MEE4099 Capstone Project - (Winter 2021-22)

Final Presentation

An End-to-End Autonomous UAV System in GPS-Denied and Unstructured Environments

Jerrin Bright, Suryaprakash R

Batch Number: D22

Supervisor:
Dr. Arockia Selvakumar

INTRODUCTION

- Demand for UAV operations will rise by 25% in next 25 years.
- Failure in several operations - Due to less workforce, poor water management, poor quality management, cost of commodities, carelessness.

Avoidance

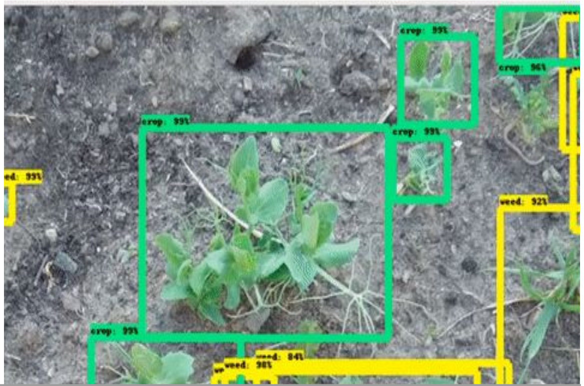
Mapping

Inspection

- Challenges
  - Mapping of dynamic environments and manpower requirement for surveillance.
  - Visual only sensors for visualization
    - Possible sensor options: Lidar, Stereo, Radar, Sonar
  - Hundreds of crashes each year by human error resulting in failure to detect small objects (wires, birds, branches).

Avoidance

Mapping



Inspection

LITERATURE SUMMARY

- High Sensor Payload
  - Realsense D435i and Realsense T265 [1]
  - Monocam and 2D Lidar [4]
- Trajectory-only planners [2, 3]
- Multiple Assumptions
  - Stop-and-go Maneuvers [5]
  - Indoor-only Navigation [6]
  - Prior Map Known [7]

- High Complexity
  - Computational Cost [8, 9]
- Not Affine to Transformation [10, 11]
- Optimizing feature relationship
  - Spatial-wise [12, 13, 14]
  - Channel-wise [15, 16, 17]

RESEARCH GAP

- Excess manpower operations.
- Reliability of sensors.
  - Possible sensor options: GPS, Lidar, Camera, Radar, Sonar
- Hundreds of crashes each year by human error resulting in failure to detect objects (especially wires, birds, branches).

SPECIFICATIONS

Drone Frame

550 mm wheel base distance, UAV frame called IRIS is selected for testing

Camera

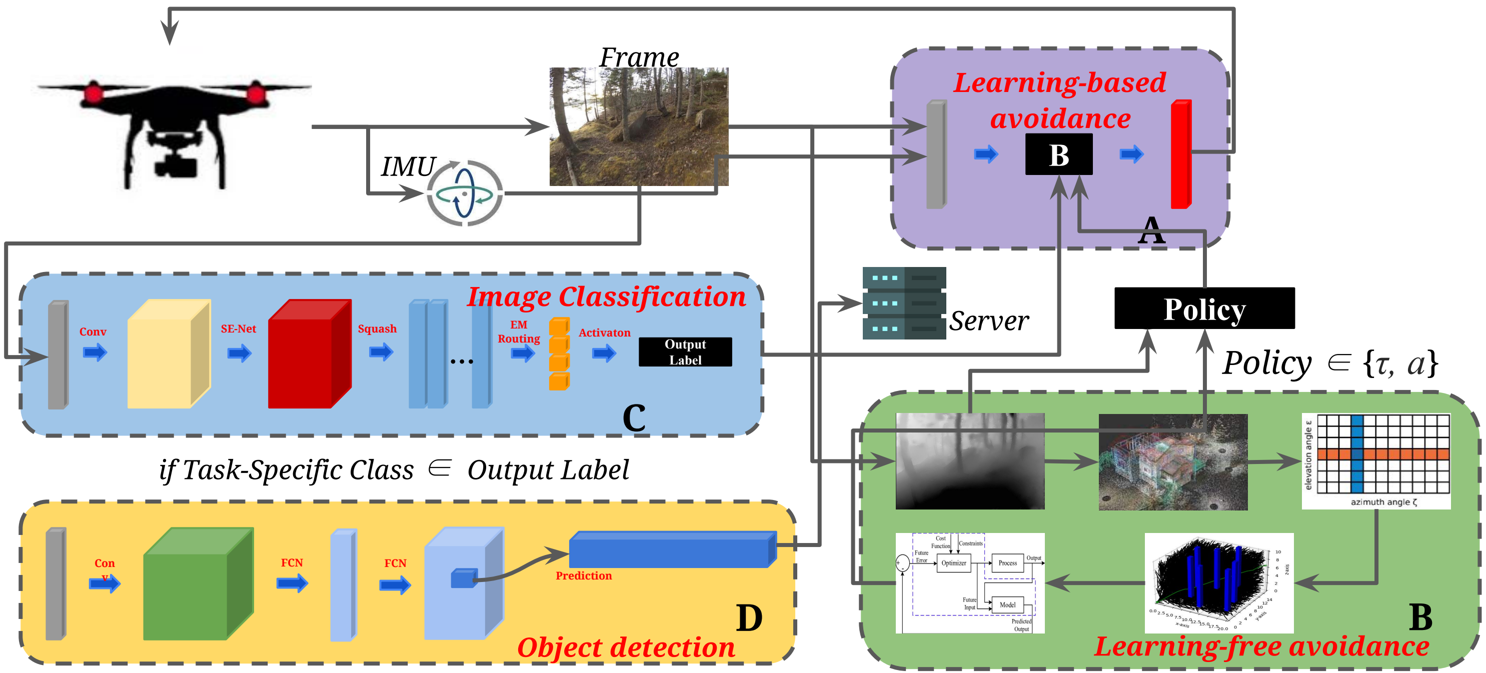
The UAV is equipped with monocular vision sensor for simulation.

AIRSIM Simulator

Tested in Africa forest envs, High mountain areas and urban fields

Simulator Settings

Wind Speed: 3m/s
Image Noise: True [With fluctuation and pixel noise



"Building a robust autonomous navigation UAV system that can do class-specific tasks."

OUTLINE

Avoidance

Inspection

Avoidance

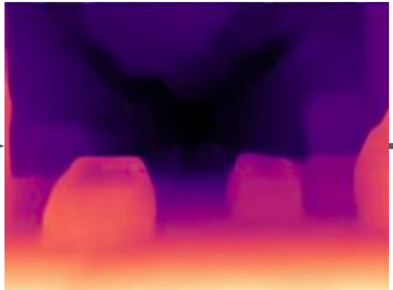
Inspection

RESEARCH QUESTION

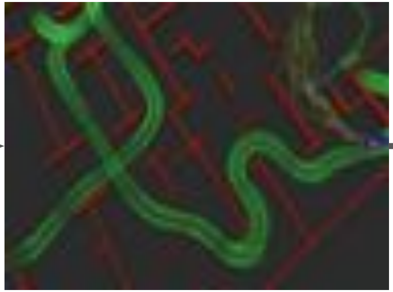
Traditional Approach:

Image
IMU

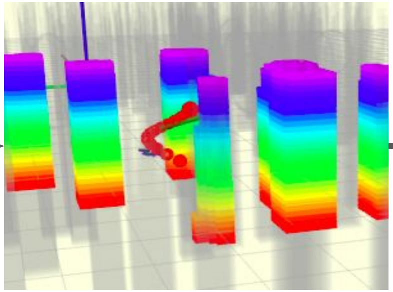
Perception



Planning



Control

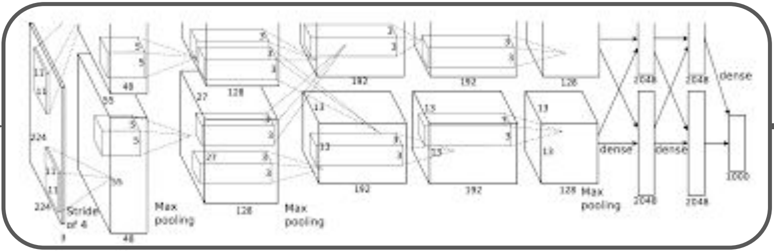


Nav
Cmd

Learning-based Approach:

