

# Autonomous UAV Navigation in Unknown Indoor Environment using Onboard Light Weight Camera

*part of*

TRADR - Teaming for Robot-Assisted Disaster Response

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- 7 Future work

- Recognize the scope and extent of the disaster damage over the affected area.
- Robots and UAVs can be of great help to analyze the scene.
- This can help to most effectively begin rescue and disaster recovery activities.

- Functioning in collapsed building, requires robot to traverse cluttered and uneven environment.
- Ground robot can traverse rough terrain but in terrains with levels it is not physically capable.
- UAV is an alternative robotic platform for rescue tasks and a host of other applications.



Ground robots that can traverse through rough surfaces

# Objective

Constraints with UAVs:

- Payload
- Computational limitations
- Fast dynamics

*The objective of this R&D is to design and implement a basic navigation system for UAVs which uses only on-board light weight camera, requires minimum computation and less power consuming.*

## Related Work

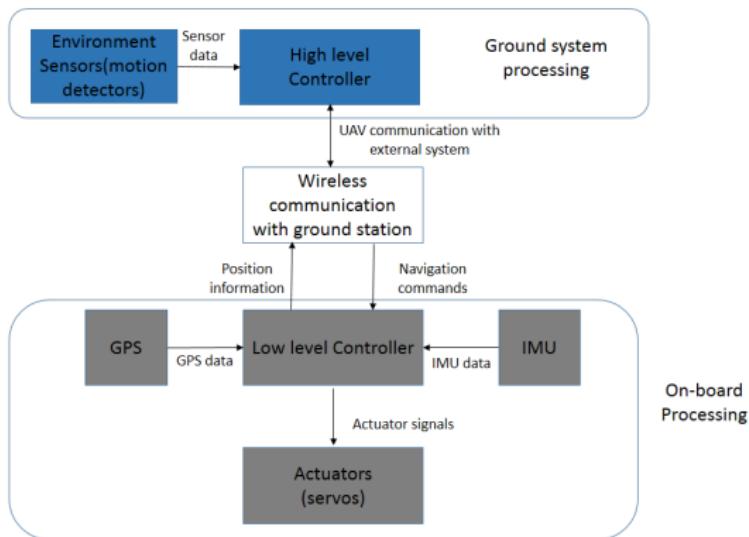
- Non Vision sensors based indoor UAV navigation:
  - Kumar & Ghose and Kwag & Kang implemented radar based navigation and obstacle avoidance.
  - Saunders used a forward looking laser range finder for path planning.

*These approaches lack in heavy weight or high power consumption.*

- Vision sensors based Unknown indoor UAV navigation:
  - Saxena and Courbon used vision to fly in known environments based on visual databases.
  - Chao, Yu Gu and Napolitano presented optical flow techniques for UAV navigation.
  - Conte and Patrick used inertial sensors and visual odometry.

*These approaches would not apply in many indoor environments that are devoid of trackable features.*

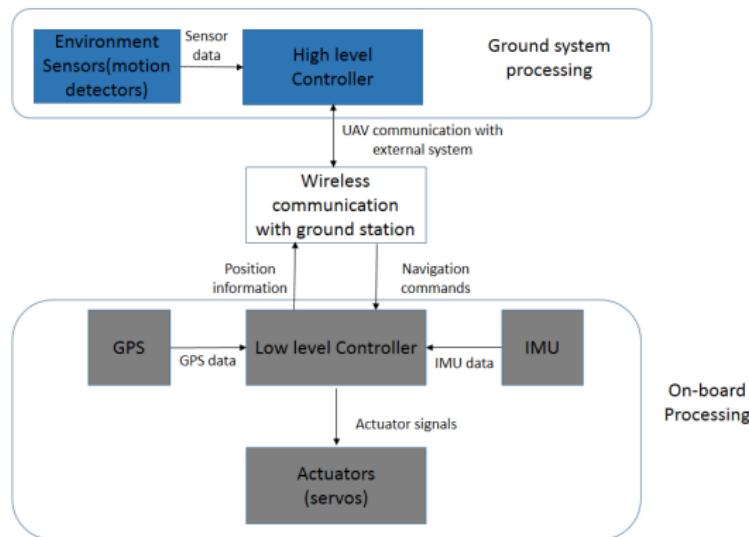
# How to handle computational limitations?



Basic drone architecture with computation on ground system

# How to handle computational limitations?

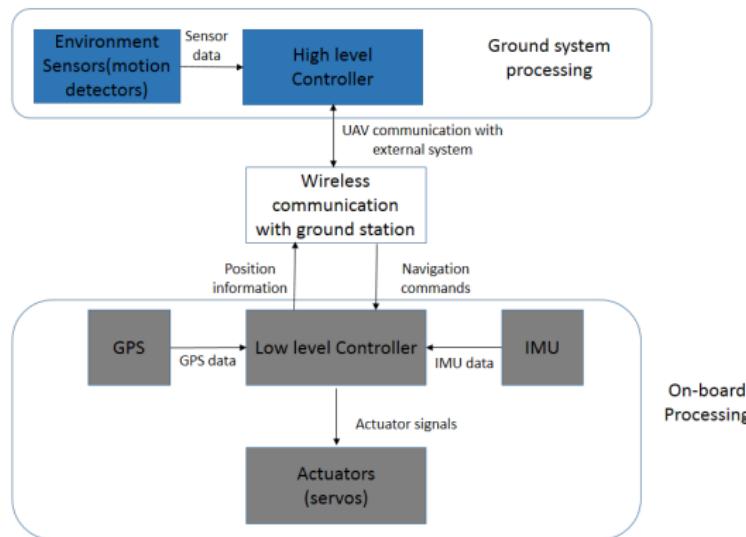
- Receive data from environment sensors(Motion trackers or camera) and UAV(IMU).



