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European Journal of Advances in Engineering and Technology, 2024, 11(3):131-135

Research Article ISSN: 2394 - 658X

Safety-Eye: On Road Safety for Self-driving Vehicles using Reinforcement Learning

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ABSTRACT

With technological advancements automotive industry is witnessing new era of transition to self-driving vehicle for everything. Self-driving cars for personal and commercial use are right across the corner to become full reality. Along with self-driving drone and robots for delivery of food and merchandise have become reality. With these advancements the safety and security of the self-driving vehicles have emerged as major concern for current times. To this end, this work proposes SafeEye a reinforcement learning based policy aware and optimized approach with federated learning to provide self-driving vehicles better and safer route map and runtime optimization. The simulation results of SafeEye based system with multiple scenarios shows promising results and opens a new research direction to explore to provide safe and informed route prediction for self-driving vehicles of next generation.

Keywords: Automotive chiplet architecture, next-generation vehicular systems, Autonomous driving, fusion sensors, ADAS, Infotainment, gem5, chiplet, Mcpat

INTRODUCTION

Self-driving vehicles have emerged as a revolutionary technology, and it has transformed the modern-day transportation landscape. Modern-day automotives have a large network of computing, sensing, and processing engines. These systems are connected to the internal and external network for exchanging boot time and runtime critical information which are used for making informed decisions at different stages. These devices have built in Global Positioning Systems (GPS), satellite networks or a connected smart application (central controller / tablet screen / phones) to help users navigate the direction from point A to point B. There has been significant research and development to aid in autonomous driving and route planning in recent years [1-6].

Self-driving cars can potentially reduce traffic accidents caused by human errors [7] and provide more safer roads to users including pedestrians [8]. The routes used by self-driving vehicles will be based on shortest distance, toll, freeway, time of the day, traffic etc. Some of the latest applications uses machine learning and AI algorithms to get runtime updates such as accidents, road work and traffic slow alerts. However, routing applications lacks in accounting for safety, user preference and current surrounding metrics such as safety (break-ins [9], vandalism [10], porch-pirates [11] etc.), pollution, ease of parking, emergency situations [12], food choices, etc. Given a city and surrounding areas have "better" and "worse" regions and local humans will be aware of the neighborhood and dynamic conditions but the self-driving vehicles (cars, robots, delivery drones etc.) currently lack in such dynamic route optimization. To this end, this work presents a novel federated learning combined with deep reinforcement learning based approach to help better route planning with dynamic changes in metrics. This work also presents promising simulation results with optimized algorithm.

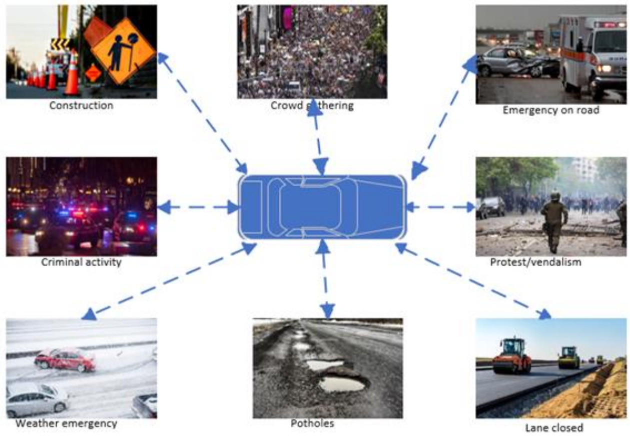

Figure 1: Non-conventional dynamic data sources that are processed with SafeEye

Fig-1 depicts various non conventional sources of data collection my various sensors in self-driving cars, drones or robots. These dynamic sources of information provides realtime conditions for optimized route predictions. SafeEye uses this data as weights on the routing map and applies coordinated policy optimization for better decision making with reinforcement learning. SafeEye algorithm collects the event markers and send it to the could server with timestamp and geolocation information. These cloud sourced information will be used by SafeEye server to perform federated learning and optimize the model over time. Thus, SafeEye simulation combines federated learning apporach with coordinated policy optimization. SafeEye will not only provide better dynamic decision making at runtime but also it will aid in better route optimization to avoid certain situations such as crowd gathering, road blockage, criminal activities, porch pirates etc for the self-driving vehicles.