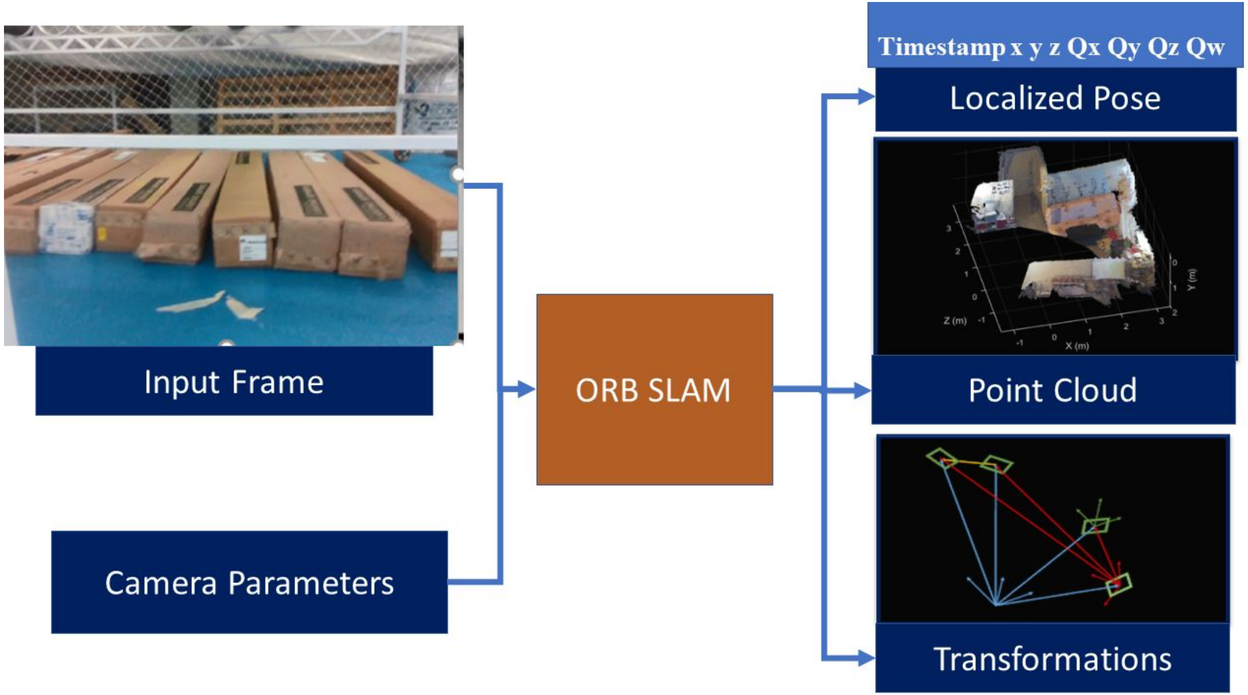
Image
IMU

Neural Network

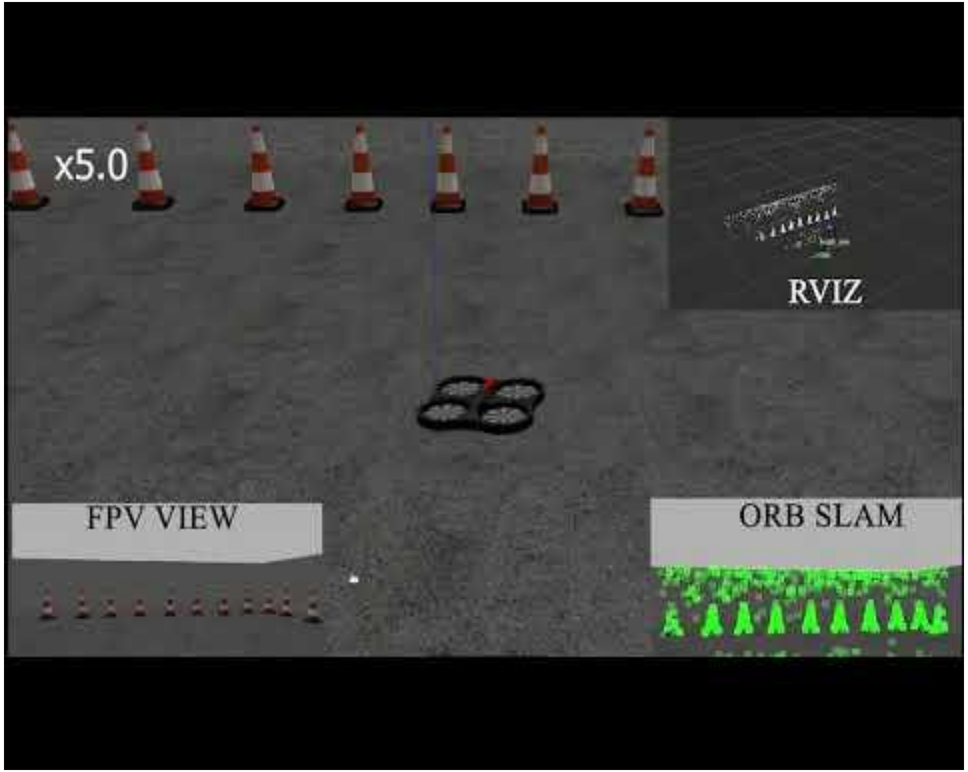


Nav
Cmd

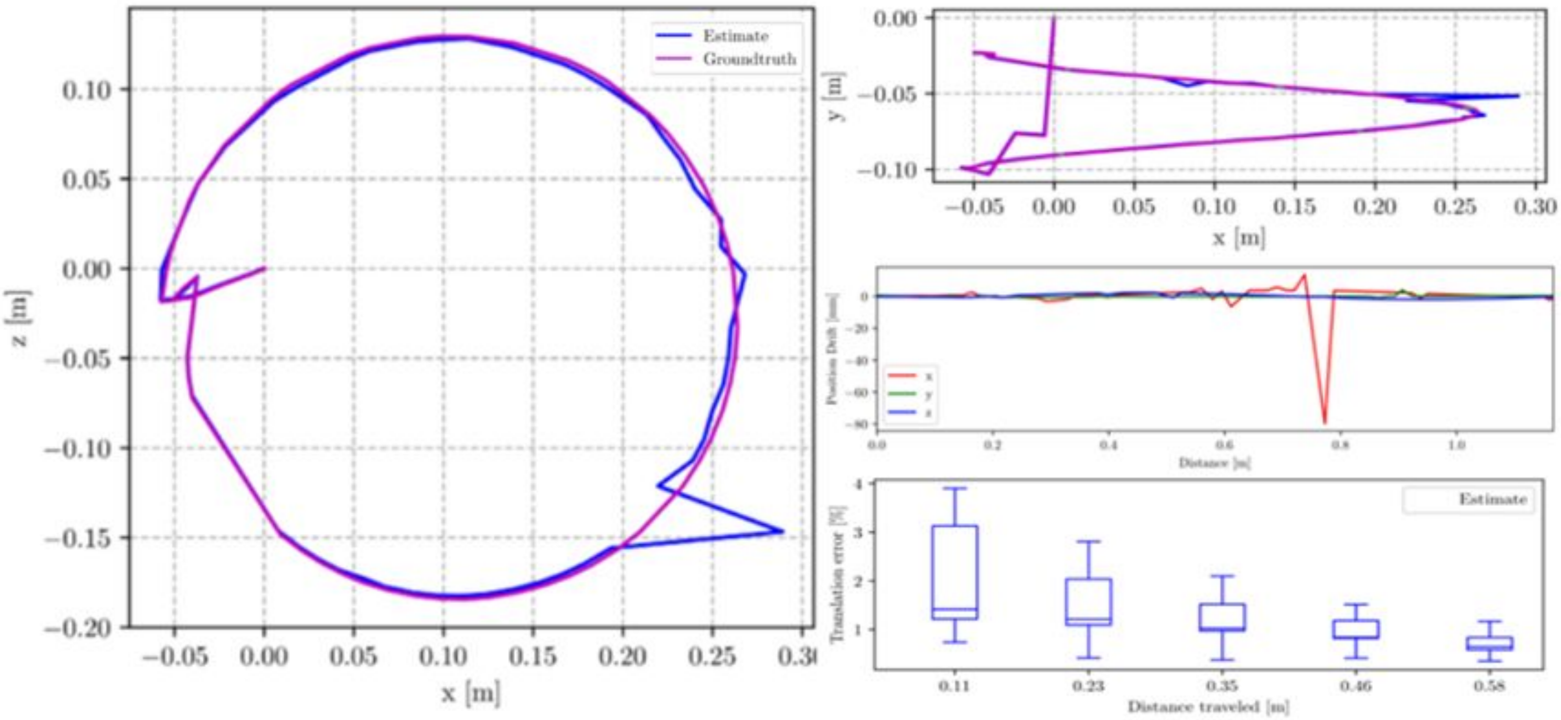
Localization - APPROACH