Basic drone architecture with computation on ground system

# How to handle computational limitations?

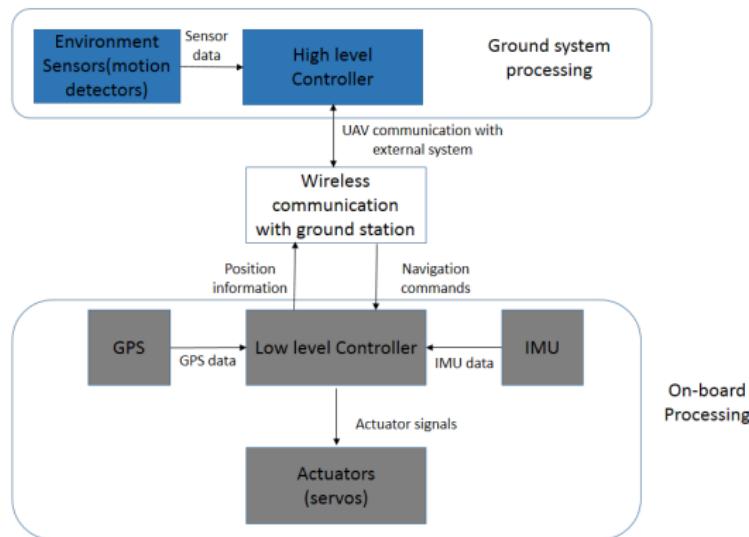
- Receive data from environment sensors(Motion trackers or camera) and UAV(IMU).
- Run autonomy algorithms(navigation algorithms) on external system(desktop computers).



Basic drone architecture with computation on ground system

# How to handle computational limitations?

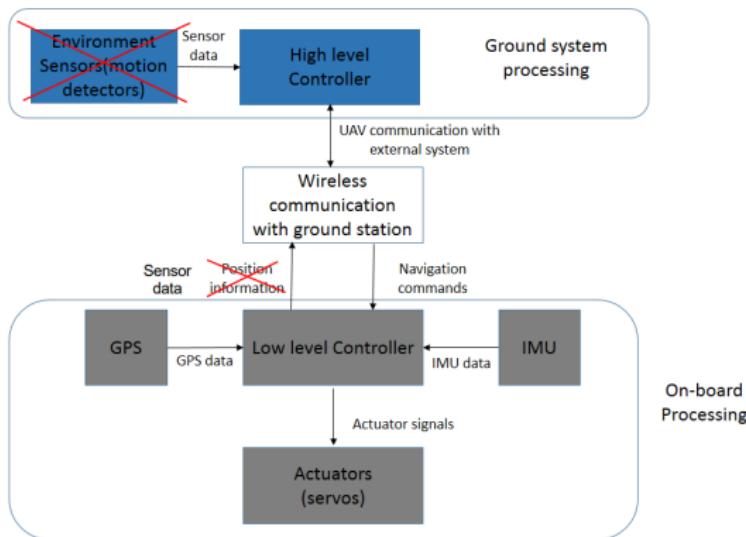
- Receive data from environment sensors(Motion trackers or camera) and UAV(IMU).
- Run autonomy algorithms(navigation algorithms) on external system(desktop computers).
- Send navigation commands back to UAV



Basic drone architecture with computation on ground system

# How to handle computational limitations?

- Receive sensor data(image cues) from UAV.
- Run autonomy algorithms(navigation algorithms) on external system(desktop computers).
- Send navigation commands back to UAV

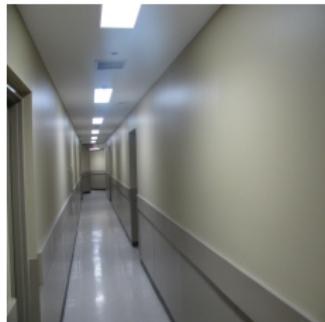
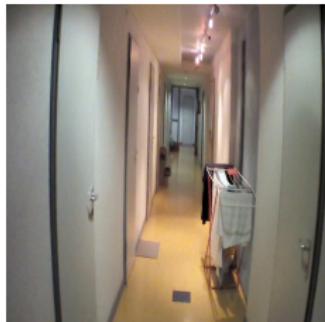


Basic drone architecture with computation on ground system

# Problem handled

Design and implement a navigation system prototype for UAV which:

- enables a UAV to autonomously explore corridor environments
- uses only on-board sensors and works without prior knowledge of the environment
- less computationally expensive (algorithm able to run onboard)
- based on simple features extraction
- suited for long-term navigation.



Corridor sample images

Primary platform is the Parrot AR.Drone 2.0 quadrotor:

- first implement our approach on the Parrot A.R. Drone
- less computational capabilities on-board, therefore computation happens on ground system
- algorithm runs on host machine –Lenovo Y560 (Intel® Core i7 CPU Q720@1.60GHzx8, 4GB RAM), running Ubuntu 12.04
- commands and images are exchanged via WiFi between host machine and AR.Drone

*If successful, implement the approach on **AscTec Pelican quadrotor**, TRADR project target platform. AscTec Pelican has computational power similar to our host machine.*

# Setup and Platform



AscTec Pelican

Technical Data	AscTec Pelican
UAV Type	Quadcopter
Onboard computer	Up to 3rd Generation Intel®Core i7 processor
Size	700 x 700 x 500 mm
Max. take off weight	1,65 kg
Max. payload	650 g
Flight time incl. payload	16 min.
Wireless communication	2,4 GHz XBee link
Sensors	HD Camera, Hokuyo laser scanner,...



