

A Proposal for a Parameterized Circulating Vector Field Guidance for Fixed Wing
Unmanned Aerial Vehicles

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Unmanned Aerial Vehicles

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ABSTRACT

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ABSTRACT

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TABLE OF CONTENTS

	Page
Abstract	3
Dedication	4
Acknowledgments	5
List of Tables	7
List of Figures	8
List of Symbols	9
List of Acronyms	10
 1 Introduction	11
1.1 Motivation and Problem Statement	11
1.2 Methods Overview	12
1.3 Phase I	12
1.4 Phase II	12
1.5 Phase III	12
1.6 Summary of Phases	13
 2 Literature Review	14
2.1 Introduction to Literature Review	14
2.2 Fixed Wing Unmanned Aerial Vehicle	14
2.2.1 Autopilot and Ground Station	14
2.3 Vector Field Guidance	17
2.3.1 Introduction to Vector Field Guidance	17
2.3.2 Potential Field	17
2.3.3 Virtual Force Field - Histogram Method	20
2.3.4 Lyapunov Vector Fields	21
2.3.5 Non-Lyapunov Vector Fields	24
2.3.6 Gradient Vector Field	26
2.4 Unmanned Aerial Vehicle Simulation	31
2.5 Literature Review Summary	32
 References	33

LIST OF TABLES

Table	Page
-------	------

LIST OF FIGURES

Figure	Page
2.1 Autopilot Navigation Guidance and Control	15
2.2 Pixhawk Autopilot	15
2.3 Unmanned Aerial System	16
2.4 Single Obstacle Potential Field Gradient [5]	18
2.5 Potential Field Local Minimum [5]	19
2.6 Obstacle Clustering [5]	20
2.7 Virtual force field histogram acting on a mobile robot	21
2.8 Lyapunov vector field for straight line and circular primitives	22
2.9 Lyapunov vector field approach curved path asymptotically	22
2.10 Elliptical VF produced by non-linear coordinate transformations a) [11] b) [12]	23
2.11 Tangent plus lyapunov vector fields for shortest path target tracking [14]	24
2.12 RRT* path planner with a VF used as a task specification	25
2.13 Vector field within a set of constrained delaunay triangles [16]	25
2.14 Attractive vector field (a) and clockwise circulation field (b)	27
2.15 Repulsive vector field a) and counterclockwise circulation field b)	27
2.16 Place holder image of UAV following ground target	28
2.17	28
2.18	29
2.19 Dubins UAV actuator saturation	31
2.20 Differential drive mobile robot simulating fixed wing UAV Dubins constraints .	32

LIST OF SYMBOLS

a Previous or Initial Axial Induction Factor (-)

LIST OF ACRONYMS

AoA Angle of Attack

1 INTRODUCTION

1.1 Motivation and Problem Statement

Fixed wing Unmanned Aerial Vehicles are used for missions such as surveillance and reconnaissance that might put pilots harms way [1]. UAVs carry out mission objectives such as waypoint navigation and loitering by following paths that are typically pre-planned [2]. Known obstacles are avoided during the planning processes to avoid collisions. Paths must be of obstacles which may not be known during planning. Obstacles are not always known during planning and once discovered a new path may have to be re-planned. Guidance that follows mission paths while avoiding obstacles without the need for re-planning may be beneficial. Gradient vector field (GVF) guidance is a path following method that provides continuous guidance that guaranteed to converge and follow an arbitrary path. Guidance for getting on and following a path is produced by summing together convergence and circulation terms that are weighted by static scalars. Obstacles have been represented as separate repulsive GVF that are later summed to the path following GVF [Wilhelm, Wambold, Clem]. Static GVF do not always route the UAV around an obstacle and could be improved. Modifying the GVF convergence and circulation weights to be functions of common UAV states could be used to produce an optimal guidance for obstacle avoidance. **The proposed research seeks to determine GVF weighting functions that construct optimal obstacle avoidance.**

1.2 Methods Overview

The proposed research will be conducted in three phases where VF guidance singularities will be demonstrated, weighting functions will be investigated, and a developed GVF will be validated on a ground robot simulating a UAV. Phases I and II will be conducted in a simulation environment that combines mission paths and obstacles into a single GVF. Phase III will be conducted with a ground robot simulating a UAV guided by the modified GVF in real-time. Dubins fixed wing constraints will be imposed in simulations and experiments.

1.3 Phase I

Recreate gradient vector fields for circular and elliptical obstacles and demonstrate singularities. A simulation environment will be built that generates GVFs consisting of mission paths and obstacles. Circular and elliptical obstacles will be investigated and the resulting singularities will be characterized. Static weights will be used and the performance of the guidance measured in distance traveled and time of flight.

1.4 Phase II

Investigate GVF weighting functions that influence obstacle avoidance. UAV closing rate, position, and range will be used to develop dynamic GVF weights for convergence and circulation. The modified GVF will be compared against a static and strictly repulsive GVF. Distance traveled and time of flight will be used to as metrics to compare the modified GVF to the unmodified GVF.

1.5 Phase III

Validate modified GVF model with ground robot experiments. The modified GVF developed in Phase II will be implemented on a differential drive ground robot

simulating a fixed wing UAV. Guidance performance while avoiding static obstacles will be demonstrated.

1.6 Summary of Phases

Each phase consists of an **objective** that will be accomplished by executing *tasks*. Completion of all objectives and phases will result in the final deliverable.