Localization - DEMO

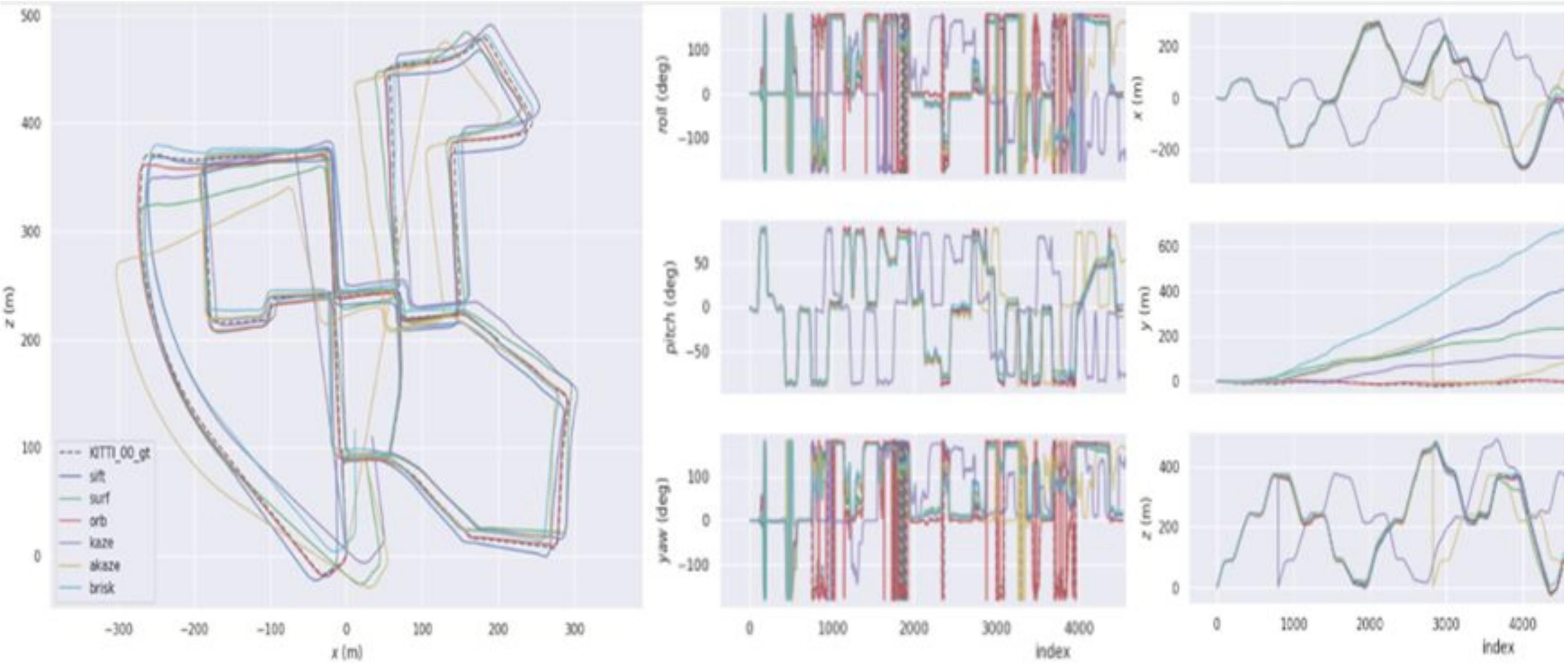


Localization - EXPERIMENTATION



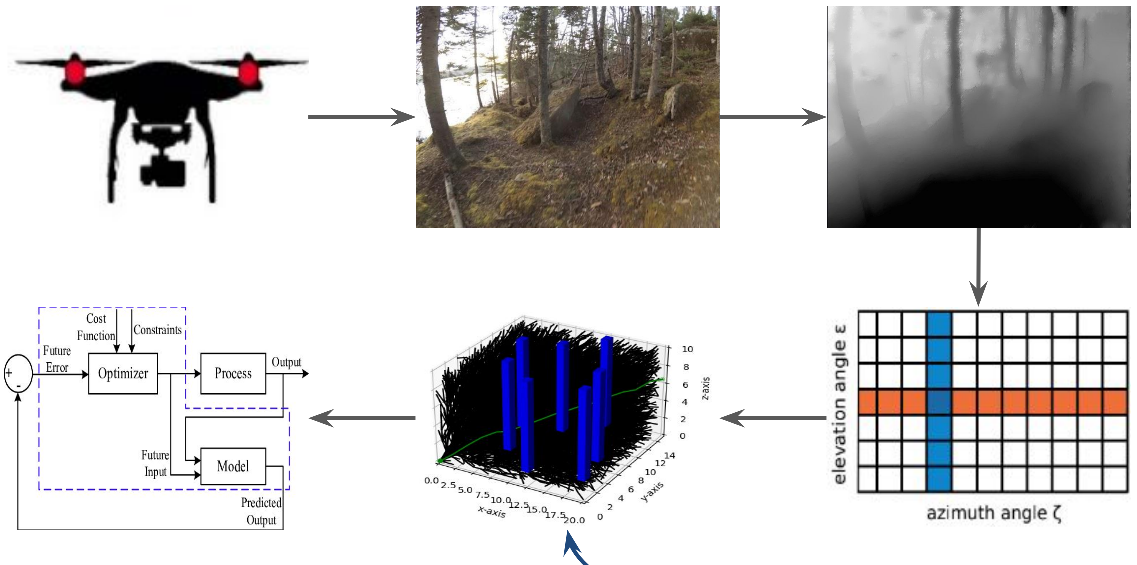
Testing in matlab for spherical trajectory