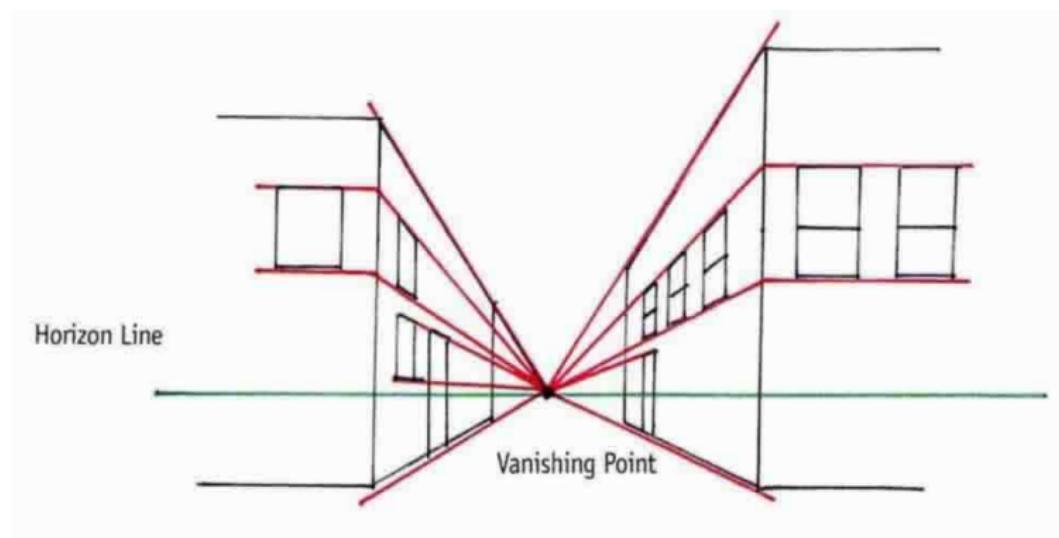
Parrot AR.Drone 2.0

Technical Data	Parrot AR Drone 2
UAV Type	Quadcopter
Onboard computer	1 GHz ARM Cortex-A8 CPU
Size	670 x 670 x 125 mm
Max. take off weight	380grams
Max. payload	250grams(unstable)
Flight time incl. payload	15 min.
Wireless communication	802.11n WiFi
Sensors	Front HD 720p camera, Bottom VGA Camera,IMU,...

- Indoor environments comprise of long straight parallel lines, and from UAVs perspective this has unique visual cues.
- Ends of the corridor are observed as vanishing points(VP) in images.
- In indoor environments, VP can be found consistently and hence can be used to locate the end of the corridor.
- If we have a VP, we command the drone to moves towards it.
- if no VP is found, drone rotates towards left until it finds a VP.

# Vanishing Point

A group of parallel lines in three-dimension (3D) space can be mapped into some intersection lines in two-dimension (2D) image and the intersection point formed by these intersection lines is called vanishing point.

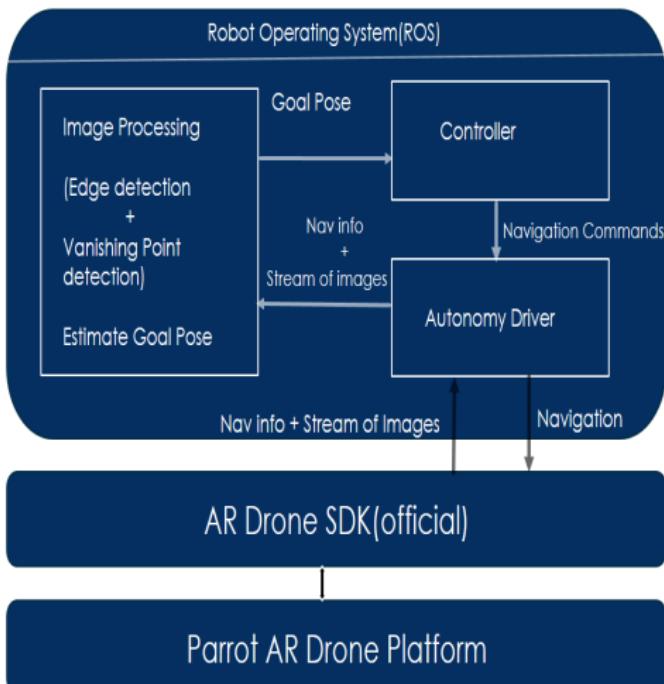


Example image of Vanishing Point

# Design Architecture

Architecture consists of 5 main components:

- Parrot AR Drone Platform
- AR Drone SDK
  - provides APIs to communicate with AR drone.
- Autonomy Driver(ROS Package)
  - interface between ROS and the AR.Drone(navigation messages, video feeds and control commands)
- Image Processing\*
- Controller\*



Component view of the Architecture

Detect vanishing point from the perspective cues from stream of images received through AR Drone.

Implemented two methods of detecting vanishing point:

- ① Classical VP based on edge detection
  - straight lines extraction from images
- ② VP based on image density clustering
  - lines those move away from us converge towards the center of the picture.

## Method 1: Classical approach based on edge detection

Detecting the parallel lines in the environment is the premise for calculating the vanishing point.  
Procedure for VP detection:

- ① Straight lines extraction
  - ① preprocessing of image
  - ② edge extracting using Canny operator
  - ③ extracting lines by PHT(Probabilistic Hough Transform)
- ② Deleting unreasonable straight lines
- ③ Locating vanishing point

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## ③ Locating vanishing point

- Enhance image for more understandable level of feature extraction (Gray scale conversion).
- Smoothen the image to reduce noise (Normalized Box filter<sup>1</sup>)