Phase I: Demonstrate Gradient Vector Field Singularities

1. *Build a GVF simulation environment*
2. *Derive GVF for circular and elliptical obstacles*
3. *Identify path and obstacles where singularities are produced*

Phase II: Investigate GVF weighting functions that influence obstacle avoidance

1. *Formulate circulation and convergence weights as functions of UAV state*
2. *Determine combination of GVF weights that produces optimal guidance in simulation*

Phase III: Validate modified GVF model with ground robot experiments

1. *Build differential drive robot*
2. *Build robotic framework to take guidance commands*
3. *Repeat simulations performed in Phase II on ground robot*

Deliverable: Adaptive GVF parameterized weights optimal guidance for path following and static obstacles

2 LITERATURE REVIEW

2.1 Introduction to Literature Review

2.2 Fixed Wing Unmanned Aerial Vehicle

Unmanned Aerial Vehicles have potential uses for military, police, and civilian communities performing tasks that may put pilots of manned aircraft in harms way. On-board sensors such as cameras can relay information making UAVs ideal for surveillance, reconnaissance, damage assessment, and natural disaster surveying. Fixed wing UAVs come in a wide range of sizes from micro to large varieties. Micro to small hand launched UAVs can be easily transported, are inexpensive, and are fast to deploy. Large UAVs can perform the same tasks as smaller varieties as well as carry weapons. UAVs are part of an Unmanned aerial system consisting of the aircraft, an autopilot, ground station, radios, and transmitters. Ground stations are used for planning missions, configuring UAV parameters, and collecting UAV sensor data. Missions are typically relayed to a UAV as a path that accomplishes tasks such as waypoint navigation and loitering. Autopilots attempt to follow the path as closely as possible using navigation, guidance, and control algorithms.

2.2.1 Autopilot and Ground Station

Autopilots are devices that control the position and attitude of a UAV by implementing guidance, navigation, and control systems. Accelerometers, gyroscopes, barometers, and compasses measure the state of a UAV and are passed to the navigation system. Measurements are often noisy and need to be fused together which is commonly done with a kalman filter [3]. The state estimates are used as feedback for both the guidance and control systems, depicted in Figure 2.1. Sensor uncertainty and wind disturbances cause the UAV to deviate from the reference path over time and needs to be corrected. The guidance system compares the estimated state of a UAV to the reference path and provides

guidance commands in the form of a heading to the control system. State estimates are also fed into the control system as feedback along with guidance commands to produce pulse width modulation commands to actuators. The actuators produce a physical output that alters the state of the UAV which is again measured and estimated by the navigation system.

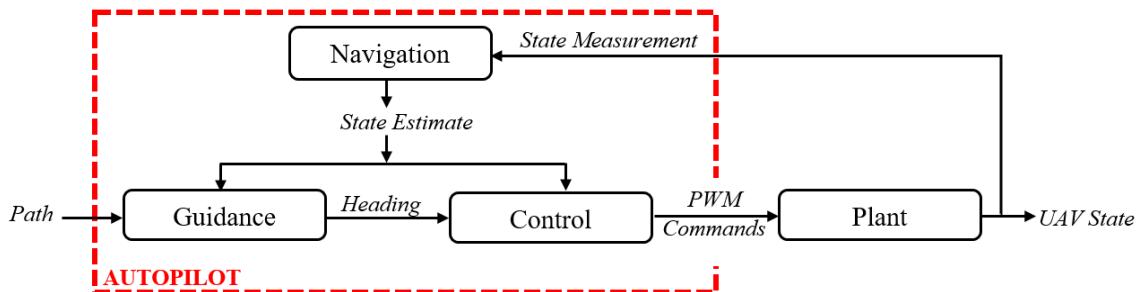


Figure 2.1: Autopilot Navigation Guidance and Control

A typical autopilot is shown in Figure 2.2 which is programmed with navigation, guidance, and control software. Accelerometers, gyroscopes, barometers and the compass are included inside the autopilot and makeup the inertial measurement unit (IMU). Additional sensors such as GPS and airspeed sensors can be connected as peripheral devices. Radios are connected to receive transmitter commands and communicate with a ground station.



Figure 2.2: Pixhawk Autopilot

Ground stations are computers that run mission management software that allow users to configure vehicles and program missions. Missions are planned at the ground station where high level mission objectives are assigned to points on a map such as waypoints and loitering maneuvers. Ground station software generates obstacle free and flyable paths that connect mission objectives and relay paths to the autopilot over radio link. Information collected by the UAV can be relayed back to the ground station for analysis. Transmitters can be used to control the UAVs movements directly. Ground stations and autopilots work together to form an Unmanned Aerial System (UAS) depicted in Figure 2.3.



Figure 2.3: Unmanned Aerial System

Once paths have been generated, such as that shown in Figure ??, they are sent to the UAV via radio link. The guidance system is then responsible for guiding the UAV to get on and follow the path. Common methods for guiding algorithms for getting on and following a path include carrot chasing, non-linear guidance law (NLGL), pure pursuit line

of sight (PLOS), linear quadratic regulator (LQR) and vector field [2]. Benchmarks for how each guidance algorithm performs is commonly quantified in control effort and tracking error with respect to the reference path. Sujit et al. compared the above guidance laws and discussed the benefits and disadvantages of the guidance laws, and in terms of control effort and tracking error LQR and vector field performed the best respectively. LQR was shown to have optimal control effort but exhibited large cross track error when subjected to high wind speeds. Vector field produced guidance with the lowest tracking error but experienced osculations once on the path.

2.3 Vector Field Guidance

2.3.1 Introduction to Vector Field Guidance

Vector field is a continuous guidance and control method that applies artificial attractive and repulsive forces to a point mass. The two broad categories of algorithms that produce vector fields consist of potential field algorithms and path following algorithms. Potential field produces guidance and control to a robot for converging to a distinct point. Path following algorithms produce guidance for converging and following a path. Several path following vector field algorithms have been investigated including gradient vector field, which provides convenient convergence and circulation weights that may be useful for providing an optimal guidance for obstacle avoidance.

