A Presentation on

Self-Driven Transport vehicles for warehouses

Under the supervision of Faisal Alam Sir

Presented by-

Khan Saad Bin Hasan
16PEB121

Arpit Varshney
16PEB154

Motivation And Objectives

- The work of transporting objects from one place to another takes huge amount of human resources.

- If this can be automated it can save huge sums of money and resources.

- This will also solve the problem of accounting in warehouses- i.e, what kind of products are in which shelves.

Background study

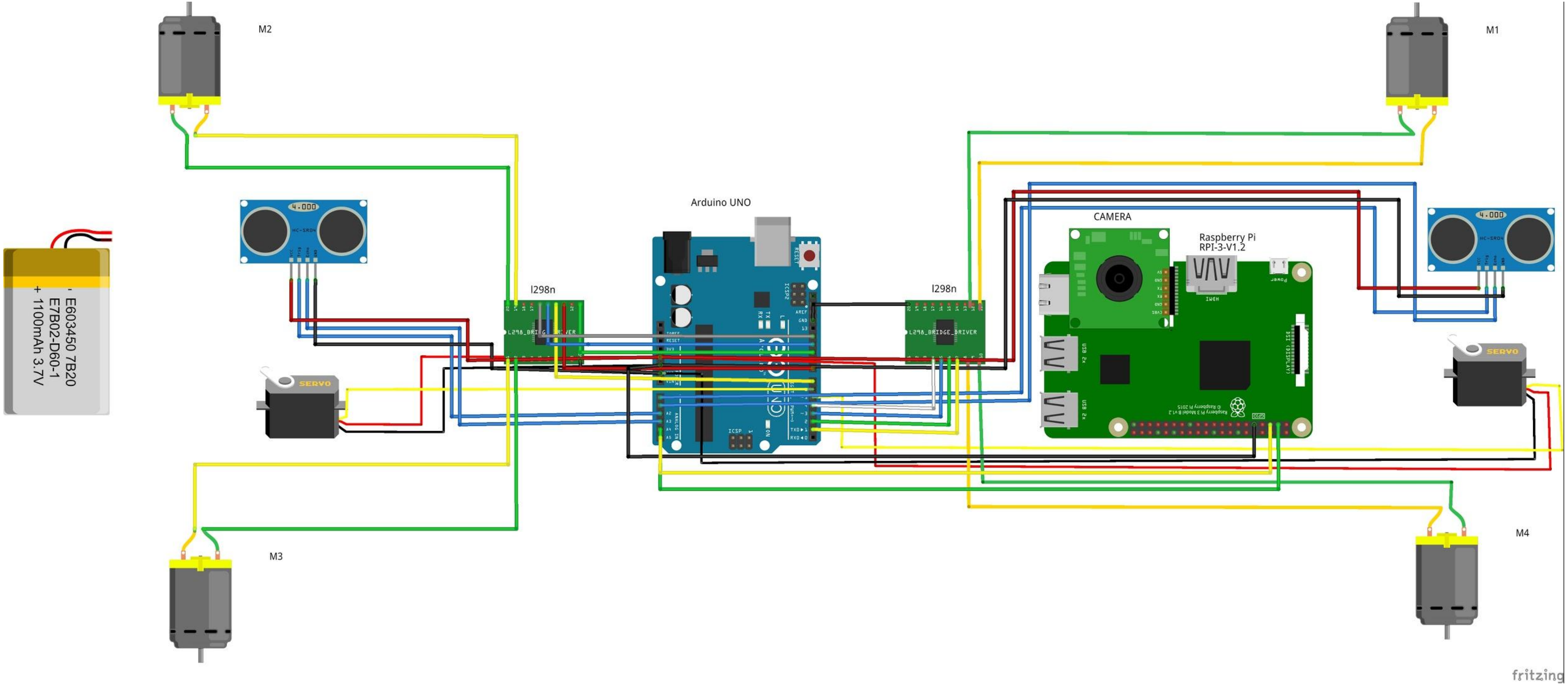
- DARPA Grand Challenge Cars - predominantly used LIDARs and laid foundation of modern self driving cars. [1]

