

v. Repeat iteratively while narrowing the parameters' range each time until convergence.

Convergence is defined when the maximal change between two subsequent iterations is less than 0.01 mm in x-y or 0.01° in azimuth. In ideal test cases were the real and virtual scans were identical and shifted by prescribed rotation and translation, the algorithm always achieved good convergence (sum of all distances below 0.01 mm^2). On average, it was found that a total of approximately 1000 function evaluations is required for each scan matching process.

The key difference with the current scan matching approach is that the matching is preformed between the newly acquired laser scan and a virtual scan of the occupancy grid that was constructed thus far. A scan matching performed on subsequent laser scans is likely to result in accumulation of errors as demonstrated in the work by Bailey [15]. The use of the virtual scan filters out most of the errors as the virtual map contains more than one scan and in a sense it is an average of all the laser scans acquired thus far.

Map Update

It was found that maintaining an accurate map is crucial to the successful and accurate navigation of the vehicle from the initial to the goal position. Therefore, updating the map with the newly acquired laser scan data is performed only if the scan matching process gives a well-minimized function (desired values in the cases presented herein are usually in the range of 200-300 mm^2, where the typical laser measurement is of the order of 1000 mm, but acceptable values can also be in the range of 400-500 mm^2). Subsequently the vehicle's current position estimate is not updated as well in case of a failed scan matching.

Path Planning

Path planning is performed using a potential field approach [19] where all the occupied cells get a positive potential producing a repelling force on the vehicle while the goal gets a negative potential producing an attracting force on the vehicle. Several techniques are used to eliminate the possibility of local minima where the repelling and attracting forces reach an equilibrium.

The potential intensity of the occupied cells controls the amount of repelling force and thus controls minimum vehicle proximity to walls. A virtual mass is assigned to the vehicle and the vehicle's acceleration at each step is calculated using $\Sigma F = ma$ where F are the repulsive forces, m is the vehicle's virtual mass and a is the acceleration. Changing m controls the curvature of the planned path (higher virtual mass results in less curvature), and thus m may be adjusted to ensure that generated paths can be carried out by the MAV of our choice.

Maneuver Performance

Each step of the algorithm produces a set of $[\Delta x, \Delta y, \Delta \psi]$ where x, y are planer motion commands and ψ is an azimuthal command, to be executed by the vehicle. The above triplet requires motion in both x and y directions - and thus this approach is designed for vehicles that can perform such motions (*e.g.* rotary wing MAVs).

In the simulation mode, this command is injected with three uncorrelated gaussian noisy signals with a standard deviation that can be calibrated to achieve an appropriate modeling of the applicable vehicle. For a relatively stable hovering platform, the standard deviations in the x-y plane were assumed to be 20 mm and the azimuthal standard deviation is 5°.

RESULTS

Corner Scenario

The algorithm was first tested on a corner scenario where no direct line of sight exists from initial to goal positions as seen in Figure 2. This scenario examines basic features and challenges such as accurate map generation, handling sharp corners in the virtual scan's ray casting, and fundamental noise tolerance.

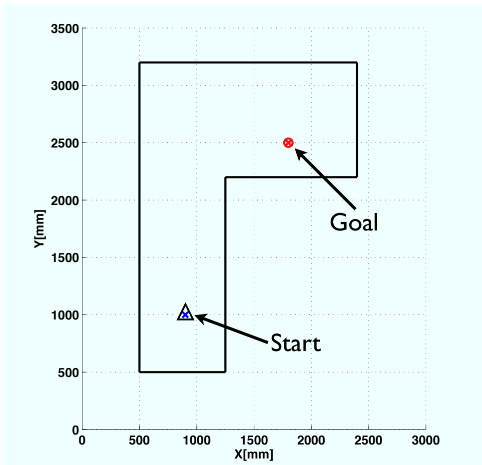


Figure 2: Scenario 1 - going around a corner, no direct line of sight between start and goal positions

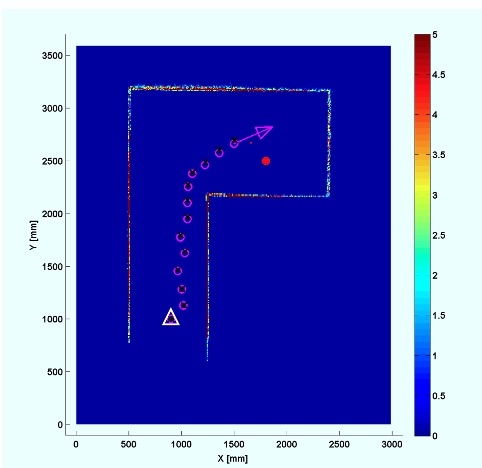


Figure 3: Scenario 1 simulation: final occupancy grid view after the course has been carried out successfully