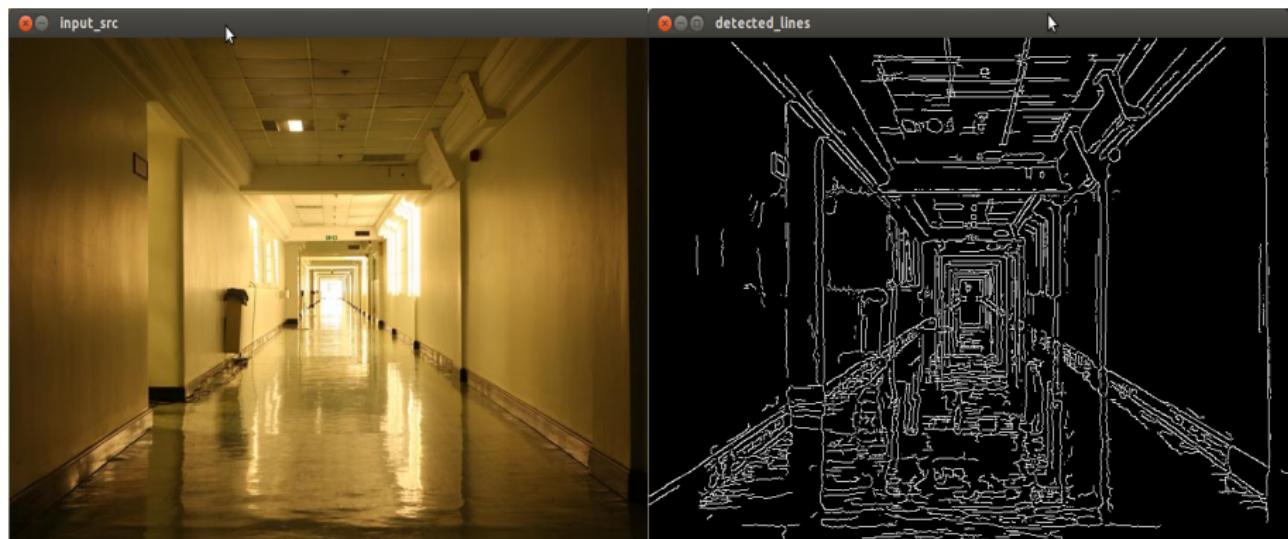
<sup>1</sup>Each output pixel is the mean of its kernel neighbors ( all of them contribute with equal weights).

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# Output of Canny operator



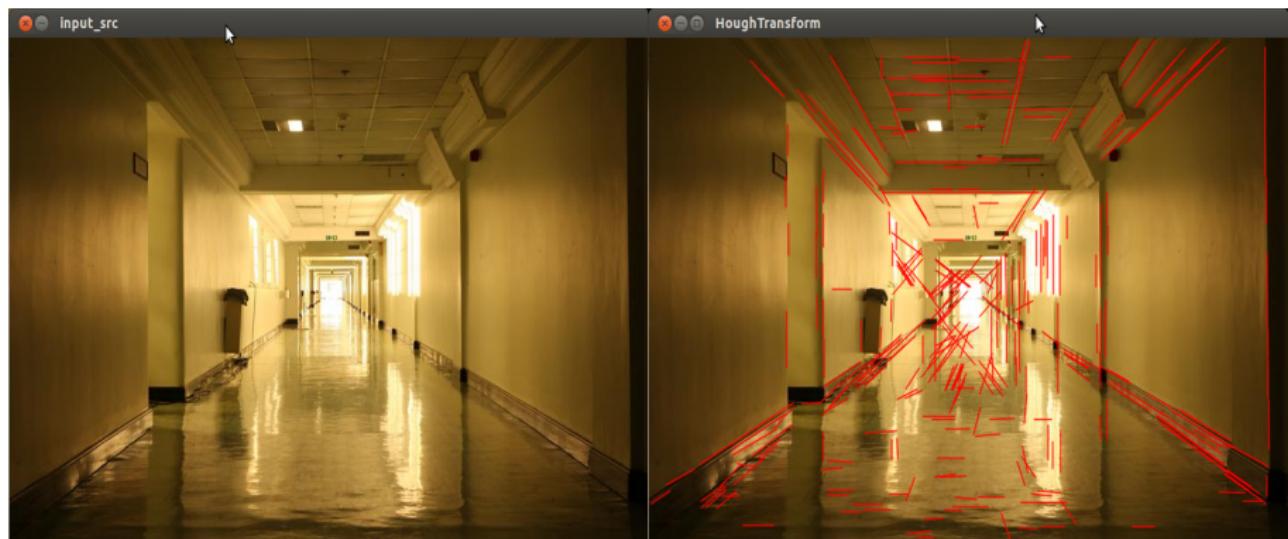
Detected edges using canny edge detector

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# Output of Probabilistic Hough Transform



Results of Hough Line Transform

## Method 1: Classical approach based on edge detection

Detecting the parallel lines in the environment is the premise for calculating the vanishing point.  
Procedure for VP detection:

### ① Straight lines extraction

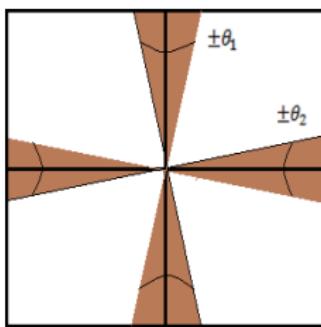
- ① preprocessing of image
- ② edge extracting using Canny operator
- ③ extracting lines by PHT(Probabilistic Hough Transform)

### ② Deleting unreasonable straight lines

### ③ Locating vanishing point

## Deleting unreasonable straight lines

- Detected lines from Hough Transform include vertical and horizontal edges.
- These lines do not converge to VP, hence not useful.
- Such lines are filtered in order to have a more accurate VP detection.
- Lines which have slope between  $\theta_1 = \pm 10^\circ$  or  $\theta_2 = \pm 10^\circ$  are deleted.



Unreasonable lines with slope between  $\theta_1 = \pm 10^\circ$  and  $\theta_2 = \pm 10^\circ$

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# Locating vanishing point

- ① divide the image plane into a  $22 \times 33$  grid  $G$
- ② calculate all intersections of the lines obtain from RHT
- ③ calculate the number of lines intersection falling in each grid element  $G(x, y)$
- ④ consider  $G(a, b)$  number of intersection lines falling in each grid element where  $a \in [0, 22)$  and  $b \in [0, 33)$ .

