Advancing Safety and Robustness: Perception-Planning System of an Autonomous Vehicle Last Mile Delivery

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Abstract **— We deployed a prototype autonomous vehicle (AV) equipped with self-driving capabilities. This is demonstrating the AV proof-of-concept (POC) of the last mile delivery within the integrated wildlife parks. The research goal is to develop an environment-aware Artificial Intelligence (AI)-enabled automated food delivery system for the Smart Zoo project. Advancing the safety and robustness of the perception-planning system of the automated driving software for the delivery use case, underscored the success of the AV prototype demonstration of the last mile delivery marking the first demonstration at the Singapore Zoo.**

Keywords — autonomous vehicle, artificial intelligence, image recognition, perception system, planning system.

I. Introduction

The Smart Urban Mobility [1] is a Singapore government initiative recognizing the potential of automation technologies into the transportation sector. Self-driving shuttles were introduced and several trials of autonomous vehicles (AV) were conducted for the first-and-last mile connectivity [2]. There's a visible shift in the last-mile delivery market towards automation increasing the demand for autonomous solutions. The COVID-19 pandemic has created a growing demand for safe and efficient last mile delivery solutions in the transportation of food, medicines, and essential goods. In transportation and logistics system we have seen drones or unmanned aerial vehicle (UAV), unmanned ground vehicle (UGV), autonomous vehicles (AV), sidewalk autonomous delivery robots (SADR) or autonomous mobile robots (AMR) as micro mobility last-mile delivery demonstrations and deployment in outdoor spaces. The contribution and benefits of these deployments in terms of safety, increased mobility, economic and societal contributions, pollution reduction, and improved efficiency and convenience [3].

In the context of Mandai Wildlife Group (MWG), the project owners is introducing a Smart Zoo initiative aimed at digital transformation and automation. MWG oversees the management of the Singapore Zoo and other wildlife park attractions, including Night Safari, River Wonders, and Bird Park, spanning a total land area of 28 hectares. The workforce consists of 2000 employees engaged in park operations, park rangers, and animal welfare. The zoo attractions draw 4.6 million visitors, comprising both local and international guests visiting Singapore. MWG recognizing this opportunity aims to enhance staff welfare and productivity by automating the food deliveries for staff across the integrated wildlife parks. This is by using an automated vehicle equipped with an environment-aware and AI-enabled system. The requirement is to demonstrate a working prototype capable of navigating various wildlife terrains through route optimization while ensuring that the packed meals remain warm. The solution should excel in open spaces and outdoor environments, reliably delivering to multiple drop-off destinations [4].

Fig. 1. The journey of the AV micro mobility last mile delivery (a) manual practice of collecting the food at the F&B restaurant by each team & to be delivered (b) AV last-mile delivery automated system on trial – Zoo staff at station#1 collecting the food meal boxes on time (c) station#2 of the AV on trial reaching its assigned destination - Zoo staff collecting the food meal boxes on time.

To address these challenges, we developed and deployed an AV equipped with sensors and an AI system capable of self-driving, object detection, obstacle avoidance, and navigation within the zoo parks. The AV is tasked with delivering pre-packed food meals to staff stationed at different locations in the zoo parks. Fig.1 illustrate the manual collection and delivery system and our AV on trial last-mile delivery on its test deployment. While in Fig.2 shows the informational map and processed point cloud map in birds eye view (BEV) of the whole delivery route. This presents the necessity for automated driving, route optimization, and adherence to predefined routes from the charging station, kitchen, and various drop-off stations. The zoo environment is characterized by low-speed zones and mixed traffic consisting of pedestrians, vehicles (passenger trams, buggies, lorry trucks, etc.), and personal mobility devices (PMDs), narrow roads with minimal lane markings and strict driving regulations. The terrain exhibits small slope gradients and uneven curbs, with ongoing construction in some areas designated for expansion. The construction safety fences may encroach upon road lanes as the development progresses (see Fig. 5 for the illustration).