- Modern Self Driving cars e.g, Wayve.ai, Waymo use Advanced Machine Learning Techniques [2][5]

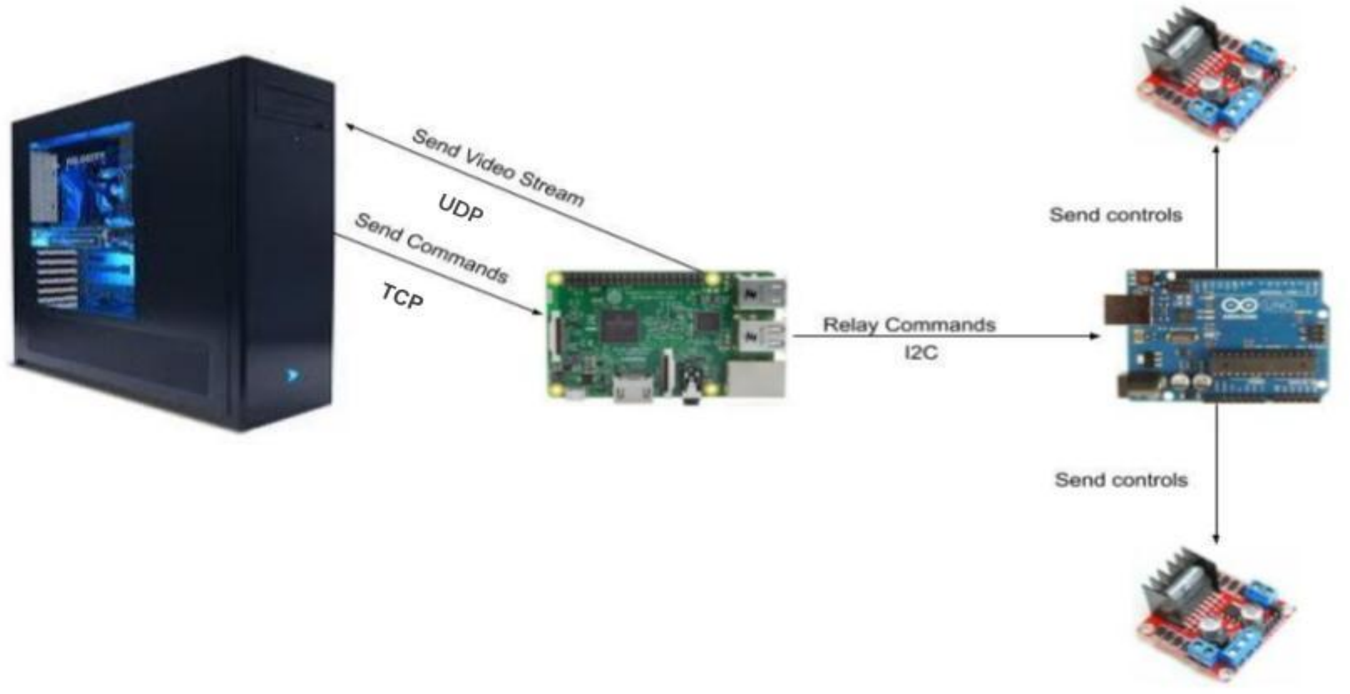
- Modern household robots e.g, roomba [3] use simpler and cheaper techniques(ultrasonic, infrared sensors)

Arduino Pin	Module	Position	Corresponding Pin
A0	Ultrasonic	Front	Trigger Pin
A1	Ultrasonic	Front	Echo Pin
A2	Ultrasonic	Back	Trigger Pin
A3	Ultrasonic	Back	Echo Pin
13	Motor Driver	Back	in4
12	Motor Driver	Back	in3
11	Motor Driver	Back	in2
10	Motor Driver	Back	in1
8	Motor Driver	Front	in4
7	Motor Driver	Front	in3
6	Servo	Back	Servo Data Pin
5	Servo	Front	Servo Data Pin
4	Motor Driver	Front	in2
2	Motor Driver	Front	in11