The grid with the maximum number of intersections is:

$$(a^*, b^*) = \operatorname{argmax}_{ab} G(a, b)$$

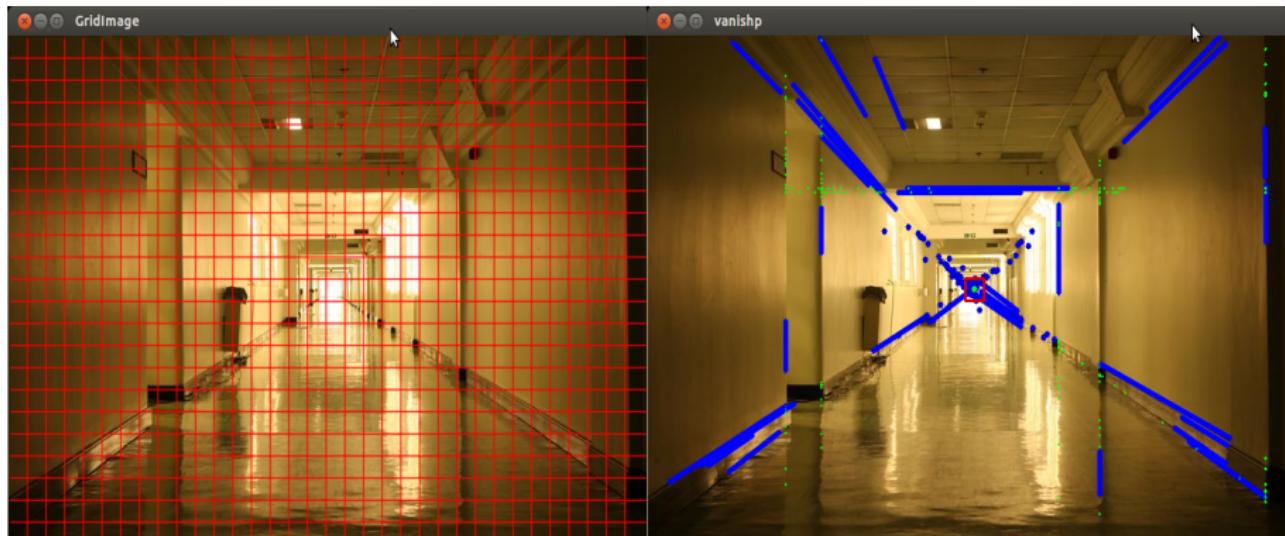
and vanishing point is given as:

$$(x_{vp}, y_{vp}) = ((a^* + 0.5) * w/33, (b^* + 0.5) * h/22)$$

w,h - width,height of image

## Locating vanishing point

Left figure shows division of image into a grid of  $22 \times 33$  and right figure displays result of extracted vanishing point using edge detection method.



Divided image into a  $22 \times 33$  grid and located vanishing point

## Method 2: VP based on image density clustering

*Density of points of intersection of lines is maximum towards the center.* Procedure for VP detection:

- ① preprocessing of image
- ② locate vanishing point

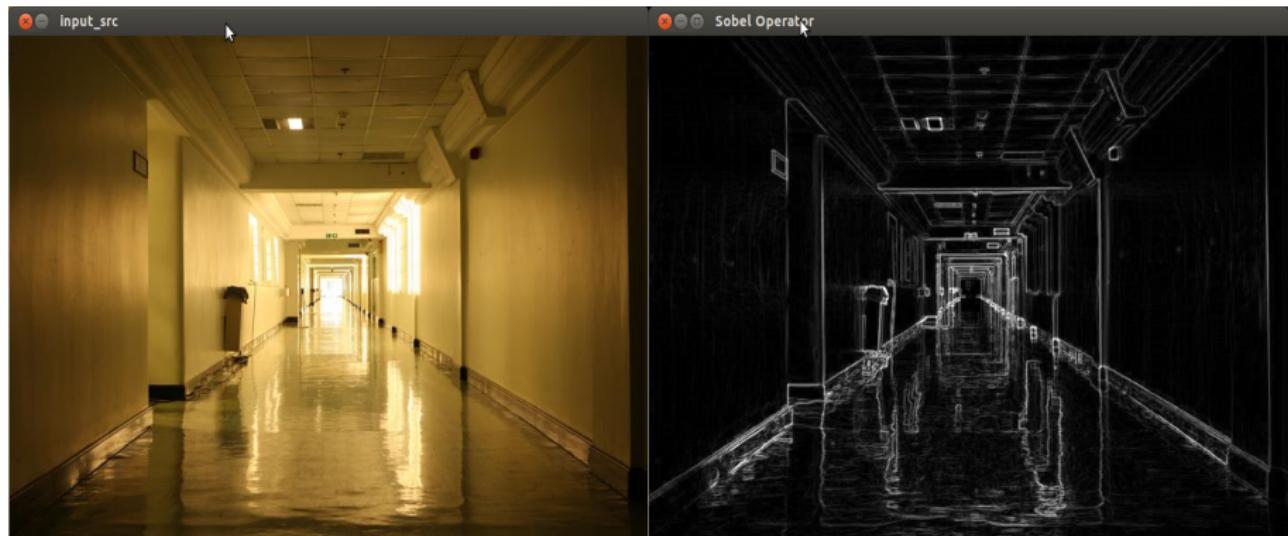
## Method 2: VP based on image density clustering

*Density of points of intersection of lines is maximum towards the center.* Procedure for VP detection:

- ① preprocessing of image
- ② locate vanishing point

## Preprocessing of image

- convert the image in to grayscale
- apply the Sobel operator in both x and y direction to find out the edges.