The complex environment and high-density traffic present safety concerns. The perception, and planning algorithms must have the functions to adapt the AV driving policy in unclear lane boundaries. Furthermore, the perception system must accurately detect and recognize Vulnerable Road

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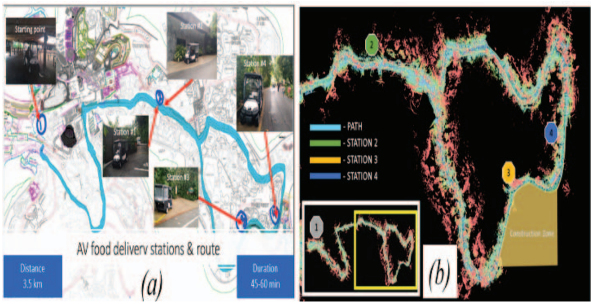

Fig.2. Singapore Zoo wildlife parks map representation (a) MWG map with road details and route overlayed with photos of the delivery stations (b) point cloud data meshed map processed (down sampled) inset section was enlarged for added information.

Users (VRUs) with special consideration for animals, to prevent collisions and ensure protection. The planning system can handle localization based on its position, especially in areas where determining self-position is challenging due to a lack of high-precision maps. Additionally, the AV must implement robust safety measures and protocols to mitigate potential risks, hazards, and unexpected events that could endanger VRUs, animals, and other vehicles on the road.

The AV proof-of-concept aims to address the identified challenges of the perception-planning system. Our contribution to the AI and AV research goals are the following:

- Examine the operational design domain (ODD) of the zoo environment. Identify the challenges of the last mile delivery use case to align with the AV capability and the AI system.
- Develop, test, and verify the various functions of the perception, and planning algorithms. Integrate the safe and robust AI system to determine the safe driving approach in low-speed zones, crowded, and high-density mixed traffic with unclear lane boundaries of roads in the zoo park.
- Evaluate the performance of the AV capability and AI system in relation to the KPI metrics agreed with the MWG project owners.

The paper consists of five sections. Section II outlines the related research on perception and planning systems, another implementation of AV last mile delivery. In Section III, describes detailed methodology and our approach in developing the AV prototype, including hardware and software integration. Section IV presents the discussion of the evaluation, assessment results, and lessons learned. Finally, the conclusion the summary of the results of the AV POC demonstration and added future research directions for enhancing the capabilities of the AV system with AI functions in other last mile delivery use cases.

II. Related Works

Some of the significant challenge in automated driving is developing robust and reliable algorithms for the perception and planning system. This section examines selected studies that have contributed to the development of the AV systems, emphasizing their impact on the safety and efficacy of last-mile delivery.

The pioneering works of Kato et al. discuss implementing Autoware on embedded systems, emphasizing LiDAR and cameras for real-time perception and navigation [5].

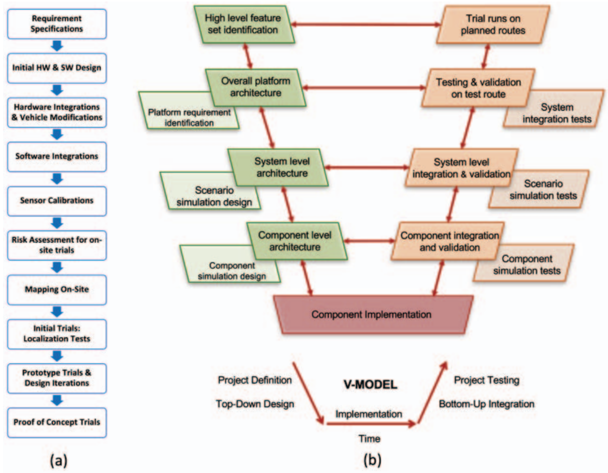

Fig.3 The process highlights the steps in the AV development process following the safety development standards (a) component development approach on each stage of the prototype development process (b) following the formal development standards adopting the V-Model.

OpenPlanner 2.0 by Darweesh et al. enhances behavior prediction and trajectory planning, integrating various sensors for dynamic environment navigation [6]. In the previous works of Tong et al. they develop a search-based motion planning framework incorporating sensor health monitoring for fault management [7]. While Carballo et al. integrate model-based support with CNNs for navigation in urban landscapes, facing challenges in varied environmental conditions. Their ongoing research aims to enhance learning algorithms and adaptability to diverse scenarios [8]. The AV prototype of Chong et al. developed an autonomous personal vehicle for urban transportation, utilizing GPS and LiDAR for navigation [9]. The works of Novotny et al. explored a ROS-based architecture for a campus delivery robot, integrating 3D LiDAR and cameras [10]. While Gao et al. designed an autonomous delivery robot with LiDAR, IMU, and GPS for mapping and navigation [11]. In the studies Masood et al. discussed the transition to fully autonomous urban freight vehicles, highlighting operational efficiency improvements [12]. Lastly, Buchegger et al. presented an autonomous vehicle for urban parcel delivery, featuring advanced path planning and obstacle avoidance systems. The challenges of navigating highly dynamic urban landscapes were noted, with a call for improvements in real-time adaptability and sensor accuracy [13].