Figure 3 shows the final occupancy grid of the simulated scenario 1. The occupancy grid cells are color-coded with the number of simulated laser "hits" (see color bar for color details), the estimated location of the vehicle is marked with magenta circles while the true positions are marked with black "x" marks (these are given in the same map for simplicity, even though they should be treated as if they are marked on the true map). The initial and goal position can be seen more clearly in Figure 2 marked by a blue "x" and a red circle with a red "x" mark in the middle, respectively. The vehicle's orientation is denoted by a magenta arrow.

Note that without loss of generality, the vehicle has a proximity condition such that when it arrives within 250 mm from the goal - it is considered that the goal has been reached. Since the size of the vehicle is expected to be of the same order of magnitude as this threshold, fulfilling this condition is practically reaching the actual goal position.

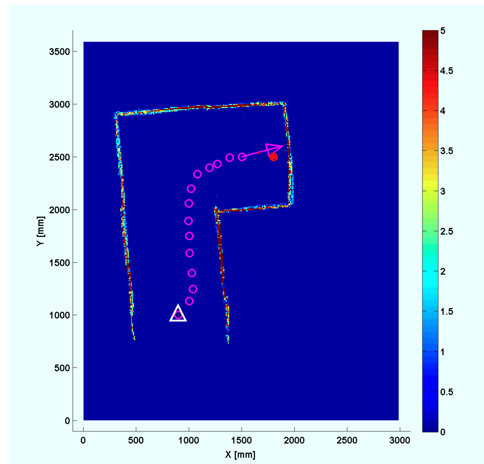


Figure 4: Scenario 1 experiment: similar occupancy grid as in the simulated case, vehicle commands have been carried out manually

Figure 4 presents experimental results for scenario number 1 within a corner maze. The laser in this experiment is manually moved (*i.e.* without maintaining accurate command execution). This replaces the simulation's injected noise as the vehicle commands are never accurately executed. Moreover, since the laser scan replaces the simulated scan - every real world effect is included in this example including non-straight walls, surface imperfections, surface connectivity (between every two walls constructing the maze), and reflectivity issues, to name a few.

The resulting occupancy grid virtual map presented in Figure 4 shows very coherent walls which means that the position estimation is very accurate (bad position estimate would have resulted in fuzzy and incoherent walls). When comparing the final position estimate distance from the wall with the actual distance of the laser scanner from the wall in the experiment, the error turned out to be about 1%. However, since this experiment is rather short it is possible that error can be accumulated over longer routes. Thus additional longer experiments were carried out.

Complex Mapping

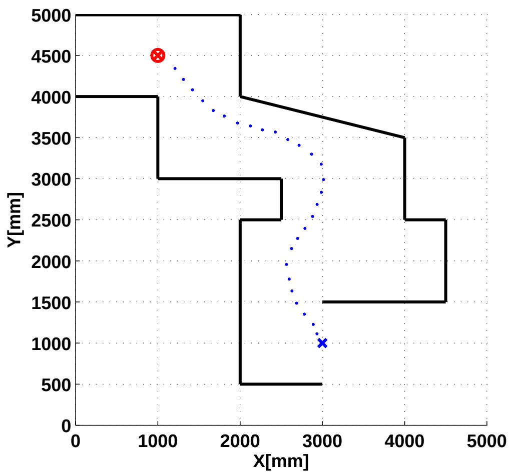


Figure 5: Scenario 2: Complex map, relatively simple path

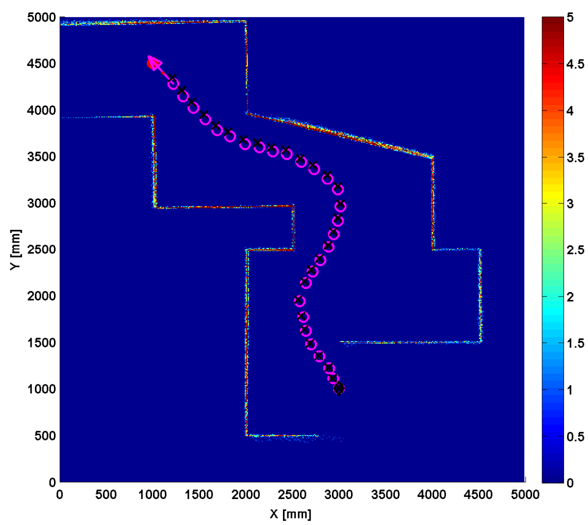


Figure 6: Scenario 2: simulation of navigating within a complex map

To further examine the capability of the algorithm to generate maps for more complex geometries, the obstacle arrangement presented in Figure 5 was simulated. The path in this case is relatively simple as the vehicle does not have to do any major re-planning due to newly observed obstacles. Therefore this case focuses on examining the mapping capabilities of the proposed algorithms. The resulting occupancy grid after the vehicle reached the goal is presented in Figure 6. The final map shows coherent walls as in the simpler corner case.