2.3.2 Potential Field

Potential field was introduced as a real-time robotic manipulator algorithm for obstacle avoidance [4]. The potential field algorithm represents a robots workspace as a gradient potential of attractive and repulsive artificial forces that drive the robot to a desired goal. Goals are given the lowest potential and act as attractive forces. Obstacles have high potential and act as repulsive forces. A simple example is depicted in Figure 2.4 consisting

of an initial state, a goal, and a single obstacle. The initial state of the robot is at the edge of a gradient where the potential is maximum. In the lowest part of the gradient a goal exists at the global minimum. Obstacles are added to the potential field, but have limited effect due to a decay function.

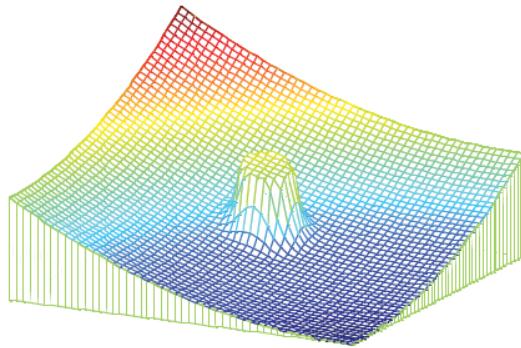


Figure 2.4: Single Obstacle Potential Field Gradient [5]

Potential field is unique in that path planning, trajectory planning, and control are lumped into a single system [6]. Transition from an initial state to a goal state traditionally occurred by executing three steps consisting of path planning, trajectory planning, and control. Path planning dealt with finding an obstacle free path from an initial state to a goal state. Trajectory planning time parametrized the obstacle free path with some high level vehicle constraints considered. Lastly, control attempts to reduce the tracking error with respect to the reference trajectory. Combining the three motion planning steps into a single algorithm has been shown to be computational inexpensive [7].

As pointed out in [8], robots using potential field are susceptible to local minimum. Encountering a local minimum prevents the robot from continuing down the gradient and into the global minimum because equilibrium has been reached prematurely. Figure 2.5 demonstrates local minimum by adding several obstacles into a goal field. Several methods have been developed to mitigate the effects of local minimums as pointed out in [7] through

the use of navigation functions. Local minimum produced as a result of closely spaced obstacles as shown in Figure 2.5 have been addressed by grouping obstacles together into a cluster [5].

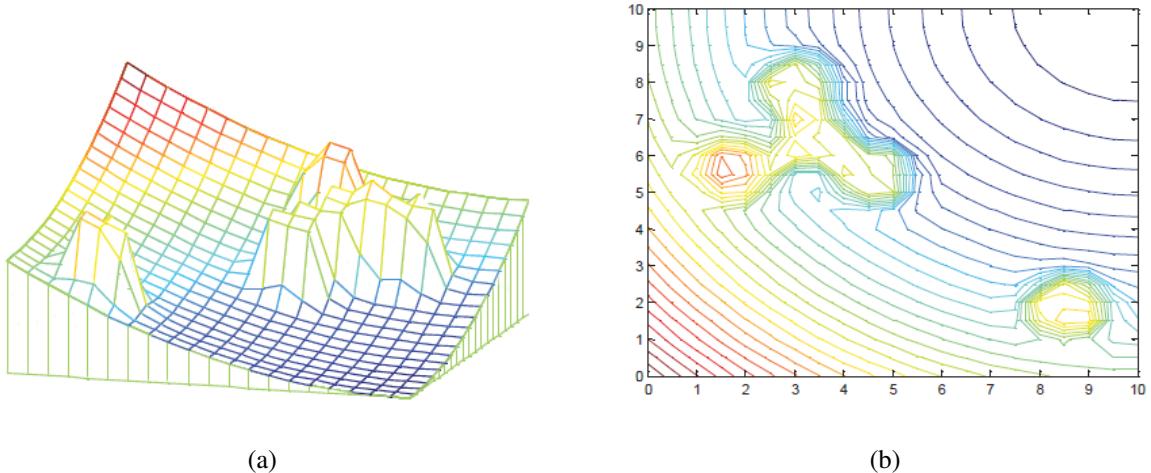


Figure 2.5: Potential Field Local Minimum [5]

Several methods have been developed to mitigate the effects of local minima as pointed out in [7] through the use of navigation functions. Local minimum produced as a result of closely spaced obstacles as shown in Figure 2.5 have been addressed by grouping obstacles together into a cluster [5]. Grouping obstacles addresses the risk of local minima before forming the potential field. If local minima are encountered after the field is generated, additional forces can be applied to push the robot away from the local minima.

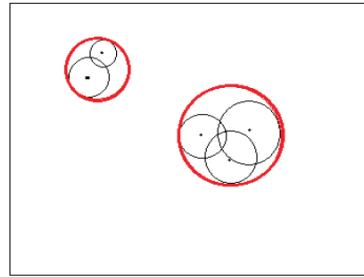


Figure 2.6: Obstacle Clustering [5]

Potential fields ability to avoid obstacles and combine path planning, trajectory planning, and control into a single system while being computationally inexpensive makes it an attractive option for many robotic systems. Fixed wing UAVs must maintain a minimum forward velocity and cannot converge to a single point, making potential field difficult to implement.

2.3.3 Virtual Force Field - Histogram Method

When the environment changes, such as a new obstacle or the goal has moved, the potential field has to be recalculated. Koren and Borenstein developed a virtual force field (VFF) histogram method that guides a mobile robot to a known goal while avoiding initially unknown obstacles [8]. VFF decomposes a robots workspace into discretized cells that contain an integer certainty value associated with the confidence that an obstacle occupies the cell. A global goal applies an artificial attractive force on the robot that pulls it closer to the goal. As the robot detects obstacles, the certainty value increases in the cell associated with the obstacles position. Cells apply artificial repulsive forces with magnitudes that depend on the certainty value and the distance to the cell.