III. Methodology

A. The AV prototype development process

In developing the AV prototype last-mile delivery system, adherence to the ISO 26262 [14] safety development standard is crucial. This standard provides a systematic approach to ensuring functional safety in automotive systems, including AVs. The development process involves hazard analysis and risk assessment to identify potential hazards and assess associated risks, defining safety goals and requirements based on these assessments. Safety mechanisms and functions are then implemented to meet these requirements, with verification and validation activities ensuring compliance throughout the development lifecycle. By following ISO 26262, the development process systematically integrates safety considerations into every aspect of the AV prototype, enhancing its safety and

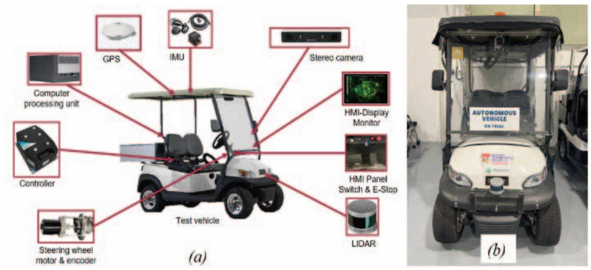

Fig. 4. Hardware & sensors integration, vehicle modification - test vehicle 2-seater golf buggy (Procar cargo elite) (a) illustration of the hardware, sensors, and interfaces (b) actual AV on trial for the last-mile delivery use case.

reliability for real-world deployment. The development process we followed in our previous work [15-16] as illustrated in Fig 3.

B. Compute, Sensors, and Actuators

The test vehicle was equipped with various sensors for detection and recognition: two Mynteye stereo cameras (front and rear view), Velodyne (VLP-16) LiDAR for HD mapping, localization, obstacle detection, and avoidance, GNSS+RTK for accurate positioning, and IMU for precise pose and relative position measurement. A custom-built steering motor and encoder were installed for steering, brake, and throttle control. The compute system, including Jetson AGX Orin, power supply, network hub, and peripherals, was mounted on a rack placed at the roof deck of the payload. The customized AV kit interfaced with the Curtis controller software for seamless operation. The components are presented in Fig. 4 with the actual AV prototype.

C. Automated Driving System

The ADS is composed of the software stack adopted from the Autoware framework. The software design consists of the ROS-based system in Ubuntu 18.04. The software integration into the AV prototype ADS software stack capable of navigating vehicles autonomously in various environments. The software stack of perception, planning, and control system has its algorithms that we adopted and modified to develop a comprehensive and robust solution for AV last-mile delivery, capable of navigating autonomously and safely in the wildlife parks drivable environment. The perception system operates the vision-based environment awareness includes various sensors such as LiDAR, cameras, GPS and IMU for environment perception, object detection, and localization. The localization module utilizes data from GPS, IMUs, and laser sensors to accurately determine the vehicle's position and orientation in the environment. The point cloud data is collected to generate the HD map of the entire zoo environment (mapping the route of the AV last-mile delivery service). The planning module generates safe and efficient driving trajectories based on sensor data, maps, and high-level mission goals, considering factors like traffic rules, vehicle dynamics, and obstacle avoidance.

D. Perception-Planning System

In this paper, we describe the perception-planning system approach in solving the safety challenges for the crowded and high-density mixed traffic with unclear lane boundaries environment in the zoo parks.

1) Perception-Planning System Architecture

The perception module has the following components:

- Object recognition – detection of dynamic objects – pose and velocity.