Similar to previous cases, the mapping quality can be characterized by examining the wall thickness. In the ideal case (no laser noise, perfect scan matching), a wall would always have a thickness of precisely one cell in the occupancy grid. Any deviation from the ideal is a result of noisy laser readings, noisy commands, and mainly bad scan matching results (causes false laser hits registration). In scenario 2, the maximum wall thickness was found to be 7 grid cells which is less than a 100 mm. In a typical indoor environment where the characteristic length is of the order of 3 meters, an error of 10 cm appears satisfactory. Moreover, one may not expect results to be better than our baseline sensor's ability, and the sensor's error at 3 meters range could be $\pm 3\%$, *i.e* ± 9 *cm* at the worst case. Hence, this agrees with the observed wall thickness.

Corridor Mapping

The final test scenario for the algorithm was its capability of generating accurate maps while maintaining good position estimation in realistic environments. The experiment was carried out on a 15 meter long corridor example in Martin Hall building at the University of Maryland. As before, the path planning in this case is rather simple since throughout the test, the start and goal positions have a direct line of sight between them. In this test case the laser was mounted on a cart (approximately 50 by 40 cm in size) which was moved through the corridor according to the output commands from the path planner. Moreover, unlike in the experimental scenario 1, the laser in this case was in motion *while* taking the scans, so the algorithm was further validated towards application on a moving platform.

The main objective was to examine the resulting map coherency. The test was successfully carried out and the final occupancy grid map is presented in Figure 7 with the true map (hand-measured) presented on top of the virtual map using dashed white lines. The effect of mesh refinement is also presented in Figure 7 as the upper figure was obtained using a coarse grid of 20 points in ψ and 100 points in the plane, while the bottom figure show results obtained with a grid of 40 points in ψ and 1600 points in the plane, using the same experimentally-recorded laser scans (but note that the algorithm is carried out from the beginning and hence virtual scans, maps, and scan matching would be different and the final occupancy grid is different). The result with the finer grid shows a significant improvement in terms of matching to the true map. However, the com-

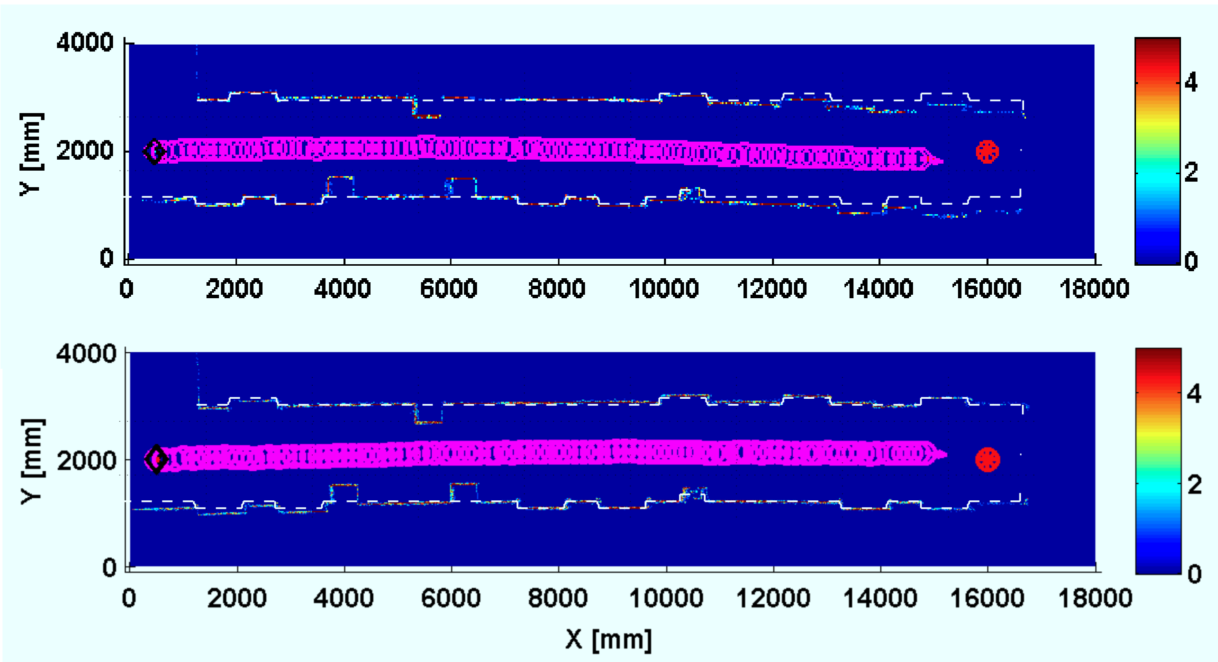
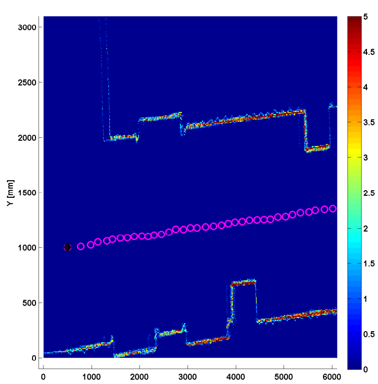
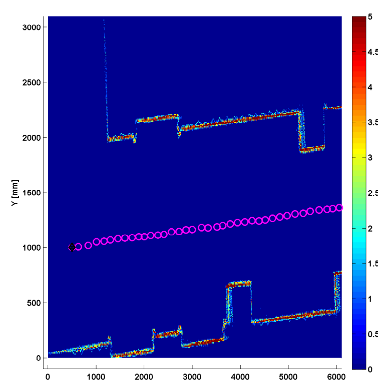