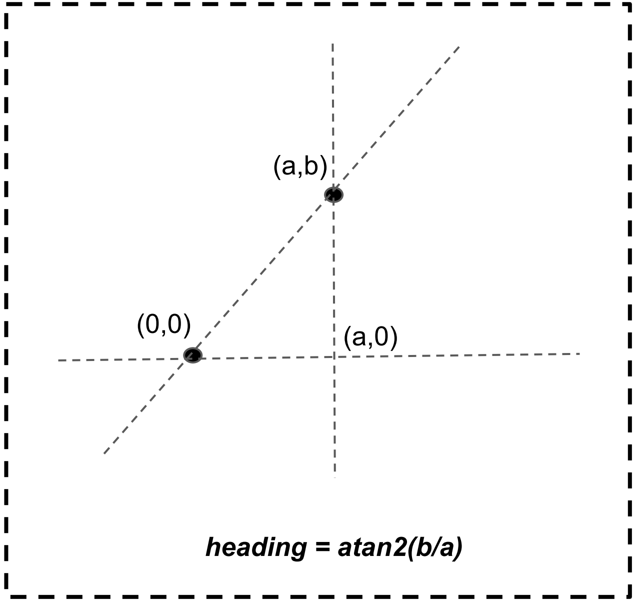
Localization - EXPERIMENTATION



Testing in python with KITTI ground truth dataset

Learning-free Avoidance - APPROACH

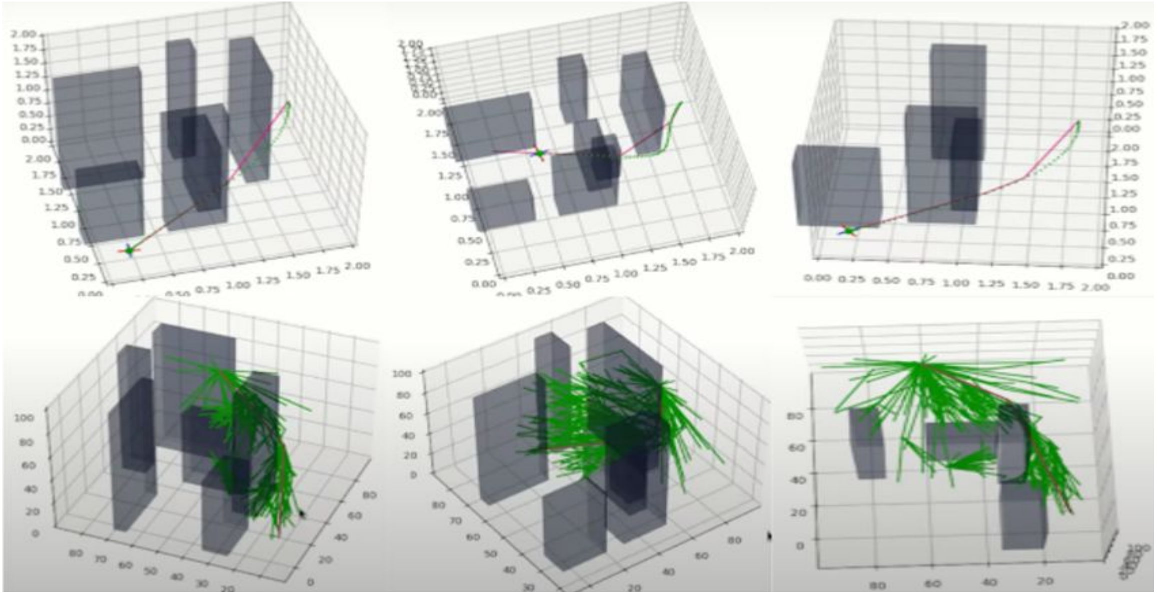




$J = [\, p_{i+prev\_i} * 4 + (1/\, d_{curr\text{-}des} + 1/d_{des\text{-}goal}) * 2 \,] / 6$

Learning-free Avoidance - DEMO

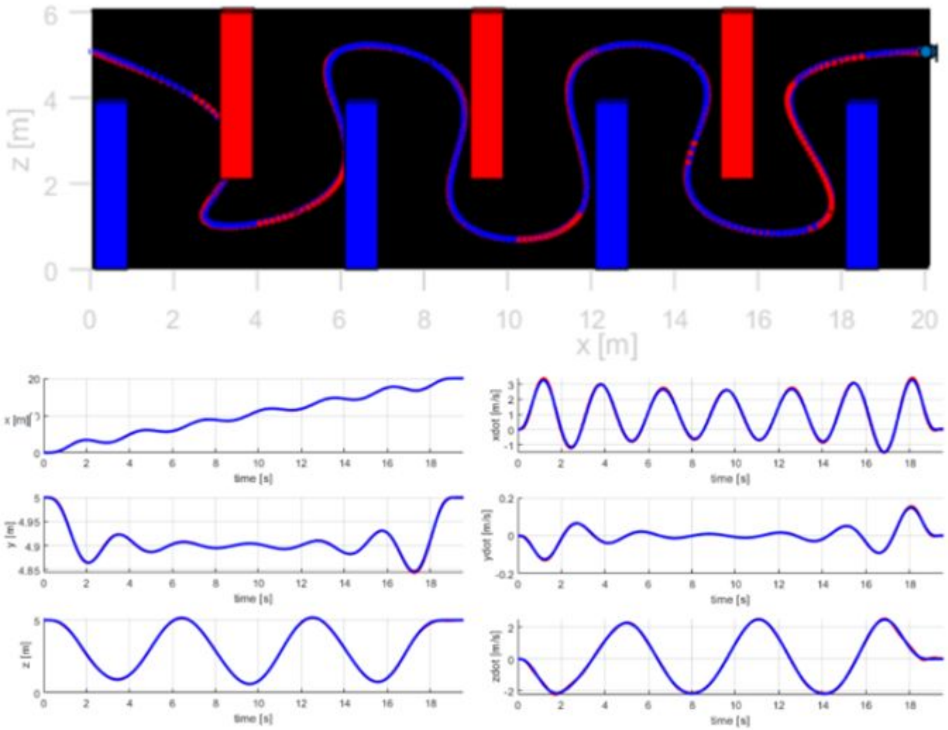
Learning-free Avoidance - EXPERIMENTATION



- Kinodynamic Planning
- RRT Planner
- MPC Control System

Evaluated in MATLAB with 3 different environments.

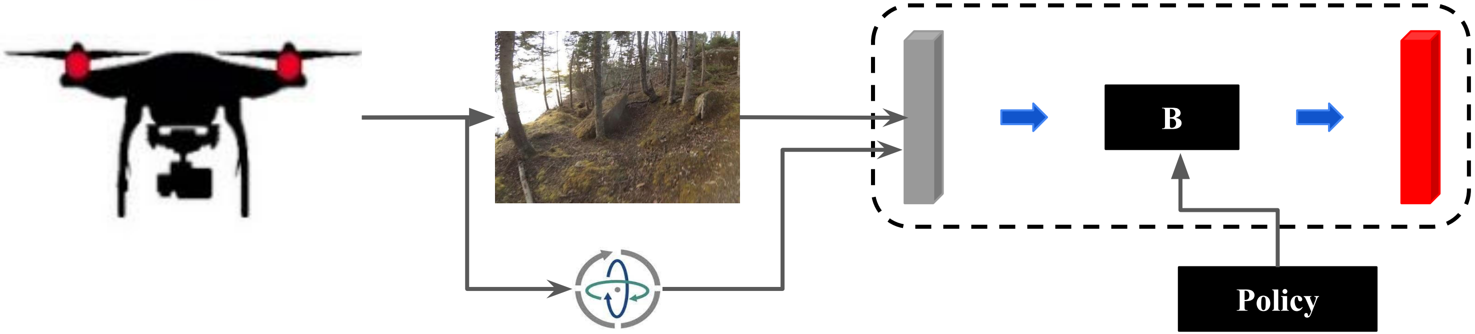
Learning-free Avoidance - EXPERIMENTATION



- Kinodynamic Planning
- A* Planner
- MPC Control System

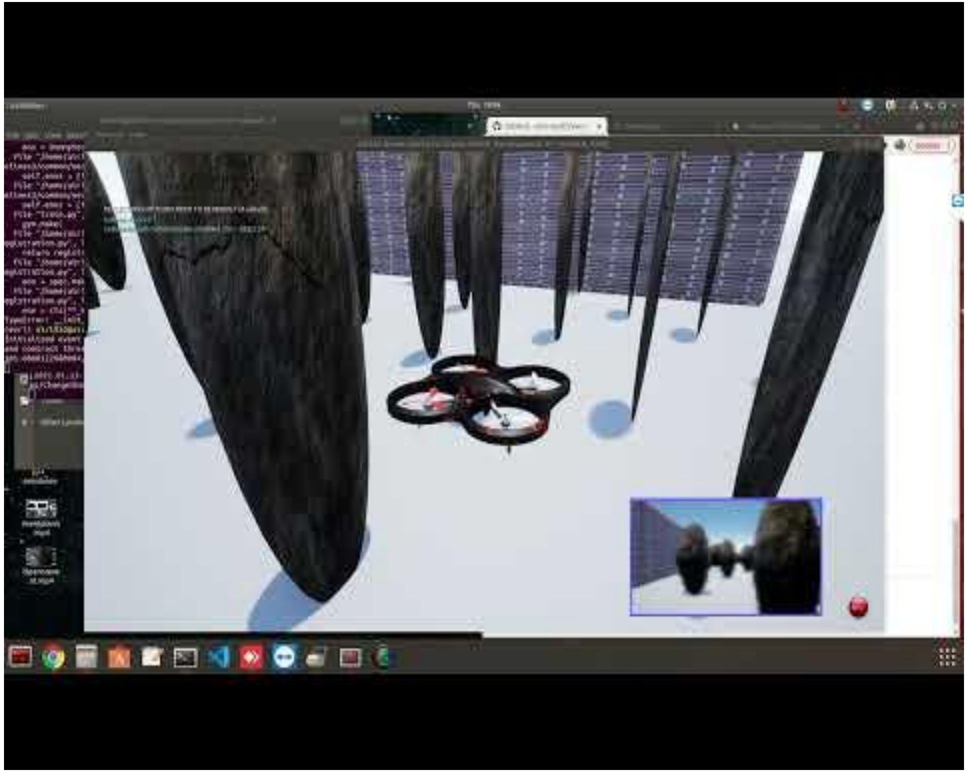
Evaluated in MATLAB with 2 different environments.