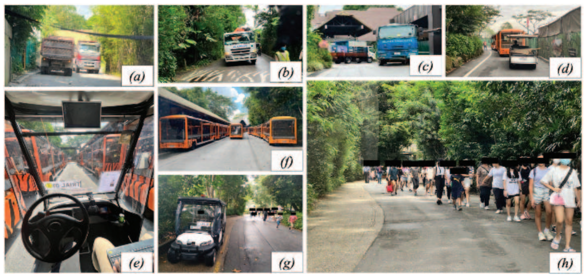

Fig. 5. Zoo environment with selected scenarios and observations. The challenges of the AV sensing and perception with the navigation and motion planning on a low-speed, mixed and heavy traffic environment. (a-c) The ongoing construction (presence of trucks), and (d) structural changes & fence encroaching the road; (e & f) parked trams along the road; (g-h) crowd of visitors in the zoo parks.

- Tracking – continuous frames of detected moving objects.
- Prediction – predicts trajectories of moving objects.

The planning node is composed of the following:

- Mission planning – route planner
- Scenario planning – lane driving and parking scenario. Lane driving scenario – behavior planning and motion planning.
- Trajectory tracking and validation.

We explored the perception-planner modules and determine the output of each that contribute to driving policy. Then determine the calculation of the best trajectory and looking into the vehicle motion, safety, instructions for the next path, and traffic rules. The verification and validation of the safe trajectory according to the use case is also considered.

2) Perception and Planner Interface

The interfacing for inputs and outputs of the perception-palnning node are the following:

- Inputs – Image, HD and vector map, (perception) obstacle and object information, occupancy map, (localization) vehicle motion, (system) operation mode, (HMI) feature executing such as lane change, intersections, (API) final position of the destination, checkpoint (midpoint) calculated into the route, and the max speed (velocity limit).
- Outputs – dynamic objects, obstacle segmentation, occupancy grid (perception), trajectory and turn signal feed to control; diagnostics report of the state of the planner (system), feature execution such as lane change, intersections; next trajectory (HMI), information for safety behavior to the planner such as objects position and avoiding obstacles and decision to stop (API).
- The route level and path information for the starting point and destination.
- Drivable area of the defined region where the trajectory is calculated.
- Trajectory are points or waypoints with certain intervals, velocities, accelerations, and positions fed into the controller. The safety distance and validation added.

3) Perception-Planner functions

Selected perception and planning component functions are highlighted in this paper. The functions are based on the scenarios observed in the zoo park according to the traffic environment. The planner functions used to the identified scenario are the following:

- Route planning
- Path planning
- Obstacle avoidance, obstacle stop, obstacle deceleration.
- Path smoothing

The following test case scenarios are:

- Scenario 1- moving pedestrians ahead of the ego vehicle
- Scenario 2 – moving pedestrians near or the side path of the ego vehicle
- Scenario 3 – passenger tram approaching the path of the ego vehicle
- Scenario 4 – moving vehicle in-front of the ego vehicle

E. Perception-Planning system methods

We explore the following methods and investigate the performance of each function.

- Setting the desired velocity to ensure it follows the speed limits, traffic rules, and safety guidelines. A representation of the path (set of waypoints). Equations to calculate the desired velocity at each waypoint based on constraints. Adjustments to these velocities based on dynamic data (e.g., detected obstacles).
- Using the waypoint follower taking the planned waypoints follower with the vehicle dynamics and kinematics. Waypoints with desired velocities. Control algorithms (like a PID controller) to minimize the error between the current state and the waypoint. Adjustments based on dynamic environment data.
- Considering the static and dynamic obstacles, traffic rules, and possible scenarios for a safe and efficient path. (1) State Space: Define the space in which the vehicle operates. This is a 2D plane (if considering only position) or higher dimensions for orientation, velocity, etc. (2) Cost Function: For any given path, there's an associated cost related to path length, time taken, energy consumption, etc. Where a cost function associated with traversing through a point in state space.