Output of sobel operator

## Method 2: VP based on image density clustering

*Density of points of intersection of lines is maximum towards the center.* Procedure for VP detection:

- ① preprocessing of image
- ② locate vanishing point

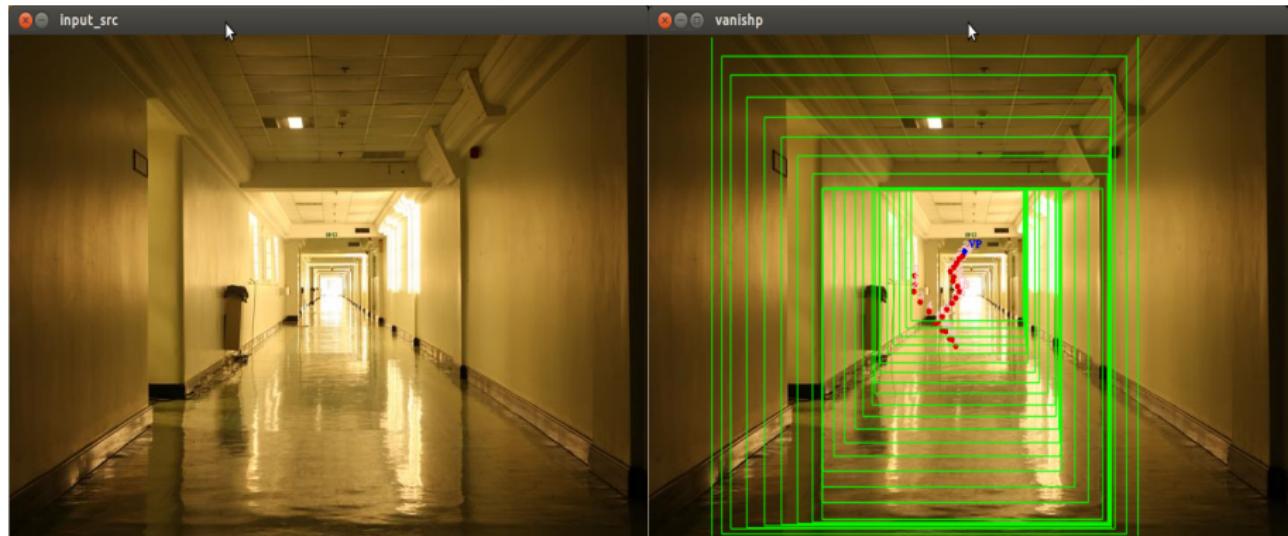
## Locate vanishing point

*VP is the point of maximum density, the aim is to find that point.*

Procedure:

- Take a square box of side size equal to the one smaller between height( $h$ ) and width( $w$ )
- Scroll through the image from left to right if  $w > h$  else top to bottom
- Keep track of density of points in each box and after the complete scroll, take the box with maximum density
- Repeat the process for 25 times and each time the scrolling area is reduced to the box selected from the last scroll.

# Locating vanishing point



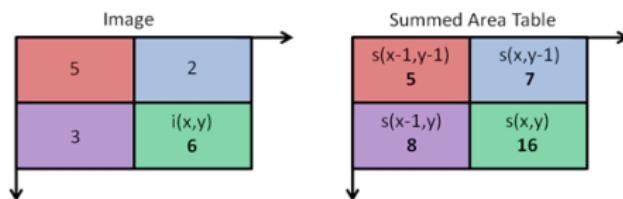
Output of density based vanishing point

## Integral image to find densities

- Calculating intensity of each pixel in a box and summing them is a time consuming process.
- Integral image helps to rapidly calculate summations over image subregions
- Every pixel in an integral image is the summation of the pixels above and to the left of it.
- We can construct the integral image of a given image with only one pass over the given image.

Value  $s$  of a pixel  $(x, y)$  in output image is :

$$s(x, y) = i(x, y) + s(x - 1, y) + s(x, y - 1) + s(x - 1, y - 1)$$



Integral image concept

[Photo credit: <https://computersciencesource.wordpress.com>]

# Integral image to find densities

1	2	2	4	1
3	4	1	5	2
2	3	3	2	4
4	1	5	4	6
6	3	2	1	3

input image

0	0	0	0	0	0
0	1	3	5	9	10
0	4	10	13	22	25
0	6	15	21	32	39
0	10	20	31	46	59
0	16	29	42	58	74

integral image

## Example of integral image

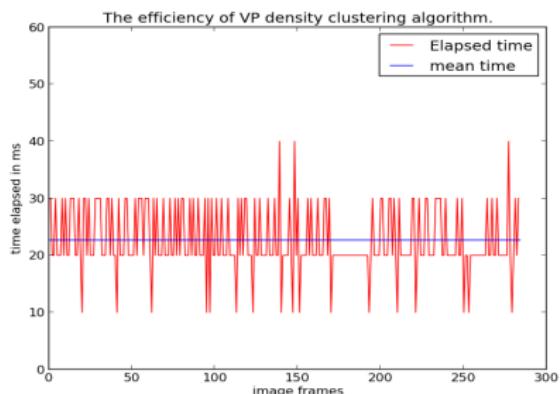
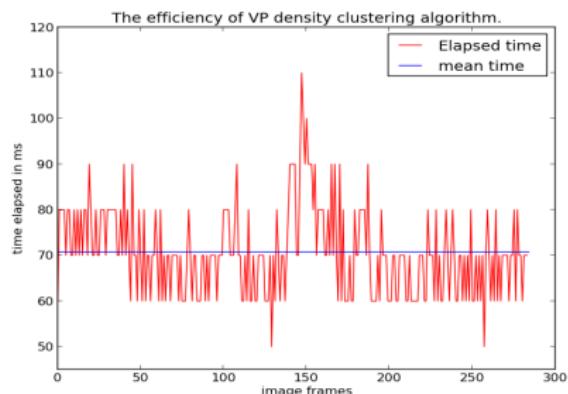
[Photo credit: <https://www.mathworks.com>]

To calculate density of any sub region in image, we need only 4 values. This process have now  $O(1)$  complexity.

$$i(x', y') = s(\text{left top}) + s(\text{bottom right}) - s(\text{top right}) - s(\text{bottom left})$$

# Edge detection Vs Image density clustering

- VP detection based on image density is faster than edge detector method
- But very sensitive in case of noise or obstacles in the environment
- Therefore, we used VP detection based on edge detection.



Time elapse by Edge detector method (left) and Density cluster(right) over 250 sample images

## Reliability of Vanishing Point detected

- Keep track of vanishing point detected in previous frame
- Resultant vanishing point is the latest vanishing point detected half plus previous vanishing point half.