Learning-based Avoidance - APPROACH

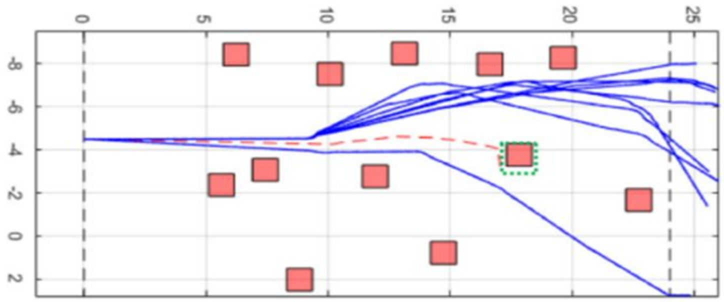


Policy → Trained using image inputs, pose and yaw angles from learning-free technique

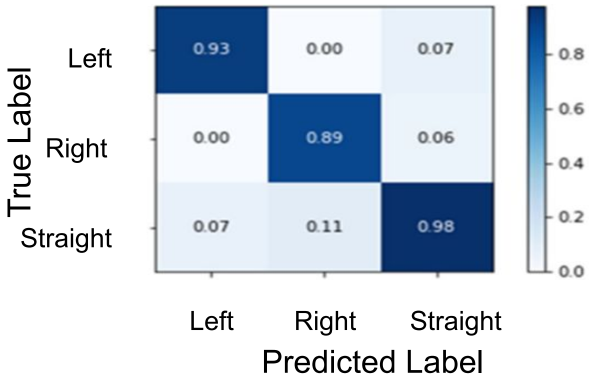
Learning-based Avoidance - DEMO



Learning-based Avoidance - EXPERIMENTATION



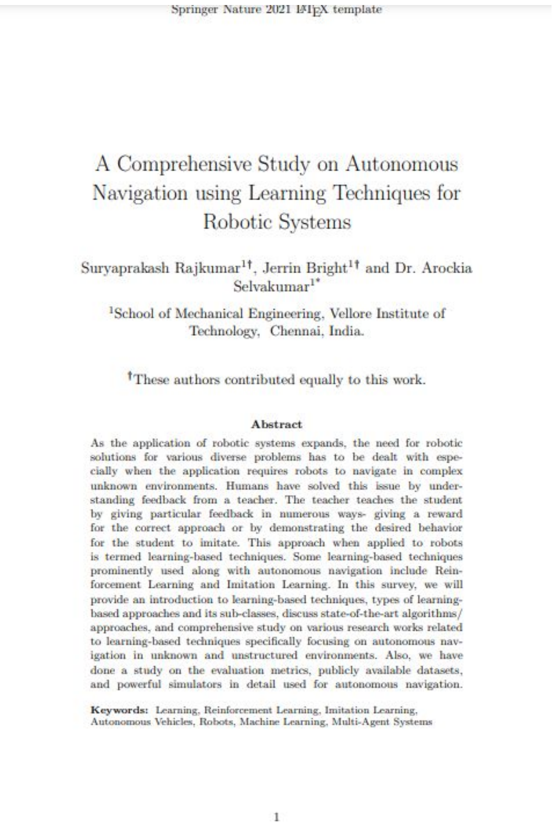
- SENet for training
- Dataset collected from learning-free approach
- Tested in the same map, 10 times



- Confusion matrix analyzing the output results with the ground truth data to test the model

Evaluated in MATLAB with 4 different environments.

CONTRIBUTION



Springer Nature 2021 LaTeX template

A Comprehensive Study on Autonomous Navigation using Learning Techniques for Robotic Systems

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[1]School of Mechanical Engineering, Vellore Institute of Technology, Chennai, India.

[†]These authors contributed equally to this work.

Abstract

As the application of robotic systems expands, the need for robotic solutions for various diverse problems has to be dealt with especially when the application requires robots to navigate in complex unknown environments. Humans have solved this issue by understanding feedback from a teacher. The teacher teaches the student by giving particular feedback in numerous ways- giving a reward for the correct approach or by demonstrating the desired behavior for the student to imitate. This approach when applied to robots is termed learning-based techniques. Some learning-based techniques prominently used along with autonomous navigation include Reinforcement Learning and Imitation Learning. In this survey, we will provide an introduction to learning-based techniques, types of learning-based approaches and its sub-classes, discuss state-of-the-art algorithms/approaches, and comprehensive study on various research works related to learning-based techniques specifically focusing on autonomous navigation in unknown and unstructured environments. Also, we have done a study on the evaluation metrics, publicly available datasets, and powerful simulators in detail used for autonomous navigation.

Keywords: Learning, Reinforcement Learning, Imitation Learning, Autonomous Vehicles, Robots, Machine Learning, Multi-Agent Systems

1

Topic: A Comprehensive Study on Autonomous Navigation using Learning Techniques for Robotic Systems.

Submitted to: MDPI Sensors Journal

Highlights:

- Reviewed 130+ state-of-the-art research works.
- Compared learning techniques and evaluated 30+ architectures.
- Compared the predominantly used simulation tools and datasets for learning techniques

OUTLINE

Avoidance

Inspection

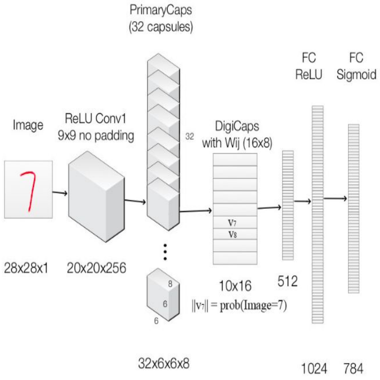
CNN

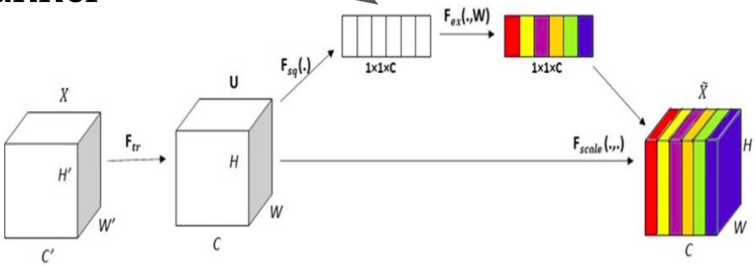
Blackbox?

Features

Spatial

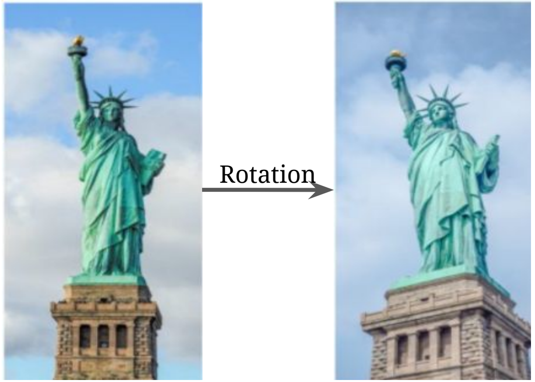
Channel



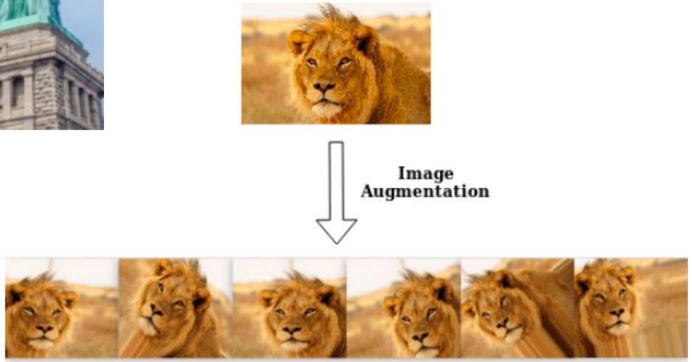


Why Capsules?