IV. Results and Discussion

The POC observations of the perception and planning system in the AV prototype last-mile delivery focus on the ways of how robust and improve the components of safety aspects of the automated driving system. In addition, improving the image recognition aspects and motion speed profile and the obstacle avoidance/detection in relation to stop and deceleration range. We highlight the identified test case scenarios namely: (1) Scenario 1- moving pedestrians and animal (monkey and peacock) ahead of the ego vehicle; (2) Scenario 2 – moving pedestrians and animal (monkey and peacock) near or the side path of the ego vehicle; (3) Scenario 3 – passenger tram approaching the path of the ego vehicle; (3) Scenario 4 – moving vehicle in-front of the ego vehicle. These scenarios informed our team on the lessons encountered

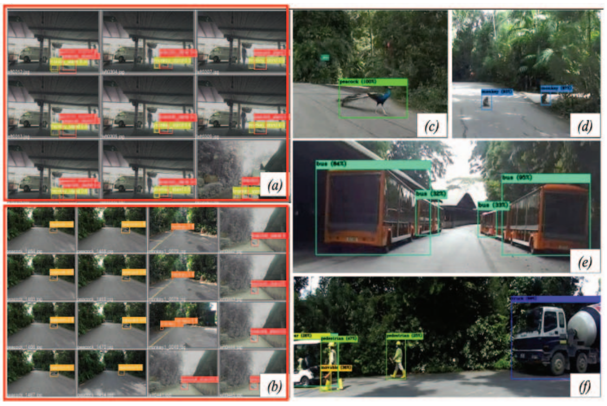

Fig. 6. The perception system approach and observations. (a) recording the initial test images (animals – peacock & monkey standee (b) training & validation of the detection pipeline (c) real peacock & (d) real monkey in real-time detection (e) tram detected as bus (f) construction truck and others misclassified object (movable for the boots) detected.

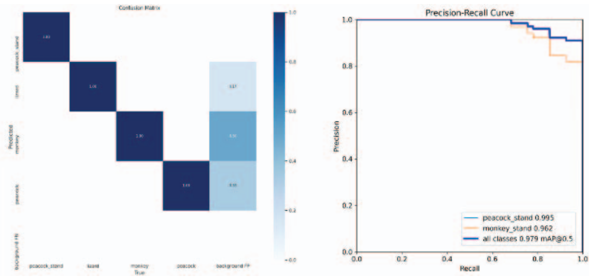

Fig. 7. Results of the training model for the object detection. Sample test for peacock and monkey standee and real animals (a) confusion matrix (b) precision and recall curve

and improve on the design consideration, safety approaches, and addressing the challenges in perception and planning system. It is also important consideration and understanding on the full details of the HD map with respect to the environmental infrastructure and other road changes and traffic events.

1) Perception

The initial observation of the animals was recorded on the mapping of the zoo environment and initial trial runs. To get the images and protect the animal (monkey and peacock) usually loitering around for this encounter we printed a mock-up cut-off board standee. This process is to record and train the images of the monkey and peacock at different backdrop of the environment. This is like Internet images being harvested and collated for the image scanning and filtering to extract the features of the image frame of interest for the object recognition task. The class labels in our collection are pedestrian, bicycle, motorcycle, car, bus, truck, animals, monkey, peacock, and movable (traffic cones). The existing training model for the image recognition from our AI system dataset is from the 500 driving hours. The dataset collectively has 500,000 annotated labels. The framework is Pytorch and using YOLO (You Only Look Once) [17] CNN object detection pipeline. The pipeline (DarkNet) has 19 CNN layers and 5 max pool layers. The curated images and training set was used in the object detection and classification in the experiment. Similarly, we incrementally adjust the dataset according to the collected data by augmenting the dataset with rotation, orientation, filtering using a special software to add variety to the image. Additional class labels of the animals were considered in the experimental data aside from the initial observation. Therefore, this process can help in the dataset and