The VFF histogram method was validated on a mobile robot platform using ultrasonic sensors in [8] and [9], avoiding obstacles and seeking a goal. Certainty cells

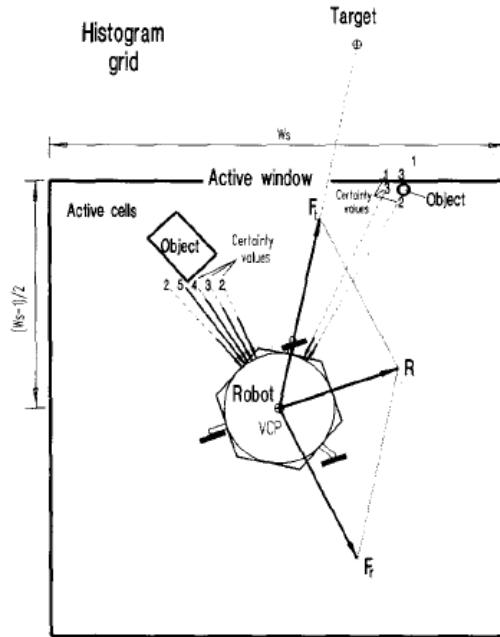


Figure 2.7: Virtual force field histogram acting on a mobile robot

in VFF only provide strictly repulsive vectors which guide the robot away, but provide no guidance for getting around the obstacle.

2.3.4 Lyapunov Vector Fields

Fixed wing UAVs must maintain a minimum forward velocity therefore cannot converge to a single point making potential field or VFF guidance difficult. Missions for UAVs are typically constructed from obstacle free paths build from straight line and circular arc primitives. Path planning provides a reference to the autopilot that guides the UAV to first arrive at and subsequently follow the desired path while under the influence of external disturbances. Arriving at and following the path are typically achieved by generating vectors normal and parallel to the path respectively. Nelson et al. introduced a vector field generation method for straight line and circular arcs using Lyapunov stability arguments [10] and is depicted in Figure 2.8.

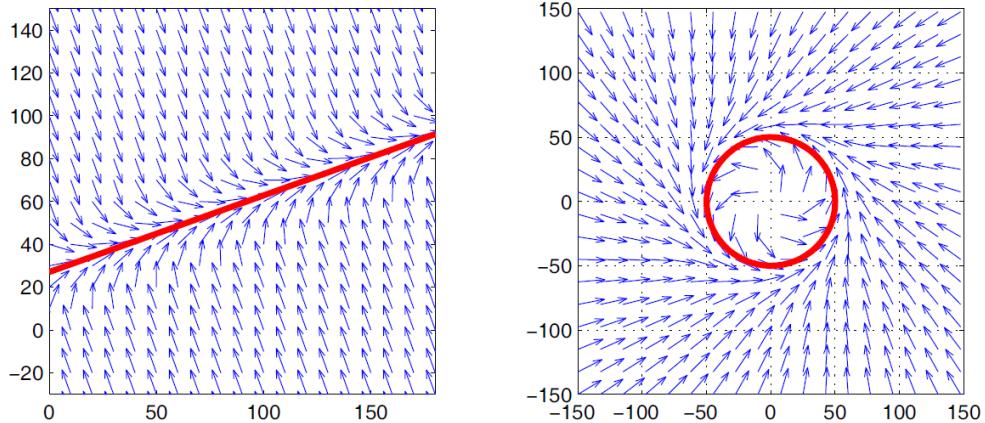


Figure 2.8: Lyapunov vector field for straight line and circular primitives

To construct flyable paths out of the primitives, it was necessary to determine how the resulting vector fields should be combined. Summing the fields directly result in **dead-zones, sinks, and singularities**. The solution was to have a single field active at any time, switching when the UAV reached the end of a primitive. Nelson's method was extended by Griffiths for curved path following and showed that the vectors asymptotically approach the curved path, shown in Figure 2.9.

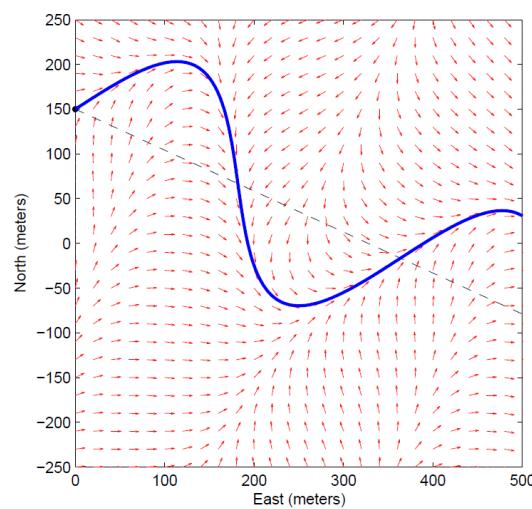


Figure 2.9: Lyapunov vector field approach curved path asymptotically

Primitive circular fields can be modified via non-linear coordinate transformations to produce globally convergent elliptical fields [11] [12]. Frew simulated and experimentally validated the transformed vector field where multiple fixed wing UAVs cooperatively tracked a moving target while maintaining a staggered distance from each other, preventing collision and multiple surveillance angles. The location of a target being tracked is not known with absolute certainty. The covariance matrix from a kalman filter to transform a circular vector field around an uncertain target was investigated in [12] and an example field is shown in Figure 2.10b.