Rotation Invariant

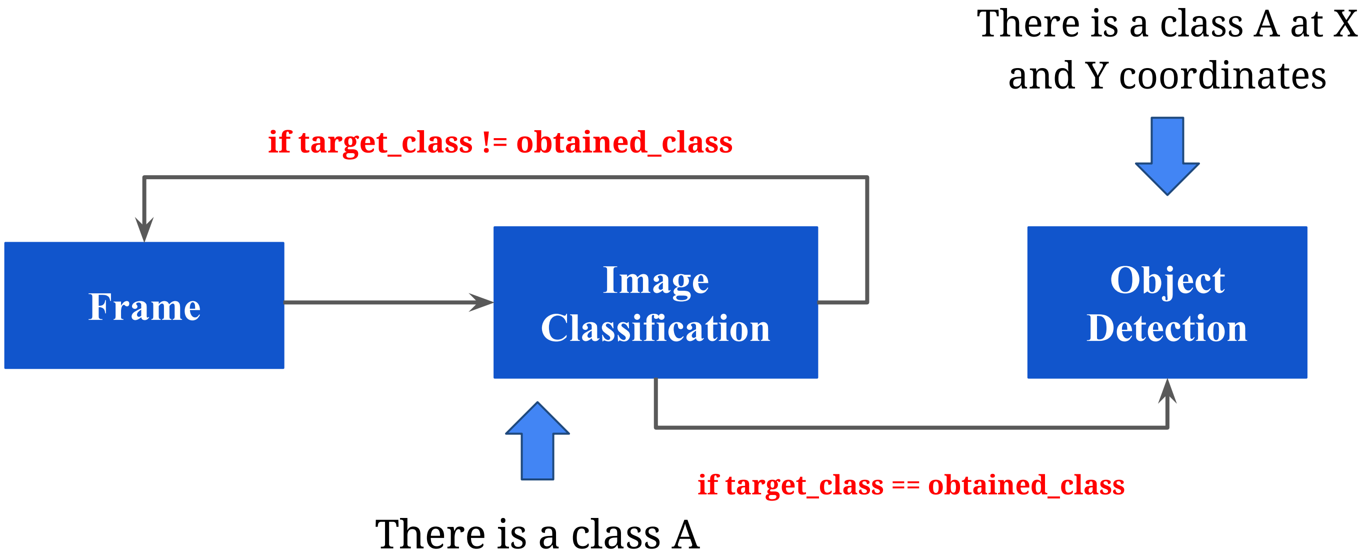


Increase in computation time and required more data to train



Weak Spatial Relationship

Mechanism



'sense-switch-act' mechanism

Image Classification - APPROACH

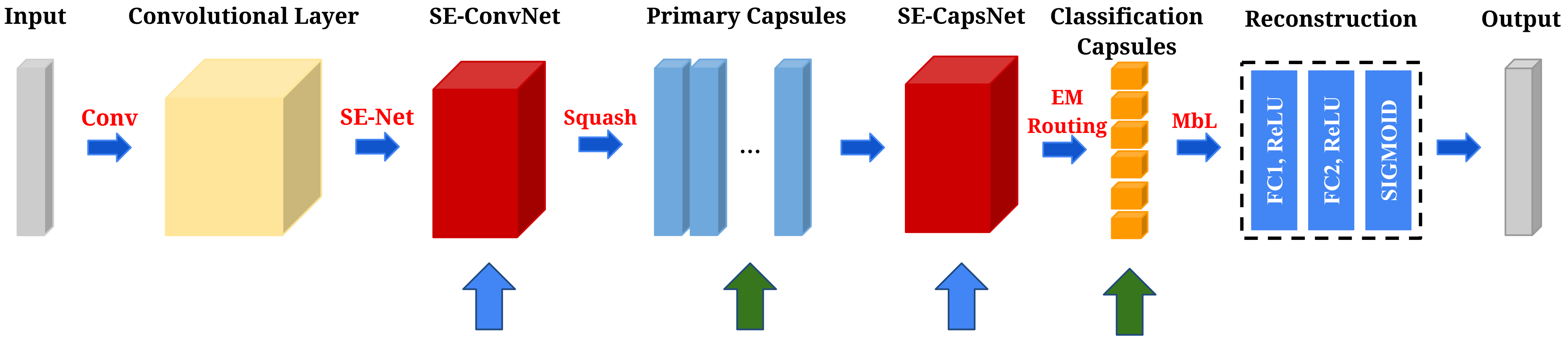
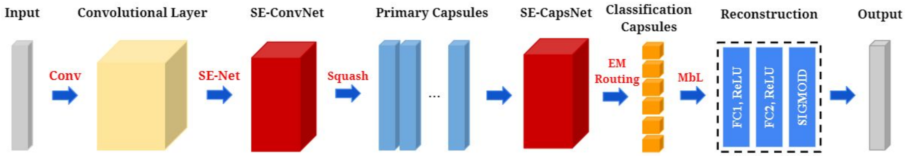


Image Classification - NOVELTY

1 ME-CapsNet



2 Pooling with Stochastic Spatial Sampling

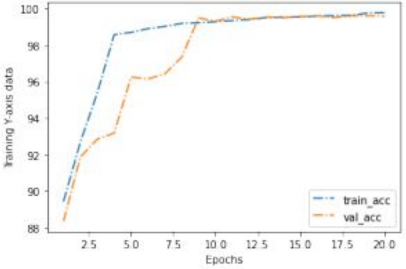
$$z_{avg} = \frac{1}{H \cdot W} \sum_{L=1}^{H} \sum_{j=1}^{W} u_c(i,j)$$ GAP

$$z_{max} = max_{i,j} \cdot u_c(i,j)$$ GMP

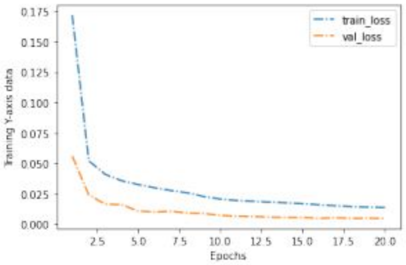
$$z_{s3p} = \mathcal{D}_g^s \cdot (z_{max})$$ S3P

