# Privacy-Aware Personalized Advanced Driver-Assistance Systems (ADAS)

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## 1 Thesis

Many of the current state-of-the-art Advanced Driver Assistance Systems (ADAS) rely solely on sensory and driving data to warn or act on behalf of the driver in dangerous situations. This research project aims to develop an adaptive agent based on reinforcement learning that is able to quantify and understand various high-level human states. These human states will then be used in conjunction with data received from ADAS on vehicles to personalize and improve the relevance of warnings and actions that are taken by these systems. The measurements taken on the human state will be context-aware and thus place significant importance on respecting the privacy of users.

## 2 Purpose

Many of the current state-of-the-art Advanced Driver Assistance Systems (ADAS) rely on data received from sensors mounted on vehicles, in addition to driving data and telemetry generated with the motion of the vehicle and driver actions. Examples of such driver assistance systems employed on modern vehicles include lane departure warning, forward collision warning, and braking assistance systems. These driver assistance systems only rely on quantifiable, generic data from the vehicle, or the environment in which the vehicle is operating.

The motivation behind this research project is to explore the question of whether or not these systems can be improved by introducing the element of the human physiological state into their decision-making process. This proposed improvement can result in driver assistance systems that are more tailored to the state of mind, health, and predicted behavior of individuals. Additionally, this research project aims to make these systems privacy-aware, ensuring that personal data collected about a human's state does not get shared.

The field of introducing human-in-the-loop interaction to systems is still in its growing stages and is yet to be effectively applied to real-world scenarios that the general public encounters on a daily basis. Promoting safer driving and preventing dangerous road events through driver assistance systems is a top concern for engineers in this field. Introducing greater human interaction in the decision-making process of these systems will help advance this cause.

# 3 Objectives and Current Project Status

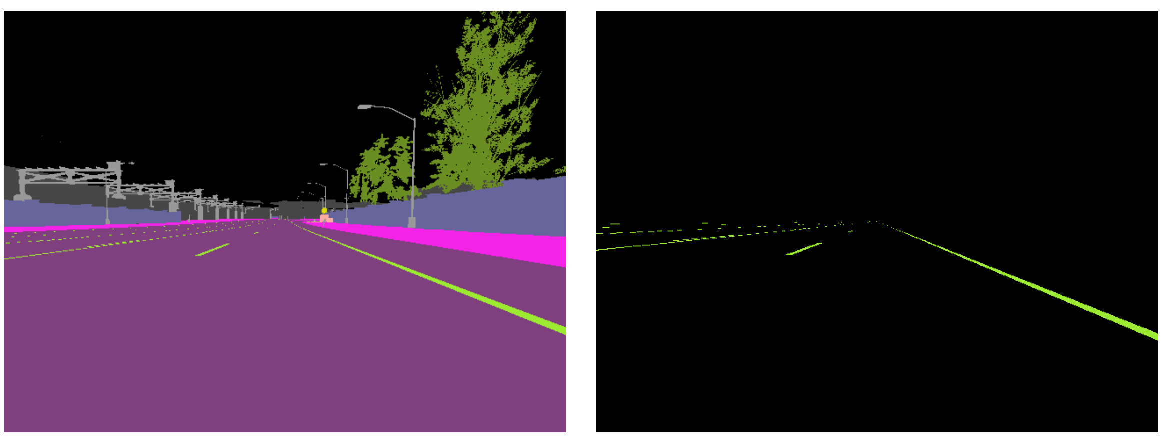
This research project aims to first understand how this sensory and telemetric data is collected to create ADAS systems, by using a modern, autonomous driving simulation environment. The simulation environment of choice is CARLA Simulator, an open-source simulator designed for autonomous driving research, based on the OpenDrive standard.

The first stages of this research project involved learning about CARLA Simulator and the various APIs and sensors available. The primary task completed was creating a lane departure warning ADAS sensor using CARLA APIs, and simulating the effects of this sensor using various driving scenarios, both autonomous and involving manual control of the vehicle. To explore how lane departure sensors work, this task was performed using two means and comparing the experimental results of each (sections 3.1 and 3.2).