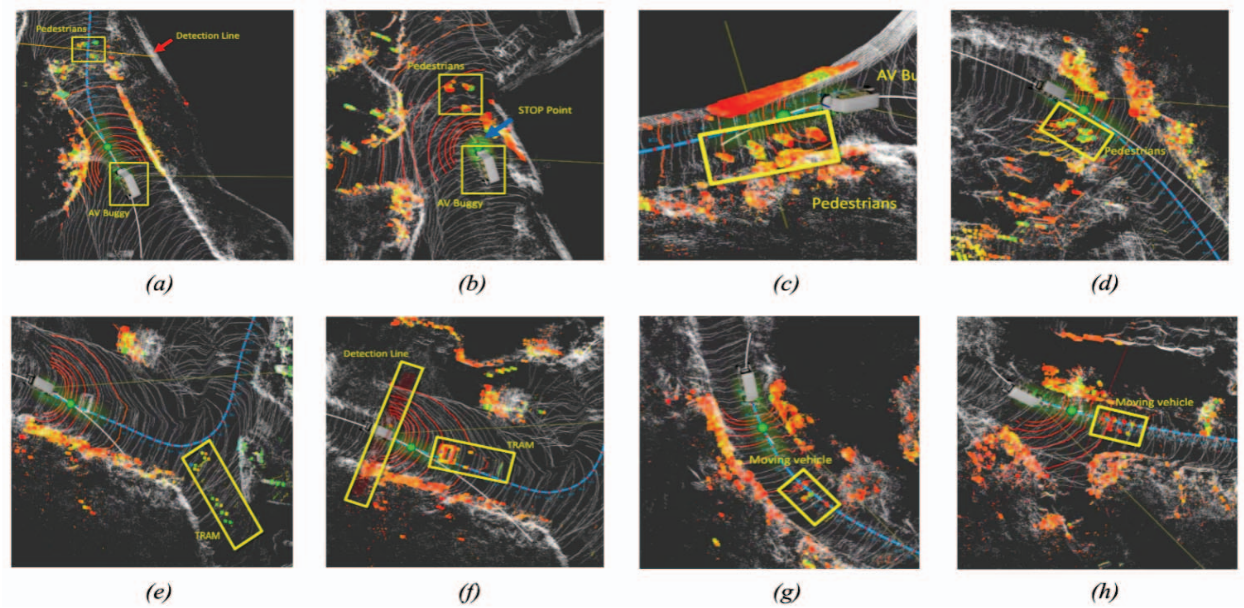

Fig.5. Test case scenarios of the path planning algorithm AV on-road trials at the Zoo parks. (a) Scenario 1 - moving pedestrians ahead of the ego vehicle. (b) Scenario 1 – moving pedestrians detected in the path of the ego vehicle. (c) Scenario 2 – moving pedestrians near on the side of the path of the ego vehicle. (d) Scenario 2 – moving pedestrians were detected but not obstructing the path of the ego vehicle. (e) Scenario 3 – passenger tram approaching the path of the ego vehicle. (f) Scenario 3 – passenger tram detected in the path and the ego vehicle stopped at safe distance (g) Scenario 4 – moving vehicle in-front of the ego vehicle. (h) Scenario 4 – the ego vehicle maintained a safe distance and speed behind the moving passenger tram.

robust collection for improving the training model. The process can also improve the planning system to observe the behaviour of the motion planning component. In addition, assess the safety aspect with respect to the identified scenarios in the experiment. The result has a mAP of 95% accuracy at 10 fps. The object detection accuracy fits to our criteria accordingly with the KPI of the AI enabled AV last-mile delivery system. See Fig. 7 of the training model mAP and precision-recall results.

2) Motion Planning & Navigation

In our implementation, effective localization relies on understanding the route and motion planning approach through pose estimation in the HD map. The map is divided into 5 sections, with the AV buggy delivery navigating from the Ulu-ulu restaurant to the Zoo area, stopping at stations 1 to 4 delivery the destination. To conserve compute resources, the HD map is loaded per section of stations along the trajectory. Waypoints are recorded at each station to facilitate proper localization within the map. Challenges in the zoo road network include missing map features and terrain variations, complicating global planning and navigation. The planning system adjusts the AV's speed based on designated limits and environmental conditions, ensuring safe operation and adaptability to dynamic situations. It continuously evaluates surroundings to generate paths that avoid collisions and navigate through crowded environments. In unpredictable scenarios, it executes safe stops and manoeuvres to prioritize VRU safety. Customizable algorithms enable improved performance in various driving conditions.

3) Test case scenarios

We record, evaluate, and analyse the performance of AV buggy delivery navigation from the different scenarios as identified in the test case. Illustrated in Fig. 5 are the selected observations.

a) *Scenario 1- moving pedestrians ahead of the ego vehicle.*
b) *Scenario 2 – moving pedestrians near or the side path of the ego vehicle.*
c) *Scenario 3 – passenger tram approaching the path of the ego vehicle.*
d) *Scenario 4 – moving vehicle in-front of the ego vehicle.*