3 Comparing various activation functions and showing its effect on the overall performance of the network

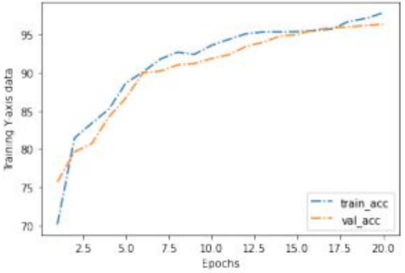
Image Classification - EXPERIMENTATION



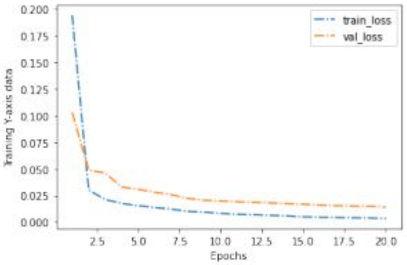
(a) MNIST Training Results



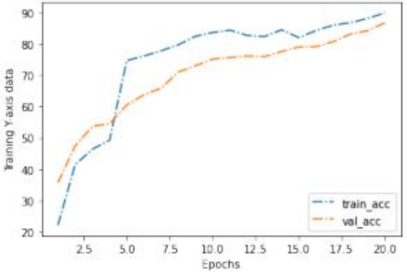
(b) MNIST Loss Results



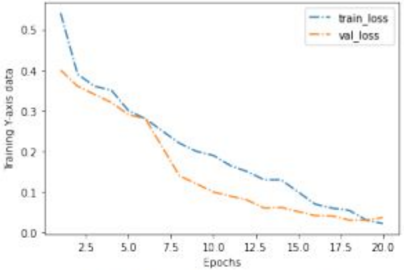
(c) FMNIST Training Results



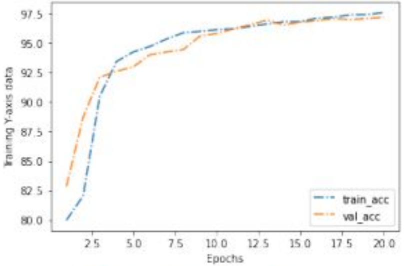
(d) FMNIST Loss Results



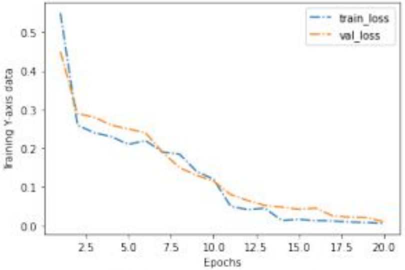
(e) CIFAR10 Training Results



(f) CIFAR10 Loss Results

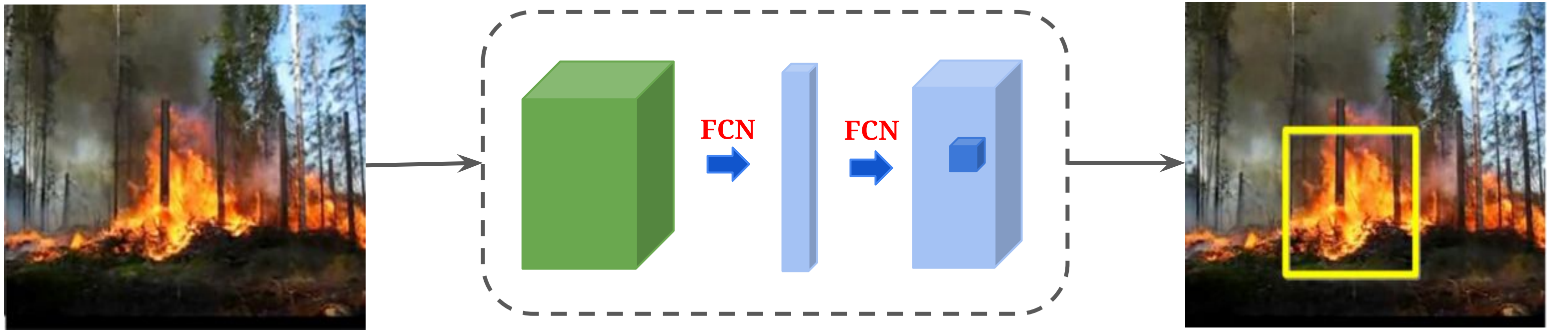


(g) KMNIST Training Results



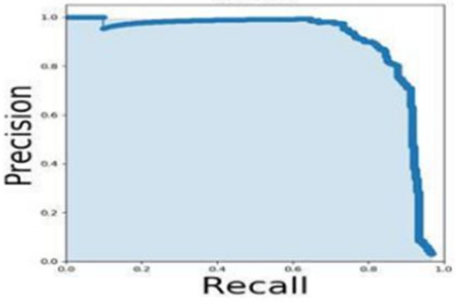
(h) KMNIST Loss Results

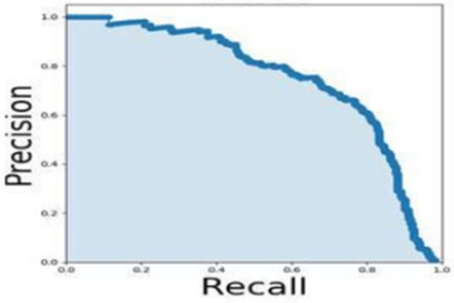
Object Detection - APPROACH



Object Detection - EXPERIMENTATION

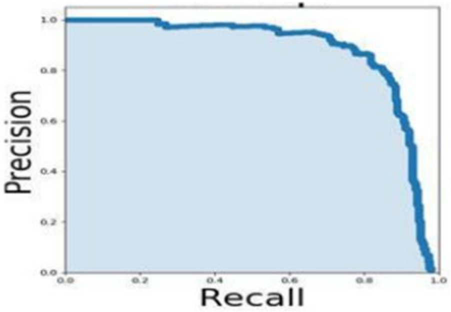
Fire





Person

Pole



Crack

Object Detection - EXPERIMENTATION

Table 1. Comparison with Capsule Network-based architectures using CIFAR10 .

	top-1% error	top -5% error
Squeeze - Max	22.57	6.09
Squeeze - Avg	22.28	6.03
Squeeze - Mix (Ours)	**21.78**	**5.83**
Excitation - Sigmoid	22.28	6.03
Excitation - ReLU	23.47	6.98
Excitation - LeakyReLU	23.22	6.91
Excitation - Tanh	23	6.38

Table 2. Different capsule dimensions

Capsule Dimension	Accuracy
8	**92.73%**
12	92.12%
16	91.17%

Table 3. Different number of capsules

Capsules	Accuracy
5	92.09%
8	**92.73%**
10	92.44%

CONTRIBUTION

MDPI

Article

ME-CapsNet: A Multi-Enhanced Capsule Networks with Expectation-Maximization Routing mechanism

Jerrin Bright [1,†], R Suryaprakash [1,†] and Arockia Selvakumar [2,*]

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† These authors contributed equally to this work.

Abstract: Convolutional Neural Networks need the construction of informative features, which are determined by channel-wise and spatial-wise information at the network's layers. Recently, much study has been done on the spatial and channel domains as distinct isolated problems in order to improve CNN's performance by improving feature interpretation. In this research, we propose a novel approach that uses sophisticated optimization for both the spatial and channel components inside each layer's receptive field. The Squeeze-Excitation Network idea was leveraged for enhancing channel-wise relationship using a novel custom pooling approach for dynamically recalibrate the channels by reconstructing their interdependencies. Capsule Networks were used to understand the spatial association between features in the feature map. Furthermore, Expectation-Maximization Routing of the capsules was done to find probability votes using transformation matrices replacing traditional CNN activations. Understanding the spatial relationship of the features helped in reducing the training dataset, as an extrapolation of different feature variants was feasible knowing the likeliness of the features. The proposed networks were tested with backbones of Residual, Inception, and VGG Networks, and the respective results were logged. Extensive experimentation results using ImageNet, MNIST, FashionMNIST and CIFAR-10 datasets demonstrated that our ME-CapsNet outperforms the State-of-the-art networks by achieving higher accuracy with minimal model complexity.

Keywords: Squeeze-Excitation, Capsules, EM Routing, Convolutional Neural Network

Citation: Bright, J.; Suryaprakash, R.; Selvakumar, A. ME-CapsNet: A Multi-Enhanced Capsule Networks with Routing mechanism. *Robotics* **2022**, *1*, 0. https://doi.org/

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Accepted:
Published:

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1. Introduction

Convolutional Neural Network (CNN) is a state-of-the-art image classification technique that is really good at detecting features, but very less effective in understanding the spatial relationship between features including its orientation, perspective, and size. Improving the classification accuracy is vital for scene understanding or any vision-based approach. Also, relaying information from one layer to layer (Routing) is done in a less effective manner. This can be done by determining prominent features via diverse representations and establishing organized routing patterns for relaying information across layers. Investigation on the different aspects of the network design (spatial, channel) is currently a very popular research area in CNN, which can drastically enhance the understanding ability of the network.

We are thus in this research work, proposing a novel network called Multi-Enhanced Capsule Networks (ME-CapsNet) which finds robust features, obtaining good channel and spatial relationships from the images. Squeeze-Excitation network [1] with very little computation difference, models the interconnection of channels by adaptively recalibrating the channel features. The likelihood and the properties of each and every feature are estimated using Capsule Networks [2]. EM Routing is used to group capsules with the parent capsule using the closeness in the proximity of the corresponding estimated votes on the pose matrix. Some contributions of this research work are mentioned here as follows:

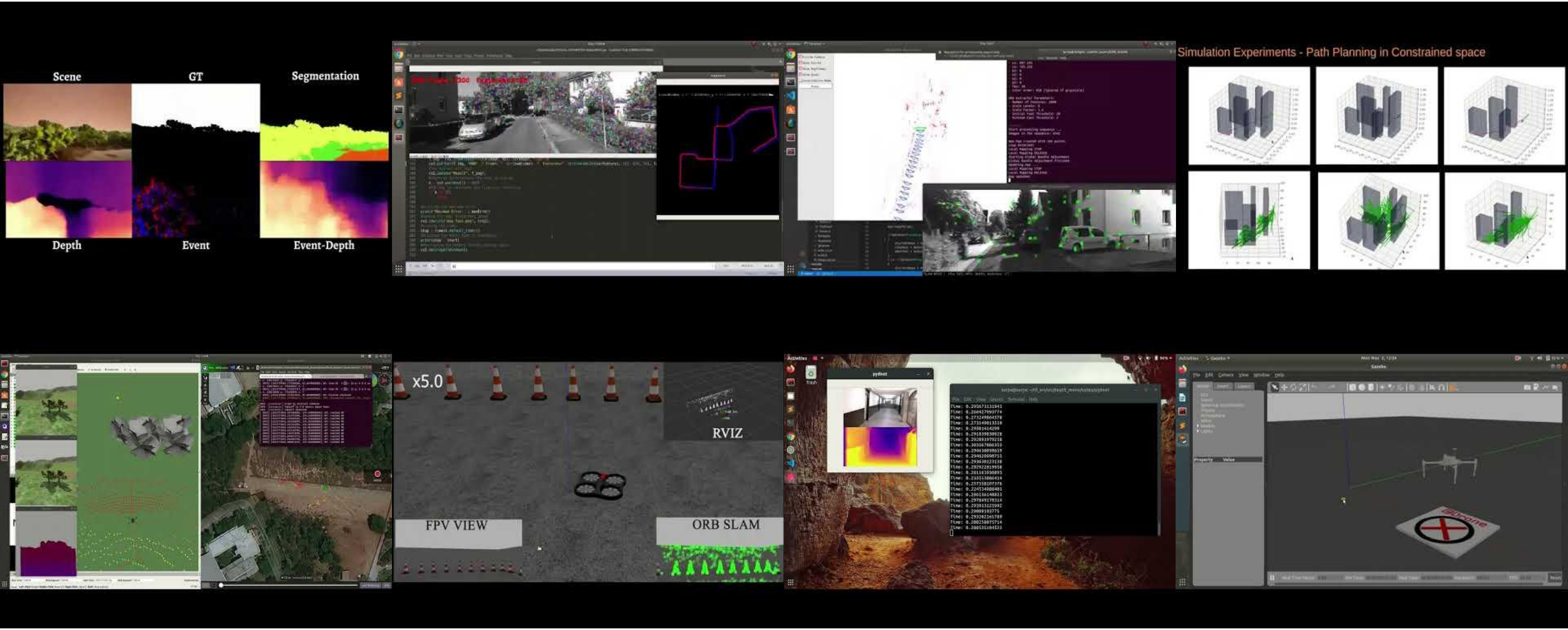
Topic: ME-CAPSNet: A Multi-Enhanced Capsule Network with Expectation-Maximization Routing Mechanism

Submitted in: IEEE CONECCT

Highlights:

- Proposed a novel architecture enhancing the features in each layer feature-wise and channel-wise simultaneously.
- Tested with predominantly used datasets (MNIST, FashionMNIST, CIFAR10, ImageNet) and proved our architecture's efficiency.
- Experimentations with various parameter tuning has been done and logged.
- Compared with various architectures and proved to have the best accuracy.

VIDEO DEMOS


Scene
GT
Segmentation
Depth
Event
Event-Depth
Simulation Experiments - Path Planning in Constrained space
x5.0
RVIZ
FPV VIEW
ORB SLAM

CODE BASE

KLT-Mono-Odometry Public
Python Updated 2 days ago

Object-Detection-PKG-ROS Public
Python Updated 2 days ago

ORB-BFMatcher Public
Python Updated 2 days ago

QuadSim-Python Public
Python Updated 2 days ago

ImageStitcher Public
Jupyter Notebook Updated 2 days ago

ORB2SLAM_Support_pkg Public
CMake Updated 2 days ago

YOLO-Object-Detection Public
Python Updated 2 days ago

TeleopKeyboard Public
Python Updated 2 days ago

Image-Classification Public
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A-Star-Path-Planning Public
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Obstacle-Avoidance Public
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CMake Updated 3 days ago

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CMake MIT License Updated 3 days ago

Obstacle-Avoidance-RRT Public
Python Updated 3 days ago

Object-detection Public
Python Updated 3 days ago

OUTLINE

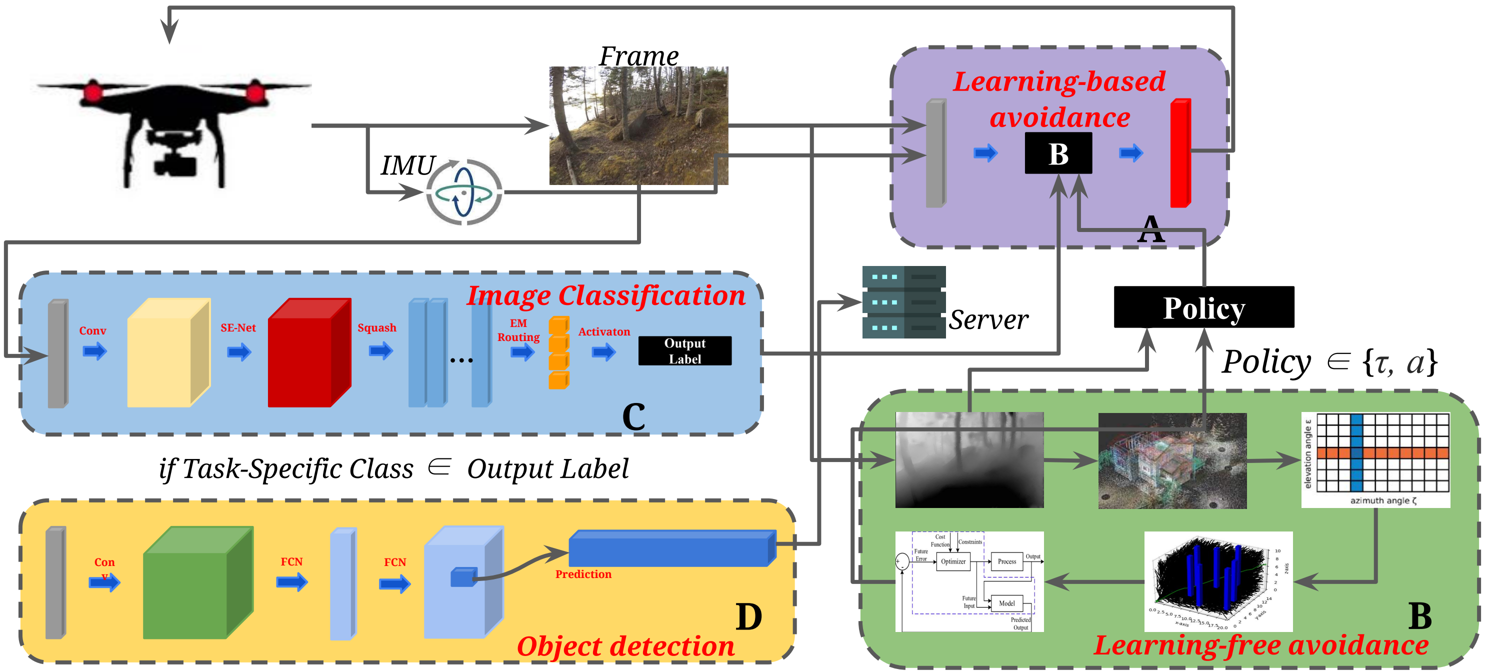
Avoidance

Learning Technique leveraging Imitation Learning

Inspection

A novel multi enhanced framework, with ME-CapsNet & YOLOv3

SUMMARY


Frame
IMU
Learning-based avoidance
B
A
Server
Policy
Policy ∈ {τ, a}
Image Classification
Conv
SE-Net
Squash
EM Routing
Activaton
Output Label
C
if Task-Specific Class ∈ Output Label
Con
FCN
FCN
Prediction
D
Object detection
B
Learning-free avoidance
azimuth angle ζ
elevation angle ε

APPLICATIONS

FOREST FIRE DETECTION

AUTONOMOUS SURVEILLANCE

PLANT WEED DETECTION

MONITORING PLANT CONDITIONS

SEARCH AND RESCUE OPERATIONS

and lots more…

GANTT CHART

Week Task	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Literature survey																
Problem Definition																
Objective of project																
Obstacle Avoidance -Learning Free																
Obstacle Avoidance -Learning based																
Inspection																
Report preparation																

In progress Completed Initiated

Open to Questions!

Thank You!