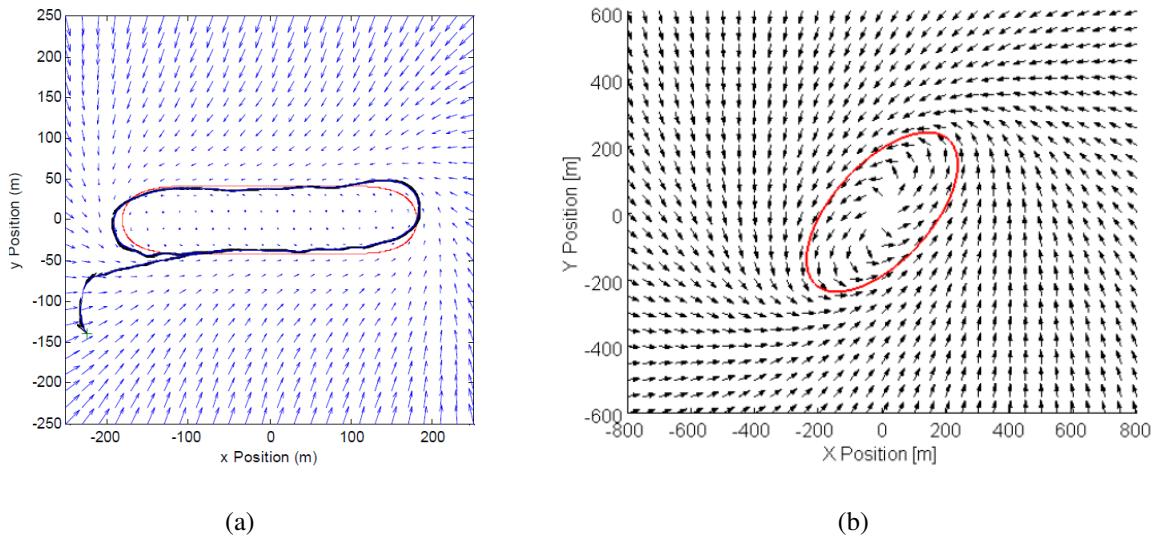


Figure 2.10: Elliptical VF produced by non-linear coordinate transformations a) [11] b) [12]

A target tracking lyapunov plus tangent vector field was introduced in [13] that produced shorter paths compared to lyapunov alone. Outside of the standoff circle, tangent vectors were said to provide the shortest distance to the circle. Inside the standoff circle, no tangent lines exist and lyapunov is used in its place. Figure 2.11 shows the difference in paths taken for lyapunov and tangent vector fields outside the standoff circle. The TPLVF was later used for path planning to avoid obstacles in [14].

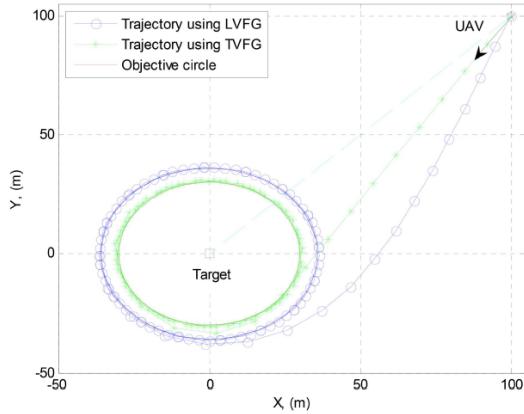


Figure 2.11: Tangent plus lyapunov vector fields for shortest path target tracking [14]

2.3.5 Non-Lyapunov Vector Fields

All methods that consider obstacles so far build a vector field that guides the UAV to an obstacle free path. Another approach is to build a vector field tending to a path and use optimal rapid random trees (RRT*) to explore the space for obstacles and select the optimal path. Pereia et al. developed such a method that builds a tree that makes up possible paths for the UAV to take. Branches extend from the root, or initial location of the UAV, randomly throughout the map with a constrained deviation from the initial vector field. When a branch encounters an obstacle it is trimmed and no longer explored. The path of minimum cost, or least distance, is selected for the UAV to use as a reference path. An example of the algorithm is shown in Figure 2.12.

For well known obstacles in urban environments, such as buildings, an optimal path can be constructed with constrained delaunay triangulation (CDT) which has been previously used in computer animation [15]. CTD was used to construct vector fields in [16] that restricts robots movements inside the triangles while moving towards a global goal. A simulation of a robot traversing a vector field inside a set of CDTs can be seen in Figure 2.13.