Arduino Pins



Circuit Diagram



Network Diagram

Real Time Object Detection - Architecture

- Object detection using yolov3[4] algorithm.
- Our Model In total consists of 106 layers
- Used the trained model on coco dataset which consist of over 80 classes.
- Object detection for the obstacle Avoidance with around 20 fps.

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Darknet-53[4]

Real Time Object Detection - Transfer Learning

- MOst of the classes - (aeroplane , traffic light , etc)are not of our Use that are present in coco dataset.

- Our data need to be consist of -chair, Table, shoes, boxes ,etc .

Output of cameras frame window

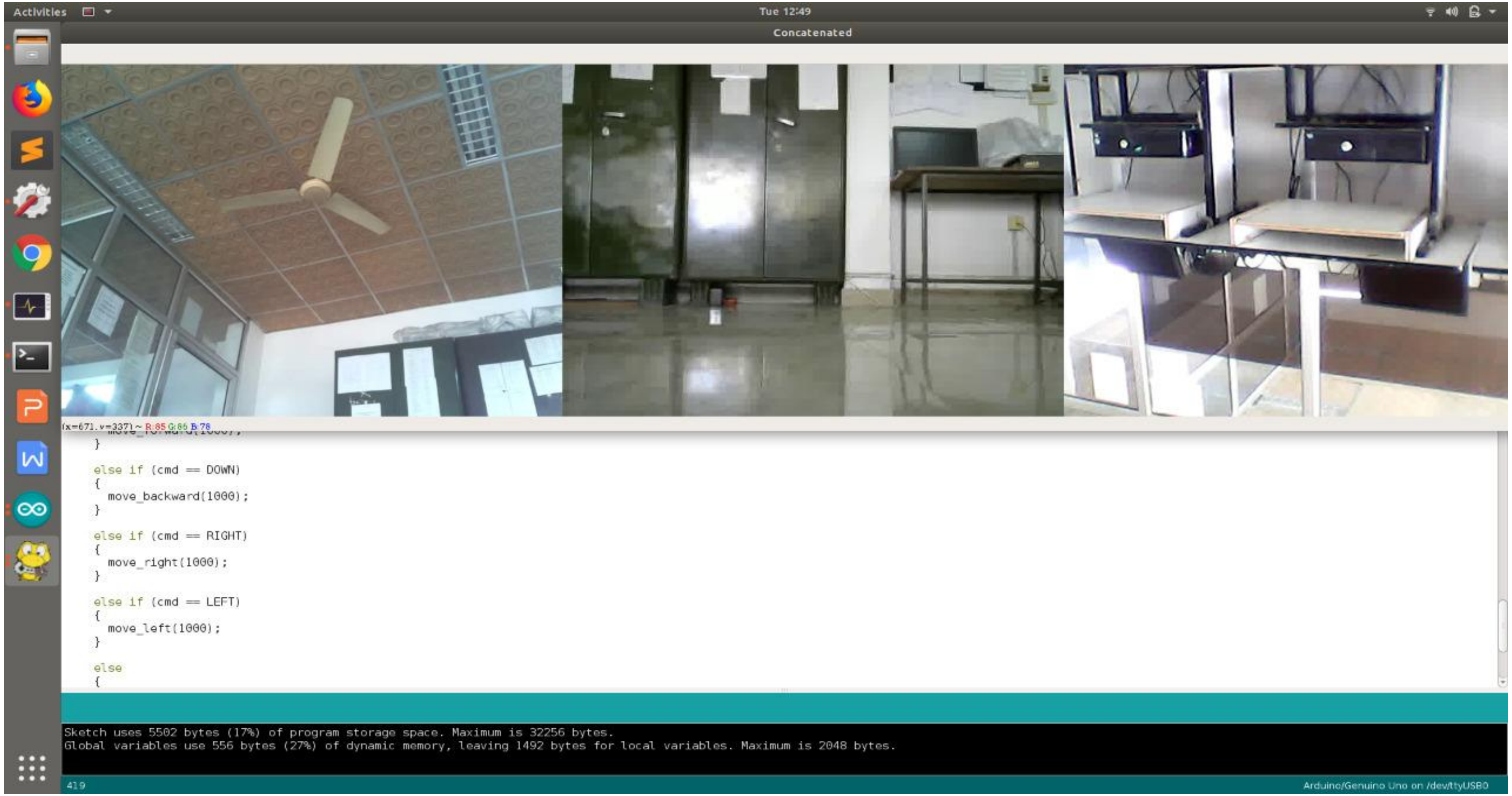


Image Stitching

- Used to Increase the field of view.
- There must be the overlap between the images.
- Detecting keypoints
  (Scale invariant feature transform).
- Match the key points in the overlapping section of the images.

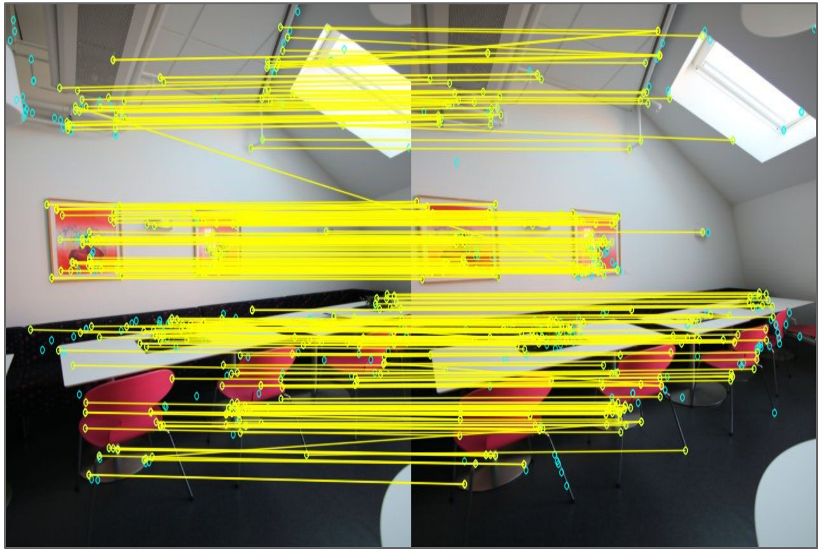


Image stitching results

Further Plans

- Testing backup algorithm.
- Find solution for motion blur and lag associated with multiple cameras.
- Better our Object Detection and Image stitching models
- lane detection
- Exploring machine learning techniques such as reinforcement learning.

References

[1] Badue, Claudine, et al. "Self-driving cars: A survey." arXiv preprint arXiv:1901.04407 (2019).

[2] Bewley, Alex, et al. "Learning to drive from simulation without real world labels." 2019 International Conference on Robotics and Automation (ICRA). IEEE, 2019.

[3] Sahu, Nogendra Kumar, et al. "Comparative Study on Floor Cleaner." Journal of Pure Applied and Industrial Physics 8.12 (2018): 233-236.

[4] Redmon, Joseph, and Ali Farhadi. "Yolov3: An incremental improvement." arXiv preprint arXiv:1804.02767 (2018).

[5] Liu, Ming-Yu, Thomas Breuel, and Jan Kautz. "Unsupervised image-to-image translation networks." Advances in neural information processing systems. 2017.

[6] Brown, M., & Lowe, D. G. (2007). Automatic panoramic image stitching using invariant features. International journal of computer vision, 74(1), 59-73.

Thank You