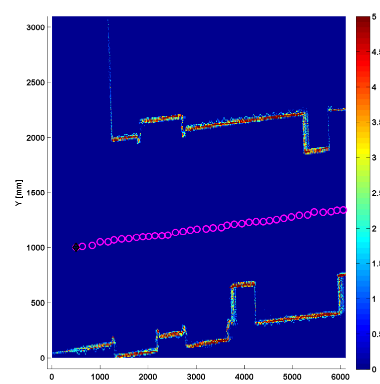
Figure 7: Corridor scenario comparison with real map -



(a) 5x5 grid



(b) 10x10 grid



(c) 20x20 grid

Figure 8: Corridor scenario close up - brute force search grid refinement

putational penalty was approximately 20 times in the scan matching required time.

Figure 8 shows a close up of the grid refinement effect on the above results where one can see that the duplicate wall appears for the low-quality mesh of 25 points (total in the plane) but does not show up when using the finer search grids. Some of the scan matching results were suboptimal, but still passed the map update threshold, resulting in wrongfully registering laser points in the occupancy grid. An example of that can be seen when examining the vertical wall at approximately $X = 1000\ mm$ between $Y = 2000\ mm$ and $Y = 4000\ mm$. That wall appears to have a duplicate image because a low quality scan matching result was accepted (cost function was below the set threshold). Thus the laser points from that step were misplaced in the occupancy grid and formed another wall image.

Algorithm robustness was further examined and it was found that although the map was occasionally not updated due to low-quality scan matching results (as explained above), the algorithm still managed to reposition itself after a few steps at its new position. This property is very important since it keeps the map from being "contaminated" by misplacing laser measurements. Maintaining a well-constructed map is an important key for successfully navigating from initial position to the goal. Map quality (using the same "wall thickness" measure as above) was evaluated to be approximately 7-10 cells throughout the corridor. Hence, as discussed before, since the laser accuracy is $\pm 3\%$ the observed wall thickness is within the laser's error margin.

CONCLUSIONS AND FUTURE WORK

This work presented a new methodology for autonomous navigation of MAVs, comprised of path planning and navigation using a modified potential field approach and a localization and mapping method that relies solely on scan matching without the requirement for a vehicle dynamic model. The method is based on scan matching performed between a laser scan of the environment and a virtual scan extracted from the virtual world represented using an occupancy grid.

The combined approach of vehicle navigation and the use of scan matching with a virtual map as a sole means for position estimation was proven to be successful experimentally on a moving ground platform.

The presented localization and mapping methodology is completely model independent and thus can be applied to non-linear vehicle models as well. The virtual scan technique developed in this work shows good results for accurately mapping and positioning the vehicle in typical environments without the knowledge of the vehicle's plan model.

The accuracy of the mapping and position estimation were comparable with current probability based SLAM methods, but the current work needs to be examined with even longer routes, where error can still be accumulated. The challenge also remains to transfer these technologies into 3D space.