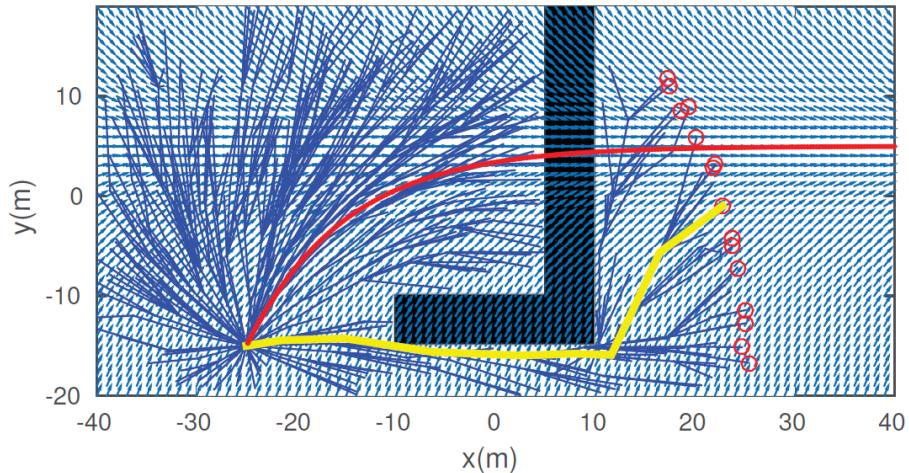


Figure 2.12: RRT* path planner with a VF used as a task specification

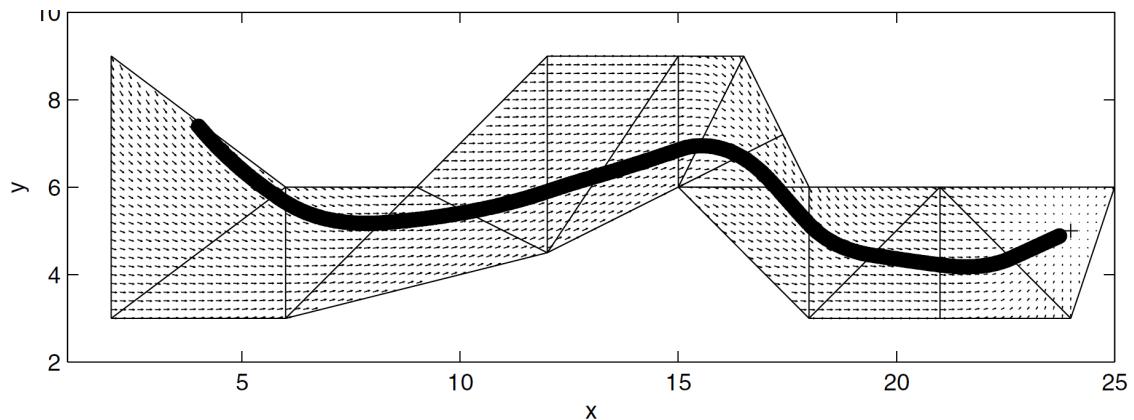


Figure 2.13: Vector field within a set of constrained delaunay triangles [16]

So far all of the vector field methods discussed have avoided obstacles by planning paths around them. Paths are typically calculated at the ground station and if communication is lost a new path may not be relayed to a UAV encountering a new obstacle. A possible solution is using vector fields to provide a repulsive force, not unlike the VFF method, immigrating around the obstacle.

2.3.6 Gradient Vector Field

The gradient vector field method was first introduced in [17] and produces an n -dimensional vector field guaranteed to converge to a path made of points that lie at the intersection of two surfaces. The total vector field \vec{V} is produced by summing together a convergence, circulation, and time varying terms seen in Equation ???. Convergence terms contribute vectors normal to the path, circulation terms contribute vectors parallel to the path, and time varying vectors account for changes in the path as a function of time.

$$\vec{V} = \mathbf{G}\vec{V}_{conv} + \mathbf{H}\vec{V}_{circ} + \mathbf{L}\vec{V}_{tv} \quad (2.1)$$

Each term is multiplied by a scalar, \mathbf{G} , \mathbf{H} , \mathbf{L} , that weights the contribution of each term on the total field \vec{V} . Only static paths will be discussed so it is assumed the time varying field is null. The advantage of GVF is the convenient access to the weighting terms that independently effect the total field. Magnitude of the weights modifies the strength of each fields influence, whereas the sign indicates the direction. Figure 2.14 shows convergence and circulation fields for a circular path where the weights \mathbf{G} and \mathbf{H} are unity and positive. The convergence field contains vectors that are normal to the circular path for all points in space, with exception to the center of the circle which is undefined. Circulation fields contain vectors that are parallel to the path for all points in space with the same exception of no definition at the center of the circle.

Modifying the signs of \mathbf{G} and \mathbf{H} to be unity and negative results in similar fields but with a 180° rotation about the center of the circle, Figure 2.15. The attractive convergence field becomes a repulsive field, where all vectors are anti-normal to the path. The circulation field changes direction and rotates counterclockwise around the path.

Repulsive fields have been used for obstacle avoidance for a UAV loitering around a moving target in [w,w,c]. A circular goal path was attached to a ground vehicle and a

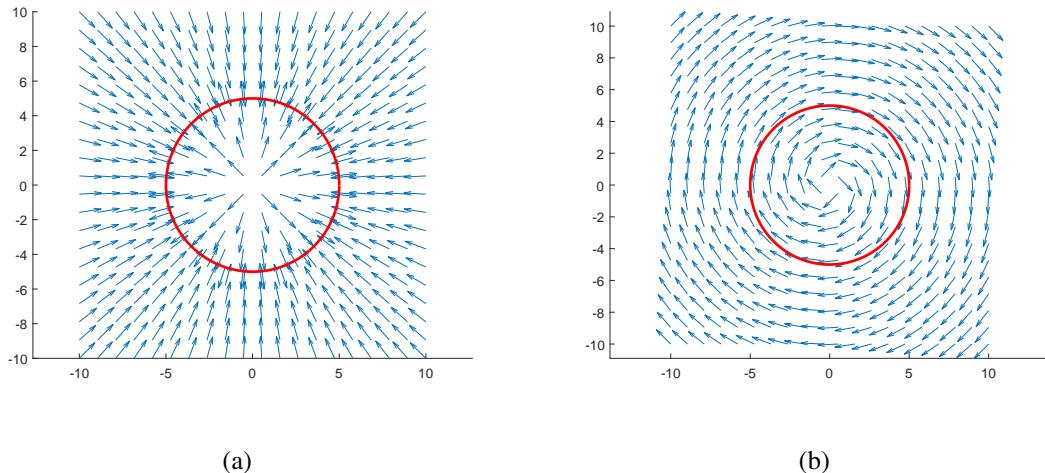


Figure 2.14: Attractive vector field (a) and clockwise circulation field (b)