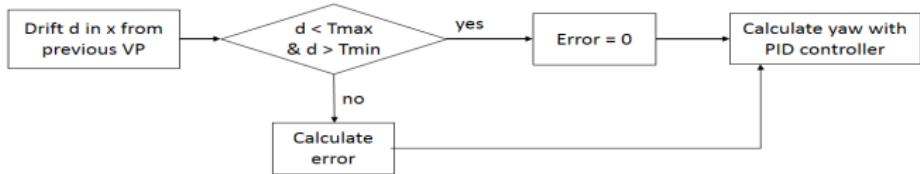
$$(x_{vp}, y_{vp}) = (current_{vp}.x/2 + previous_{vp}.x/2, current_{vp}.y/2 + previous_{vp}.y/2)$$

*This can be further optimized by keeping track of last few output points and calculate average of all previous and latest detected point as the output of the current frame.*

- Controller receives estimated pose from image processing module and sends flight commands to the AR.Drone via ardrone autonomy.
- Aim to maintain at zero, the horizontal distance between the vanishing point and the center of the image.
- PID controller is used in our approach to directly control the quadrocopter.
  - P: helps to reduce the error
  - I: helps to maintain the stable state(hold state)
  - D: damps occurring oscillations
- Separate controller for yaw angle and command velocities

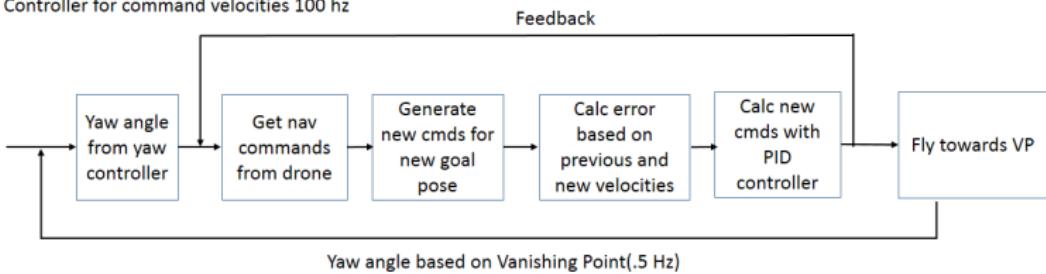
# Controller

Yaw angle based on Vanishing Point(.5 Hz)



Controller for yaw angle

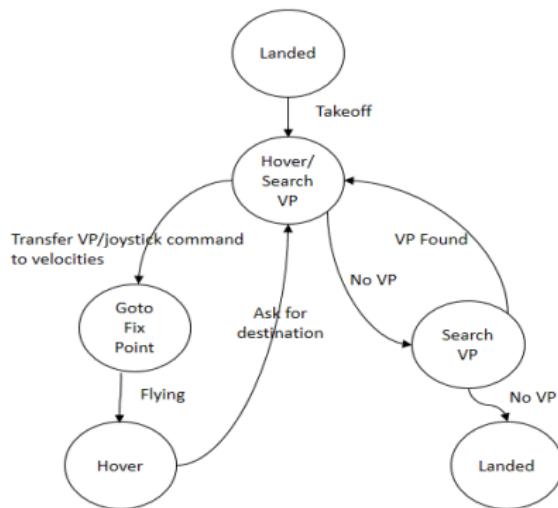
Controller for command velocities 100 hz



Controller for navigation commands

- Vanishing point auto mode can be suppressed by joystick mode.

State diagram of the drone



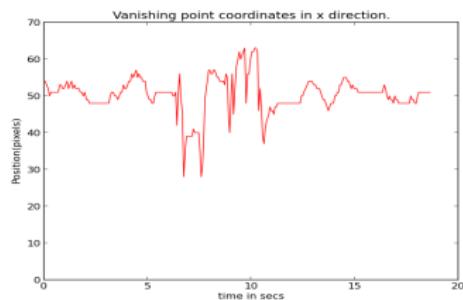
State diagram of drone

# Experimental results

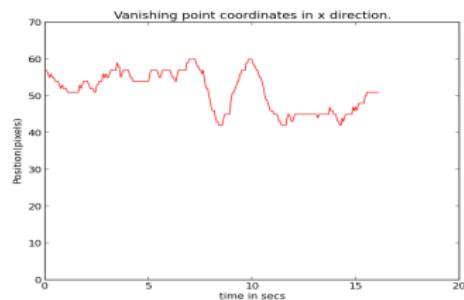
Tested our approach in several corridors such as narrow, broad, corridors with obstacles and dark corridors.

- Accuracy of vanishing point detection approach

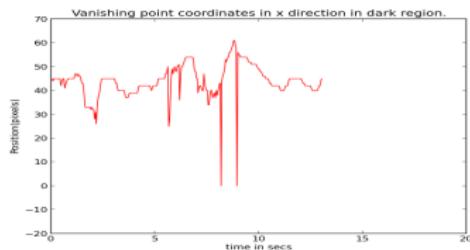
*with sharp maneuvers*



*without sharp maneuvers*



*Dark Corridor(bad illumination)*



## VP Evaluation

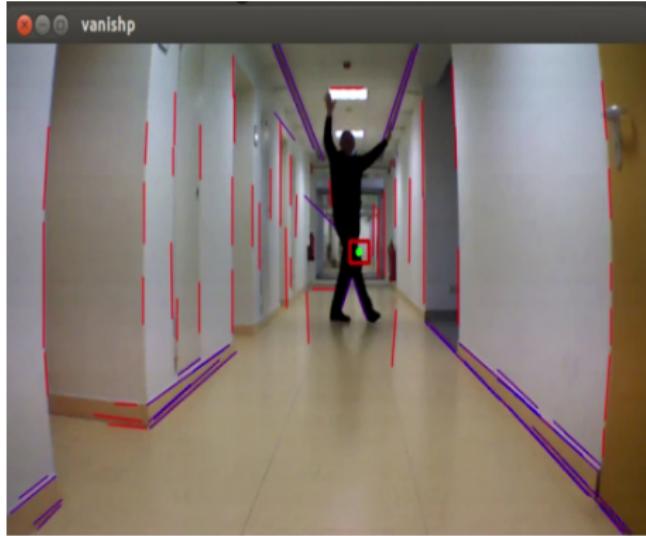
- Different corridors for VP testing

Current system does not consider obstacles if there are enough lines to calculate the vanishing point