Currently, the project has advanced to a stage where an intelligent agent is being developed using principles of Q-learning, a branch of reinforcement learning. This intelligent agent takes in driving data from the vehicle and integrates with sensory hardware to continuously learn about when to issue a lane departure warning to a particular driver.

## 3.1 Visual-based lane departure warning

Figure 1: Output of semantic segmentation camera

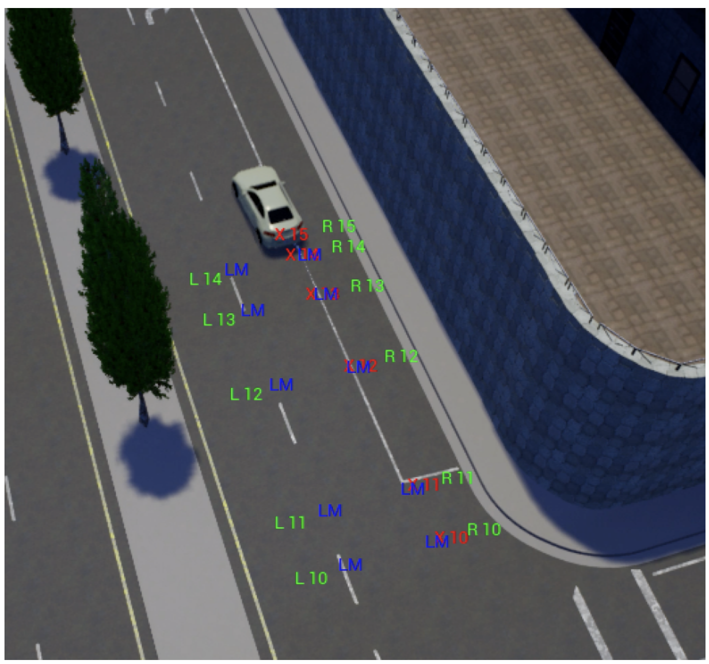


**(a)** Unmasked output **(b)** Road line-masked output

The first method of creating a lane departure warning sensor in CARLA involves visually interfacing with the built-in cameras available to vehicles in the simulation environment. The ideal camera for this is the semantic segmentation camera, which classifies different pixels in an image into multiple classes based on their meaning in the environment in which they reside. In CARLA, such classes of pixels include those that reference buildings, pedestrians, poles, vehicles, traffic signs, or road lines. The road line data is used in this implementation to capture data about the location of lane markings and how they change as the vehicle is in motion. **Figure 1A** shows the standard output of the semantic segmentation camera taken in a customizable driving scenario. As images like **figure 1A** were received by the semantic segmentation camera, a masking algorithm was applied in order to hide all classes of pixels that did not correspond to road lines. **Figure 1B** shows the output of that masking algorithm applied onto **figure 1A**, only showing the CARLA defined "road lines", or lane markings. This masking was applied in order to establish a basis for a lane departure warning system. This system operates by computing the difference between multiple masked frames at once (initially set at $n = 2$ frames) from the continuous sequence of frames received from the camera as the vehicle is in motion. Multiple linear algebra-based algorithms have been employed to compute this difference, as well as interfacing with APIs from SciPy. This visual method for creating a lane-departure warning ADAS system is a work in progress.