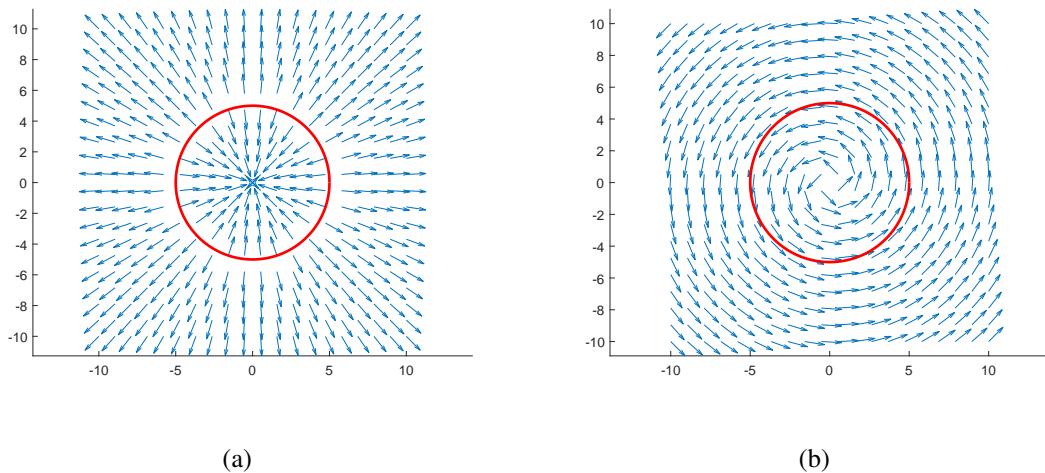


Figure 2.15: Repulsive vector field a) and counterclockwise circulation field b)

convergence and circulation vector field was generated. Circular paths were with small radii were placed on top of obstacles with strictly repulsive weights. Notice in Figure 2.15a that inside of the path, vectors guide inward, which is not desired for obstacle avoidance. The problem is alleviated by reducing the radius significantly. Goal and obstacle field are

summed together to provide a total field that provides guidance to a UAV. Loitering is accomplished while avoiding two obstacles, as shown in Figure 2.16

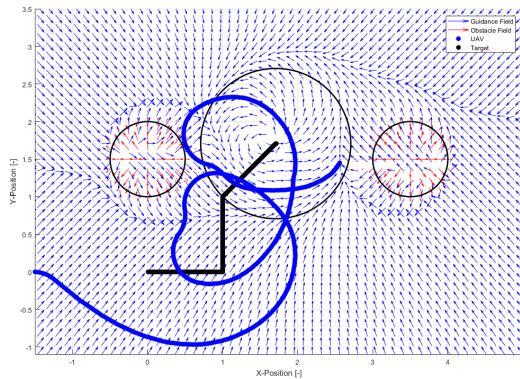


Figure 2.16: Place holder image of UAV following ground target

Similar to potential field and VFF, the strength of the repulsive field depends on the distance from an obstacle. In [w,w,c], a tangent hyperbolic decay function was assigned to the obstacle fields which varied the total strength from null to unity, shown in Figure 2.17.

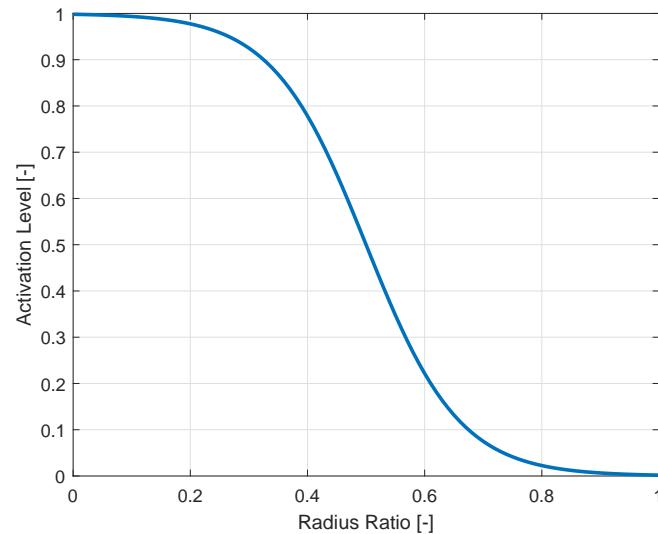


Figure 2.17:

Constructing the paths for a UAV flying at constant altitude requires three-dimensional surfaces intersecting to form two-dimensional paths. Consider a UAV in 2-dimensional space tracking a path τ , which is made of points that lie at the intersection of two surfaces. Each of the surfaces α_i is continuous, differentiable, and is a function of the set $q = [x, y, z]$. The convergence field \vec{V}_{conv} is produced by the sum of surfaces multiplied by their respective partial gradient $\nabla_q \alpha_i$. The definition of the convergence field is summarized in Equations 2.2 and 2.3.

$$\vec{V}_{conv} = \mathbf{G} \sum_{i=1}^{n-1} \alpha_i \nabla_q \alpha_i \quad (2.2)$$

$$\nabla_q = \begin{bmatrix} \frac{\partial}{\partial x} \\ \frac{\partial}{\partial y} \\ \frac{\partial}{\partial z} \end{bmatrix} \quad (2.3)$$

To produce a circular path of radius r the intersection of a cylinder and plane are used, as shown in Equations 2.4-2.5 and pictured in Figure 2.18.