RELATED WORK

With the advancement in self-driving automotives industry many researchers have explore different Machine Learning (ML) and Artificial Intelligence (AI) techniques for enhancing self-driving experience. Multi Agent Reinforcement Learning (MARLA) has emerged as powerful approach to solve complex decision-making problems. The typical task settings are divided in three categories namely fully cooperative task which focuses on communication [13-14] and credit assignment [15-17]. Second category is competitive tasks which focuses on meaningful opponents [18,19]. Third is mixed approach [20-22]. CoPo [23] presents cooperative policy optimization simulator for dynamic tasks handling at runtime.

Second key aspect of the related work is to find suitable traffic simulator for evaluating the proposed technique. Various traffic flow simulators such as CARLA [24], SUMO [23], CityFlow [25], and FLOW [26] uses RL agents to steer the low-level controllers for investigating specified traffic conditions. SMARTS [27] evaluates the interaction between social vehicles dynamic traffic environments and RL agents. Maps based application such as Google maps, apple map, waze. Safety and neighbourhood watch apps such as citizen, crime-alert, neighbourhood watch etc, are few examples of route mapping apps that uses runtime reinforcement learning and adds weights and biases on the route selection. However, they do not count of cooperation-based policy optimization which from the simulation results aids in the safe self-driving vehicle experience.

SAFE EYE ARCHITECTURE

Fig. 2 Shows high-level system design of SafeEye. The server will send initial model for training to the client application running on the self-driving vehicle upon installation. The automotive sensors data such as ultrasonic range sensors, LiDAR, radar, HD cameras readings are feed into the RL based modified CoPo algorithm during runtime.

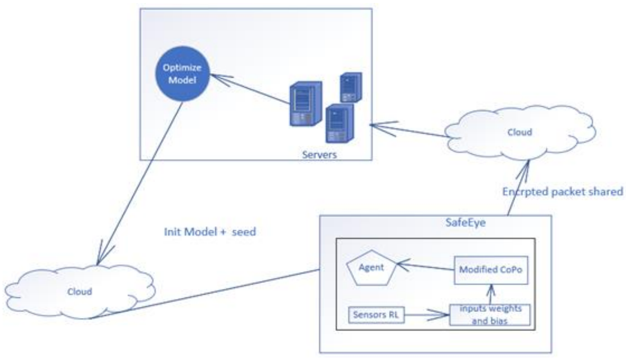

Figure 2: High-level system design for SafeEye

It will result in adding the weights and bias to the x and y coordinates of the geo location during runtime. The algorithm will take this weights and biasing with geo coordinates into account for cooperative policy optimization and agent will act based on not only past but current situation of the environment in which it is. The server collects the feedback of each client and use it for optimizing the training model and refeeds it to client application periodically. Thus, live updates of the geolocation and surrounding conditions are given to the modified CoPo algorithm. The policies are optimized on the client agent by combining local policy updates and the feedback received from the server as global policy updates.

The localized policy optimization is performed using Eq1

$$r_{i,t}^{N} = \frac{\sum_{j \in \mathcal{N}_{d_n}(i,t)} r_{j,t}}{|\mathcal{N}_{d_n}(i,t)|}, \text{ wherein } \mathcal{N}_{d_n}(i,t) = \{j : ||\mathrm{Pos}(i) - \mathrm{Pos}(j)|| \leq d_n\}. \quad (1)$$

Where, Ndn (i, t) defines the neighbourhood of agent i for the given radius dn at step t. The key reason for adding the global policy is to make route prediction accuracy high. As the vehicles are running in the road with dynamic surrounding and conditions of the neighbouring vehicles will also affect the reward given to the agent. When a consensus based global policy weights and biases were added to the routing algorithm. It improved the performance significantly. The co-ordinated and weighted rewards are defined using following equation:

$$r_{i,t}^{C} = \cos(\phi) r_{i,t} + \sin(\phi) r_{i,t}^{N}. \quad (2)$$

SafeEye approach for adding weights and Biases

Implementation of routing methods based on a weighted graph approach, whereby each path between two defined locations consists of a set of weighted edges (corresponding to road segments). The weights of the edges are determined by factors such as distance, speed, road aspects, pollution, weather, and safety metrics. A UI interface with sliders for different aspects can be used to control the settings for the routing method to suggest routes based on user preferences (e.g., speed and safety, avoiding construction zones, etc.)

Creation of an online database to dynamically update the edge weights in a defined area as referenced by location (lat, lon) and the time of day and routing algorithms for two end points based on the weights from previous step. This database can utilize data from public sources and optionally from sensors placed on fleet vehicles, which regularly drive through the defined area.

Creation of a hardware module for the sensors to be mounted on fleet vehicles, including speed and camera sensors, and corresponding analysis algorithms. The cameras can analyze scenery and record e.g., instances of lane closures and construction presence and mark these aspects by uploading the information to the online database service.