## 3.2 Location-based lane departure warning

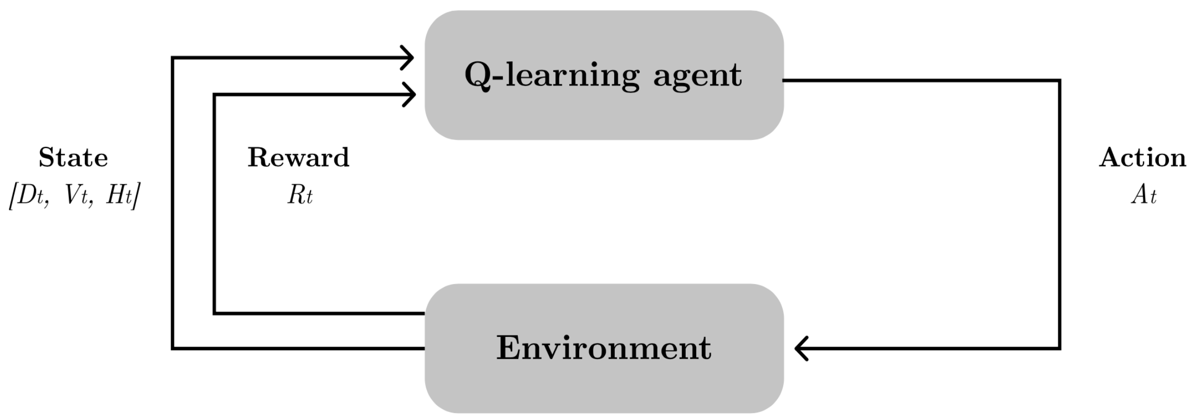
Figure 2: Location of lane markings on CARLA server




The second method of creating a lane departure warning sensor using CARLA involves analyzing vehicle location data in comparison with pre-defined waypoint data provided by the simulator. CARLA waypoints are vector-like objects that describe points in a road and provide information about the location and size of lanes. By continuously polling the location of the vehicle and relaying waypoint data about the nearest left and right lanes to the vehicle, an algorithm was created in order to determine the position of lane markings and how they relate to the vehicle in motion. **Figure 2** shows the calculated locations of lane markings (blue), centers of right and left lanes (green), and the vehicle's location (red) on a simulator window, as a vehicle is in motion. If the vehicle is steering towards any of these lane markings on its right or left side and reaches a preset threshold between these lane markings, a warning is engaged. This method is implemented through a client-server model; the client program is a manually-controlled driving environment, relaying waypoint and location data to the server program, which remotely is able to compute whether or not the vehicle in motion is approaching a lane marking. If the vehicle is approaching a lane from its left or right side, the server program sends a warning to the client. This client program is by default relaying data to the server at around 60 times per second, and the server program is able to filter that data and sample it for computation at a pre-defined sampling rate.

## 3.3 Q-learning agent and hardware interaction

Figure 3: Diagram of a typical reinforcement learning scenario




The current stage of the project is taking all of the lane departure techniques learned in sections 3.1 and 3.2, and integrating them into a new intelligent agent that uses reinforcement learning to continuously learn from the behavior of a particular driver in order to issue warnings at the appropriate time. Reinforcement learning is a subset of machine learning, focused on developing computer agents that learn from their actions in a particular environment. In the case of this project, the agent is the intelligent ADAS sensor, the environment is the vehicle within CARLA Simulator, and an action can either be a warning issued or not issued. An agent starts by taking an action at a certain state, and receiving a reward from the environment based on how useful that action was at that particular state. The agent aims to maximize their rewards as they learn about their environment. The branch of reinforcement learning that will be used in this project is called Q-learning, which aims to identify an optimal policy for selecting an action at a particular state based on a specific function, shown in equation 2. Q-learning is model-free, meaning the agent is always learning, and does not require a set initial training phase. **Figure 3** demonstrates the cycle of a typical Q-learning scenario for this application.

In addition, hardware is being introduced in this stage of the project. Currently, the only hardware device being tested with this project is the Oura Ring, a consumer-grade sleep and activity tracker that could provide useful information about a particular human's attentiveness and probability for distraction as they are driving.