The verification and validation of each test case scenario were conducted in simulation and calibrated during pilot tests in zoo parks. Analysis of vehicle speed and distance relative to trajectory and obstacles was performed. Graphs illustrating the four scenarios were plotted. In Scenario 1, with pedestrians ahead, the ego-vehicle slowed down, maintained a safe distance, and temporarily parked until the path cleared. In Scenario 2, pedestrians near the vehicle's path were detected, but the vehicle continued navigation at reduced speed,

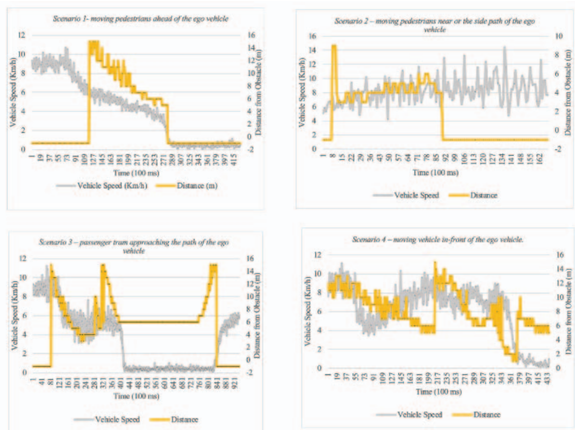

Fig. 8. Observations for the test case scenarios (a) moving pedestrians ahead of the ego vehicle - The pedestrian in the point of being detected as an obstacle and safely avoiding on its trajectory. (b) moving pedestrians near or the side path of the ego vehicle. Pedestrians were detected but it continued to navigate as the pedestrians were not obstructing the path (c) passenger tram approaching the path of the ego vehicle, The vehicle travelling speed at 8-10kph. It has detected the tram ahead. However, there was no clear area to move aside so it has stopped instead and waited the path to be cleared. (d) moving vehicle in-front of the ego vehicle at 10-14m travelling at 8-10kph. The AV maintained a safe distance and speed behind the moving vehicle.

maintaining a safe distance. Scenario 3 involved a passenger tram approaching; the vehicle stopped as no clear area for manoeuvring was available. In Scenario 4, with a vehicle in front, the ego-vehicle maintained a safe distance and speed, following traffic rules. Deviations between planned and actual trajectories were observed, highlighting the importance of map updates and detailed navigation data. Alternative map formats were considered for improved planning. Safety measures included emergency stop buttons and safety driver training.

V. Conclusions

The POC AV system in our demonstration provided our team several considerations in the initial design and development. This to address a wide range of driving scenarios, including challenging environments such as low-speed zones, crowded areas, and high-density mixed traffic conditions with unclear lane boundaries. Achieving safe driving in this context requires safe and robust perception and planning algorithms that can handle complex and dynamic situations.

The AV last-mile delivery demonstration was able achieve the goal of delivering the food meal boxes on its designated drop offs. The covered distance was 3.5km and the duration is 40-60mins. The AV system was able to follow the ODD. The KPIs of the delivery system were achieved following the trials performed. The navigation was able to navigate from pick-up (collection point) to drop off-points 85% of the time without human intervention. This translate to 85% of the delivery was successfully completed on the assessment and evaluation period. The overall assessment was achieved in terms of the safe and timely navigation and successful delivery drop-offs of the food meal boxes at designated points.

The lesson learned on the challenges of the perception and planning system is still open research. The perception-planner system we implemented and deployed for the object recognition and motion planner is to scale with the designed functionality. The robust perception, navigation, and planning algorithm with respect to high density of dynamic objects and crowded environment in the zoo park is more towards the perception challenge. However, this is also translated to prediction and decision associated with the mission and behavior planning. We observed that prior knowledge of the road information is essential for the planner algorithm. This is understanding the road features. The lane marking, center lines, stop lines, crosswalk, and others features that other mapping tools add layers of information to the road traffic such as vectors or HD maps. This makes the AV understand the environment and dependent to make the navigation on the right track. This annotation of the HD map is part of the information to support the navigation and decision-making process in the autonomous driving software stack. The AV prototype last-mile delivery was able to maintain the target speed and the right path. Although, the planned path is being disrupted by the crowded environment and obstacles in the road traffic. The described scenario on this research is to keep the AV in the lane. The POC in Mandai zoo provided a more open opportunity for our ADS to improve on the challenges in the perception and planning algorithm for complex environment.

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