Evaluation

The simulation was performed by modifying the CoPo simulator and including the weights and biases from the sensors RL learning. The modified algorithm and simulation were tested on following four scenarios for success rate and accuracy.

Table 1: Depicts the success rate of different techniques compared to SafeEye

Technique	Potholes	Intersection	Lane closures	accidents
IPO	64.67	60.47	72.43	83.5
MFPO	66	69.43	67.43	81
CoPo	72.6	78.34	74.21	75.6
SafeEye	75.3	83.23	80.54	79.32

Scenario 1: when Potholes and not favourable weather conditions were feed to the simulation motel with modified CoPo. The generated weight and biases were used for making policy-based prediction and optimized route selection the accuracy of the SafeEye was increased by 3% compared to that of CoPo.

Scenario 2: Depicts when self-driving vehicle is on the road in the intersection with ongoing traffic with signal lights offs and the request for new route prediction comes to the client. The accuracy of this route and policy-based prediction with SafeEye reaches 83.23 % correct results.

Scenario 3 and Scenario 4 depicts road conditions blocked by accident and or construction on the road and lane closure as a result. In both the cases from the simulation results SafeEye outperforms the other state-of-the-art techniques and provides better route and policy-based selection coordinated route prediction.

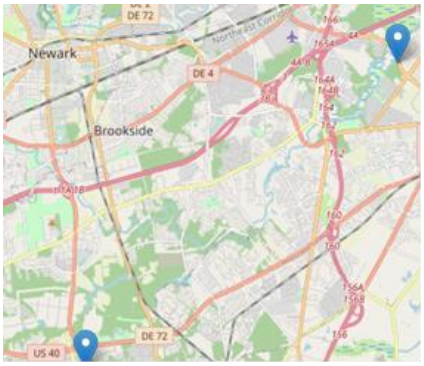

Figure 3: Simple Directional map

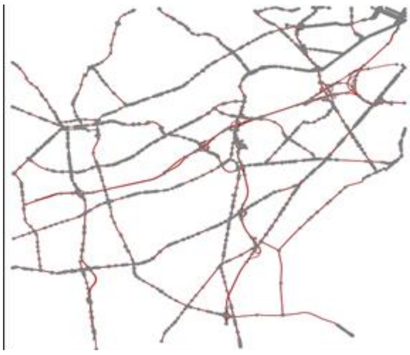

Figure 4: Map with nodes and edges

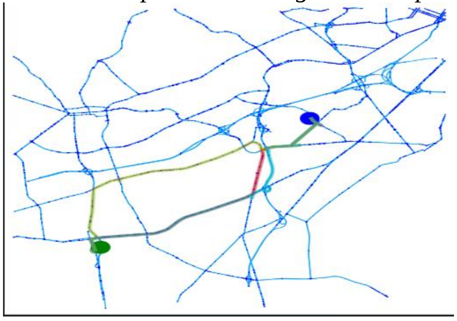

Figure 5: SafeEye route map with safety weight/bias.

Figure 3 depicts the map plugin based on shortest distance between two endpoints. Figure 4 represents the Map with additional layer of CoPo based optimization for the route. Figure 5 shows the SafeEye provided route options based on safety weights and biases. The red colour road indicates the scratchy area and recommends the self-driving vehicle to potentially avoid it by choosing alternate green path.

Challenges, considerations and future improvements

SafeEye simulation results shows promising optimized route selection and recommendation with confined environment. However, it assumes that the biases and rewards are correctly awarded to the RL based agent so that feedback loop can help modified CoPo algorithm to aid in better route selection. Furthermore, the server databased can be enhanced to combine multiple sources of information such as police records, area safety updates, public events announcements etc.

CONCLUSIONS

With the increased commercialization of self-f=driving cars, robots, and drone the secure and safe route selection and dynamic decision making based on the current surrounding conditions becomes vital. Previous works have demonstrated use of reinforcement learning to tackle some of these issues. However, they lack in dynamic cooperated policy optimization to handle real world scenarios such as pothole, crime activity, roadblocks, constructions, weather impacts etc. Safe Eye provides the dynamic cooperated policy-based decision optimization along with usage of federated learning enabled it to proliferate the learning to the could server network and with applied weights and biases this federated learning-based approach optimizes the training model to handle such situations in the future better. The simulation results shows that SafeEye based route maps is successfully able to avoid the scratchy neighborhood during the specific time of the day and alerted the user to chose alternate route.

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