### 3.3.1 Relevant equations

$$S_t = [D_t, V_t, H_t] \tag{1}$$

$$Q'(S_t, A_t) = Q(S_t, A_t) + \alpha * (R_t + \gamma * \max Q(S_{t+1}, A) - Q(S_t, A_t)) \tag{2}$$

Currently, the Q-learning agent being developed uses the location-based lane departure warning sensor that was created in previous stages of the project (see section 3.2). Future stages may see the addition of more ADAS sensors. The data from the lane departure warning sensor is relayed from a client program to the intelligent agent (which is the successor to the server program described in section 3.2). The intelligent agent then uses the location-based data from the client as well as hardware data from the Oura Ring in order to formulate a three-element vector to classify a driver's current state, $S_t$ (shown in equation 1). The first element of the state vector, $D_t$, represents the vehicle's distance from either of the adjacent lane markings. The second element, $V_t$, represents the vehicle's current velocity relative to the posted speed limit on their particular stretch of road. The third element, $H_t$, classifies the driver's human state into several categories based on attentiveness data received from the Oura Ring.

Based on a state $S_t$, the intelligent agent takes an action $A_t$– choosing whether or not to issue a lane departure warning. The agent then waits until the driver responds to that warning, and captures a final state, $S_{t+1}$. Based on pre-defined rules for transitions between states, a reward is associated with an $(S_t, A_t)$ pair. For example, if the driver transitions to a "safer" state after a warning has been issued, the reward will be positive. The Q-learning function, shown in equation 2, helps produce a "quality value", or Q-value, for a particular state transition based on the initial state/action pair, and the final state the driver has reached. $\alpha$ and $\gamma$ are experimental parameters, referring to the learning rate and discount factor of the experiment, respectively. The Q-values for all of the state and action pairs are stored by the agent in a tabular format for each driver.

## 3.4 Future objectives

In the future, the Q-learning intelligent agent will be improved in order to accurately learn about the behaviors of various drivers. The algorithm for predicting a driver's human state based on data from the Oura Ring will be fine tuned to ensure accuracy. In addition, other hardware sensors may be introduced if the budget permits. Other ADAS sensors may also be created and integrated with the Q-learning agent, including forward collision warning and blind spot monitoring. Creating the privacy-aware aspect of this project will occur in later stages when the Q-learning agent is in a refined state.

# 4 Approach

This project will primarily involve developing algorithms and agents with the help of open-source software, such as CARLA Simulator. CARLA will be the primary simulation environment that will be interfaced with in this project, due to its versatility and variety of available driving environments. As mentioned in section 3.3, a branch of reinforcement learning called Q-learning will be studied and applied to create the intelligent agent that continuously learns about a human's driving behavior and physiological state in order to issue ADAS warnings at the correct time.

The research process will involve interacting with various mediums including hardware and simulation environments. Currently, the Oura Ring is the primary form of hardware being used to relay critical sensory data to the intelligent agent. Due to the ability to create comprehensive models of the human state with the help of this hardware, simulations, and no outside human subjects, this project is feasible given the remote learning situation during the 2020-2021 academic year.

This project will be conducted under the Campuswide Honors Collegium's undergraduate research guidance, and thus a comprehensive thesis will be written at its completion.

# 5 Responsibilities

This project is individual and not group-based. Armand Ahadi-Sarkani assumes full responsibility for all research work, under the guidance of Prof. Salma Elmalaki, Assistant Professor of Teaching in the Electrical Engineering and Computer Science department. Meetings about research and thesis planning occur approximately every week in a remote format. Credit for this project is being given through EECS 199 and ENGR H199 in the fall.

# 6 Timeline

| Objective | Estimated Completion |
|---|---|
| Improving metrics for lane departure warning system | June 2020 |
| Purchasing and collecting data from hardware sensors | June - August 2020 |
| Interfacing hardware sensors with CARLA Simulator | July - August 2020 |
| Integrating human state data and creating reinforcement learning agent for lane departure warning sensor | August - December 2020 |
| Creating other ADAS sensors, implementing privacy awareness | Winter Quarter 2021 |
| Complete Campuswide Honors Thesis | Winter Quarter 2021 |

# 7 Works Cited

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