### *Dark corridor example*



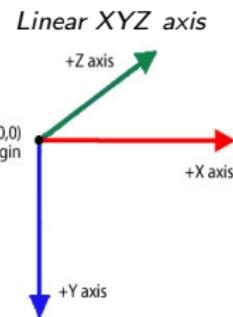
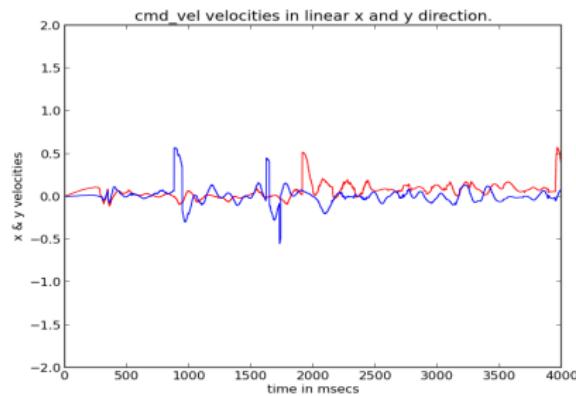
## *VP with obstacle*



# Controller Evaluation

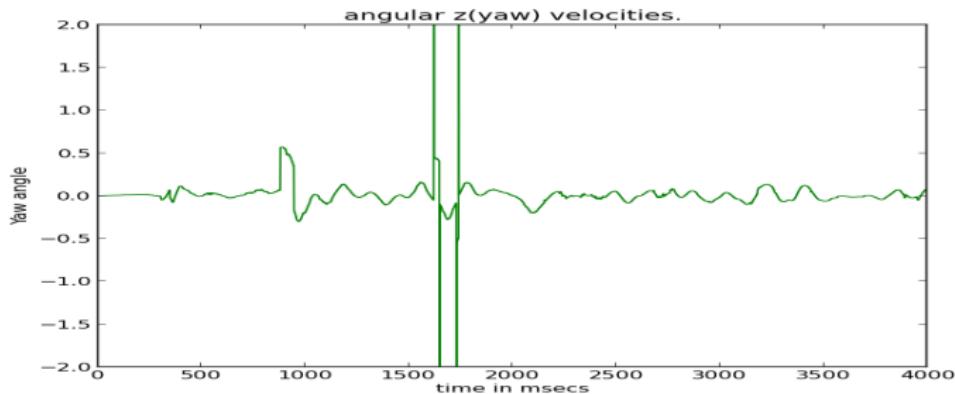
We evaluated controller based on the variation in Linear x (horizontal) ,Linear y (vertical) and angular z (yaw) velocities

*Linear roll and pitch velocities on real flight*



# Controller Evaluation

Variation in yaw angle shows the robustness of the controller



Angular velocities of the drone during flight

## Future work

- **Density based VP detection** is promising and less computationally expensive. Can be improved for useful VP based navigation
- **Edge based VP detection:** Vanishing point is sometimes found on the edge which is not accepted for drone to fly. This needs to be improved and made more reliable.
- **Onboard Computation:** Currently algorithm works on host machine, still need to be implemented on Asctec Pelican.

# VIDEOS

## References

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THANK YOU

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# Edge extracting using Canny operator

## Canny Edge detector - optimal Edge detector

- Gaussian Filter De-noising

- Gradient Operator Sobel

Finds the intensity gradient of the image in vertical and horizontal direction using Sobel Operators.

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}, \quad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix}$$

The magnitude  $|\bar{G}|$  and orientation  $\theta$  of the image gradient are thus given by:

$$\|\bar{G}(x, y)\| = \sqrt{\bar{G}_x^2 + \bar{G}_y^2}, \quad \theta = \arctan\left(\frac{\bar{G}_y}{\bar{G}_x}\right)$$

- Control of Gradient Value

Suppress any pixel value (i.e. set it equal to zero) that is not considered to be an edge.

- Hysteresis

Track along the remaining pixels that have not been suppressed.

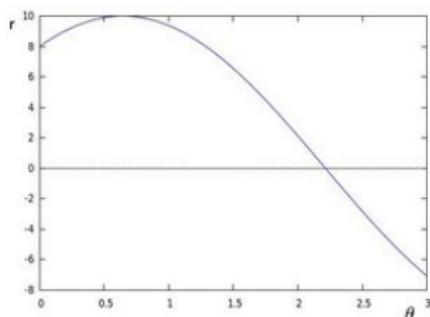
# Extracting lines by PHT(Probabilistic Hough Transform)

- The algorithm is based on the parametric representation of a line:

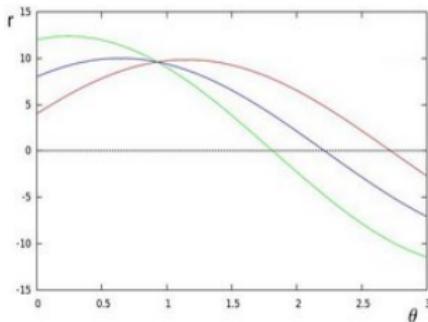
$$\rho = x \cos \theta + y \sin \theta$$

where  $\rho$  is perpendicular distance from the origin to the line and  $\theta$  is angle between horizontal axis and this perpendicular.

- Family of lines that goes through a point  $(x, y)$ , gives a sinusoid.



$(\rho, \theta)$  plot for points  $(x, y)$



$(\rho, \theta)$  plots for 3 points  $(x, y)$  intersecting at one single point

- Same operation is done for all the points in an image. If curves of two different points intersect in the plane  $(\theta - \rho)$ , that means both points belong to a same line.