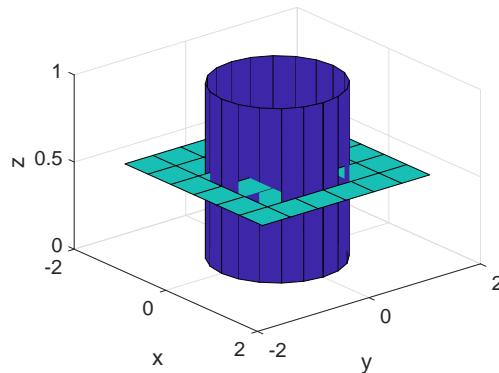


Figure 2.18:

$$\alpha_1 = x^2 + y^2 - r^2 \quad (2.4)$$

$$\alpha_2 = z \quad (2.5)$$

Convergence vector field term is produced by taking the wedge product of the partials $\nabla_q \alpha_i$, which in three dimensions simplifies to the cross product as shown in Equations 2.6 and 2.7.

$$\vec{V}_{circ} = \mathbf{H} \wedge_{i=1}^{n-1} \nabla_q \alpha_i \quad (2.6)$$

$$\vec{V}_{circ} = \mathbf{H}(\nabla_q \alpha_1 \times \nabla_q \alpha_2) \quad (2.7)$$

Circulation and convergence terms may have different magnitudes depending on the location of origin of a vector and the equations used for surfaces. Normalizing each component prior to weighting allows for more predictable results when assigning values. So far the VF weights have been used for high level specification of the desired behavior for a UAV, whether it be for convergence, avoidance, or circulation. Furthermore, there is no guarantee that when using a vector field for avoidance that the UAV will not violate the no-fly zone. If the UAV turn rate is at saturation an increased reference command will do nothing to aid in avoidance. A demonstration of saturation is seen in Figure 2.19 where a UAV is provided guidance by a convergent and circulating vector field about a circular path.

If the VF was adjusted earlier at an earlier state, the tracking error may be reduced. When using an obstacle, determining which direction the UAV must fly around the obstacle is important to reduce distance flown. Determining functions for the sign and magnitude of the vector field weights to produce an optimal guidance.

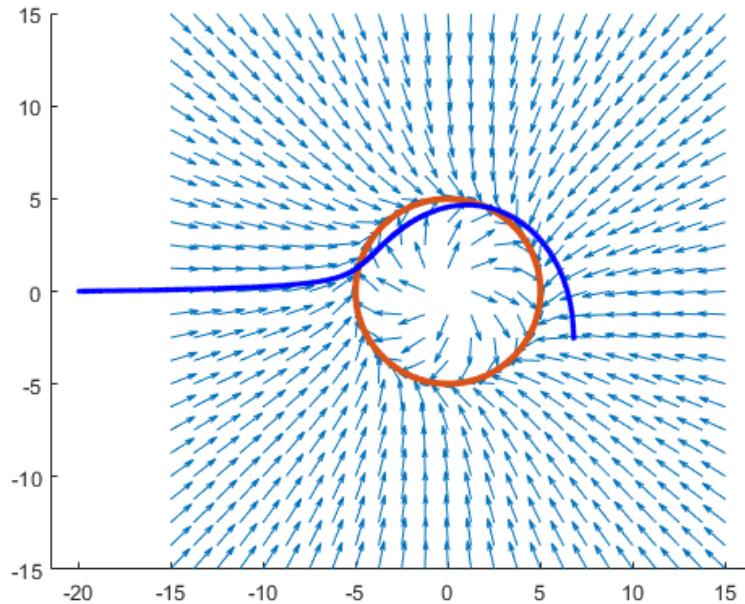


Figure 2.19: Dubins UAV actuator saturation

2.4 Unmanned Aerial Vehicle Simulation

Testing new guidance, navigation, and control algorithms can be costly, require significant time, and requires an adequately large airspace. Ground stations need to be established which require power and shelter. Some small fixed wing UAVs may not be suitable to fly in all weather, therefore test flights may be canceled due to weather conditions. Lastly, larger UAVs need to have FAA clearance before flight which has to be pre-approved and takes time. Before spending the time to reserve airspace and allocate man hours for flight tests it is important to test algorithms in a controlled environment. One way to accomplish testing without actual flight is through validation through mobile robots simulating fixed wing constraints [18], [19], [20]. Programming a mobile robot, such as one shown in Figure

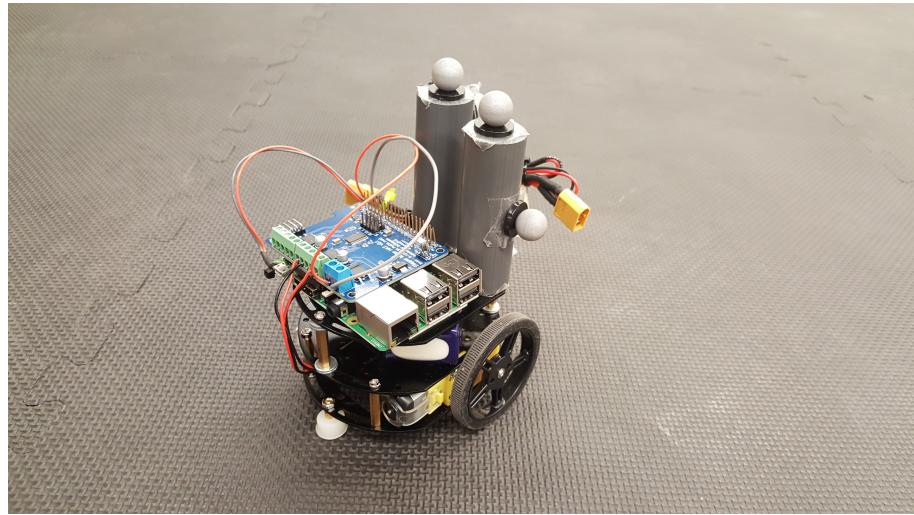


Figure 2.20: Differential drive mobile robot simulating fixed wing UAV Dubins constraints

2.5 Literature Review Summary

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