END TO END LEARNING FOR AUTONOMOUS DRIVING ON UNPAVED ROADS, A STUDY TOWARDS AUTOMATED WILDLIFE PATROL - 1ST AFRICANLP WORKSHOP, INTERNATIONAL CONFERENCE ON LEARNING REPRESENTATIONS (ICLR 2020)

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EnD To END LEARNING FOR AUTONOMOUS DRIVING ON UNPAVED ROADS

A STUDY TOWARDS AUTOMATED WILDLIFE PATROL

PRESENTATION BY: KHUSHAL BRAHMBHATT & RONALD OJINO

INTRODUCTION

Aim

- To investigate the technological feasibility of deploying UGVs for automated wildlife patrol.

Objectives

- Preliminary feasibility study based on metadata collected from park officials
- Data collection of driving data from national park trails in Kenya
- Steering wheel prediction using deep learning

FEASIBILITY STUDY

Mara Triangle

<u>Vehicles used in parks</u>

- Models (4 WD off-road e.g suzuki, land cruiser)
- Power requirements
- Fuel consumption

<u>Costs</u>

- Fuel/maintenance
- Labour

<u>Terrain</u>

- Dirt roads
- Clear feasible path used daily by vehicles.
- Changes in weather making navigation difficult.

Preliminary analysis of data from Mara Triangle

- Community/staff receptive to technologies
- Coverage area/ surveillance issues
    - 510 sq km divided into 3 patrol sectors, 3 patrol vehicles per sector
- Labour
    - 91 rangers
    - Shortage during peak season (July to Nov)

Costs

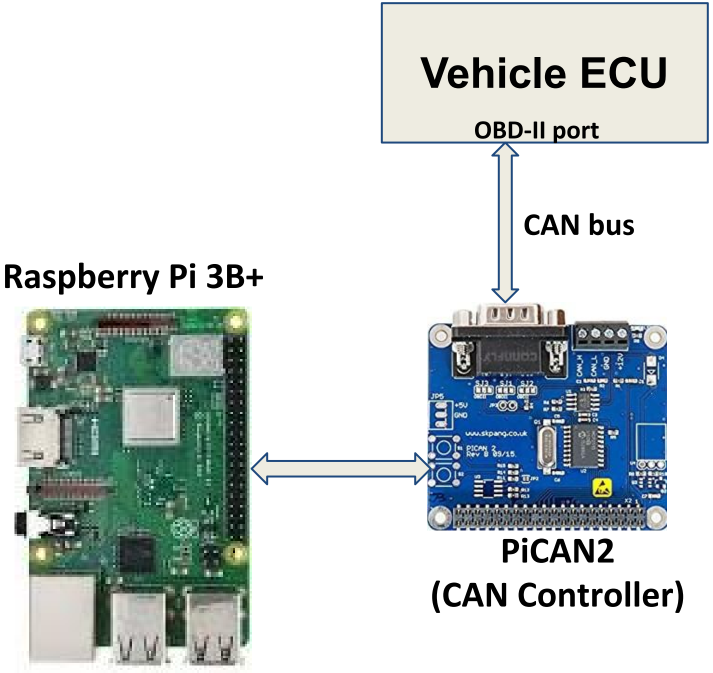
- Total Fuel Costs = Ksh. 300,000 per month
- Maintenance costs = Ksh. 25,000 per month

Deployment feasibility

- Use hybrid power supply combination
- Specialized vehicle design for the terrain
- Cost benefit analysis - Economically feasible
- Duration (reliability)
- Season variability
- Better vantage of monitoring activities in larger areas

DATA COLLECTION

Data Acquisition System



Data recorded

- 8.5hrs/115km from Nairobi National Park
- 2.5hrs/30km from Ruma National Park
- 9hrs/425km on paved roads (highways in Kenya)

Parameters recorded:

1. Driving video
2. Steering wheel angle
3. Steering wheel torque
4. Vehicle speed
5. Accelerator pedal position
6. Brake pedal position
7. Individual tyre speeds
8. GPS coordinates

Challenges in data collection

- Decoding driving signals from CAN bus

```
(1584248936.117048) can0 3A0#000000000000002B
(1584248936.117398) can0 4AC#0800200041000380
(1584248936.118188) can0 224#0000000000000008
(1584248936.120790) can0 1C4#00000000000000CD
(1584248936.124102) can0 020#0000072B
(1584248936.124329) can0 230#00000000000039
(1584248936.124571) can0 024#020701F741FC80EA
(1584248936.124805) can0 025#00100001787878A6
(1584248936.125386) can0 260#000000000000006A
(1584248936.127271) can0 127#00100008073DAD39
(1584248936.130225) can0 320#000000000000002B
```

Timestamp — Parameter id — Data byte

Challenges in data collection

- Camera lag when interfacing to Raspberry Pi
- Power limitations for laptop
- Driving a low-body vehicle on rough terrain
- Unreliable internet connectivity
- Data quality - windshield cleanliness, camera vibrations

STEERING PREDICTION

Data preprocessing:

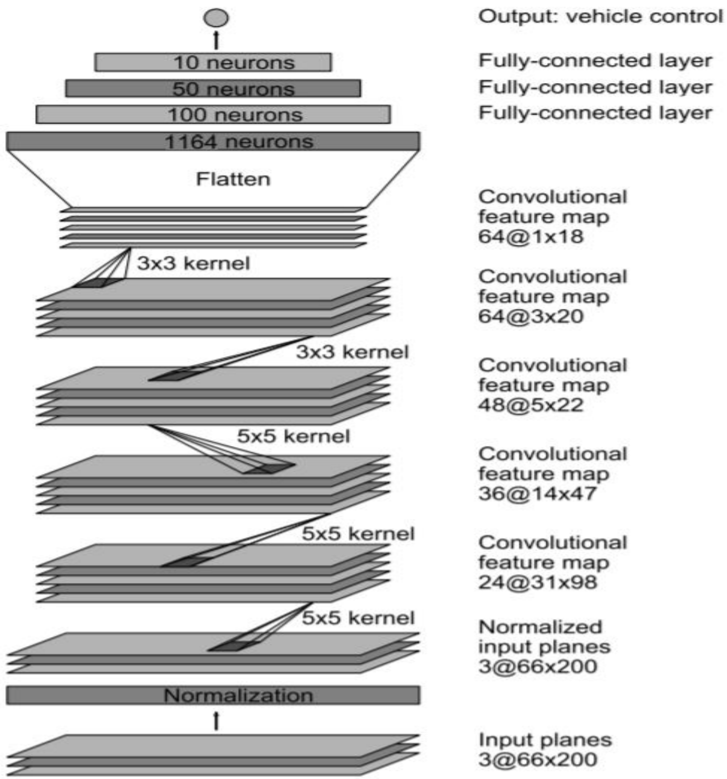
1. Identifying and removing video segments containing:
   - U-turns
   - Reverse
   - Overtaking
   - Stopped
   - Road view completely blocked by vehicle ahead
   - Navigating around potholes/bad roads

Data preprocessing:

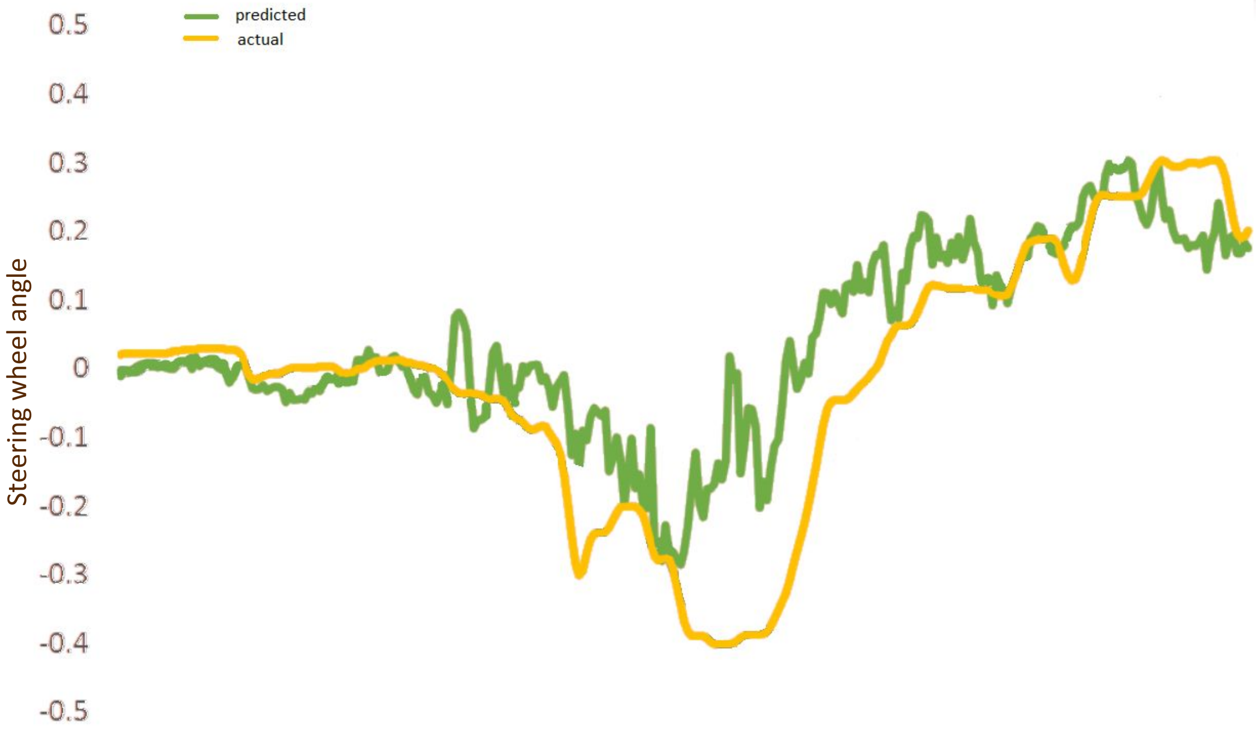
2. Uniform data distribution
3. Distortion correction
4. Image cropping and resizing
5. Extract driving signals from CAN logs
6. Match video timestamps to closest CAN timestamps to generate data sample
7. Data augmentation - shadows, lighting, horizontal flips

Sample data images

Network architecture



Results


predicted
actual
Steering wheel angle
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5

Future work

- Use more driving parameters for training
- Use a temporal method for training e.g. LSTM
- Conduct a more detailed feasibility study with the Mara Conservancy

Thank you.