Future Work

The algorithms presented here would be implemented on a small Computer to be mounted on an MAV and tested on different rotary wing configurations with a conventional main-tail rotor MAV as the main goal. The issue of scanning while in motion should be further addressed as the helicopter would not be in perfect hover conditions when each laser scan is taken.

As part of the future work, the 2D assumption can be alleviated by using a "2.5D" world representation where 2D slices make up a 3D representation of the surroundings. The assumption of the vehicle's slow motion can be alleviated with commercially available faster laser scanners. Testing the algorithm on scenarios with curved walls and thus less corners would also be beneficial in determining its robustness.

REFERENCES

[1] Kunchev Voemir, Jain Lakhmi, Ivancevic Vladimir, and Finn Anthony. Path planning and obstacle avoidance for autonomous mobile robots: A review. volume 4253, pages 537–544, 2006. 10^{th} International Conference on Knowledge-Based Intelligent Information and Engineering Systems.

[2] Hugh Durrant-Whyte and Tim Bailey. Simultaneous localisation and mapping (slam): Part i the essential algorithms. *IEEE Robotics and Automation Magazine*, 13(2):99–110, 2006.

[3] M.W.M.G. Dissanayake, P. Newman, S. Clark, H.F. Durrant-Whyte, and M. Csorba. A solution to the simultaneous localization and map building (slam) problem. *IEEE Transactions on Robotics and Automation*, 17(3):229–241, 2001.

[4] Slawomir Grzonka, Giorgio Grisetti, and Wolfram Burgard. Autonomous indoor navigation using a small-size quadrotor. page 455Ð463, 2008. Workshop Proceedings SIMPAR.

[5] M. Achtelik, A. Bachrach, R. He, S. Prentice, and N. Roy. Autonomous navigation and exploration of a quadrotor helicopter in gps-denied indoor environments. 2009. In IARC First Symposium on Indoor Flight Issues.

[6] Y Okubo, C Ye, and J Borenstein. Characterization of the hokuyo URG-04LX laser rangefinder for mobile robot obstacle negotiation. 2010. SPIE Defense, Security + Sensing, Unmanned Systems Technology XI.

[7] Yoichi Okubo, Cang Ye, and Johann Borenstein. Characterization of the hokuyo urg-04lx laser rangefinder for mobile robot obstacle negotiation. 2009. Presented at the SPIE Defense, Security + Sensing, Unmanned Systems Technology XI, Conference 7332: Unmanned, Robotic, and Layered Systems. Orlando, FL, April 13-17, 2009, Reference: Proc. SPIE Vol. 7332.

[8] Sebastian Thrun. Learning occupancy grid maps with forward sensor models. *Autonomous robots*, 15(2):111–127, 2003.

[9] Alberto Elfes. Using occupancy grids for mobile robot perception and navigation. *Computer*, 22(6):46–57, 1989.

[10] Bernt Schiele and James L. Crowley. A comparison of position estimation techniques using occupancy grids. *Robotics and autonomous systems*, 12(3-4):163–161, 1994.

[11] J.S. Gutmann and C. Schlegel. Amos: Comparison of scan matching approaches for self-localization in indoor environments. pages 61–67, 1996. Proceedings of the 1st Euromicro Workshop on Advanced Mobile Robots.

[12] F. Lu and E. Milios. Robot pose estimation in unknown environments by matching 2d range scans. *Journal of Intelligent and Robotic Systems*, 18(3):249–275, 1997.

[13] T. Röfer. Using histogram correlation to create consistent laser scan maps. pages 625–630, 2002. Proceedings of the IEEE International Conference on Robotics Systems (IROS-2002). EPFL, Luasanne, Switzerland.

[14] X Yuan, CX Zhao, and ZM Tang. Lidar scan-matching for mobile robot localization. *Information Technology Journal*, 9(1):27–33, 2010.

[15] T. Bailey and E. Nebot. Localisation in large-scale environments. *Robotics and Autonomous Systems*, 37:261–281, 2001.

[16] A. Censi. An ICP variant using a point-to-line metric. pages 19–25, 2008. Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on.

[17] P. Nunez, R. Vazquez-Martin, A. Bandera, and F. Sandoval. Fast laser scan matching approach based on adaptive curvature estimation for mobile robots. *Robotica*, 27:469–479, 2009.

[18] Albert Diosi and Lindsay Kleeman. Fast laser scan matching using polar coordinates. *Int J Robot Res*, 26(10):1125–1153, Jan 2007.

[19] Svetlana Potyagaylo and Omri Rand. Planning and operational algorithms for autonomous helicopter. 2009. American Helicopter Society 65th Annual Forum, Grapevine, Texas, May 27-29.