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SMART TRAFFIC MANAGEMENT USING AV'S AND LIDAR

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Abstract: The current urban transport systems are predicted to be disrupted by autonomous vehicle (AV)technologies. The multi-sensor system of AVs may produce a lot of data, which is frequently used for safety and localization purposes. In this paper, a valuable framework for real-time measurement is proposed and shown. Autonomous vehicle (AV) technology is anticipated to upend the current urban transportation infrastructure. The multi-sensor system utilized by AVs can produce data, which is frequently used for localization and safety purposes. A useful framework for real-time measurement is suggested and shown in this paper. AV and LiDAR data are used to determine local traffic conditions. Fundamental traffic flow elements such as volume, Along with the traffic time-space graphs, density, and speed are computed. Using AV data for applications related to traffic control and furthermore related given in this kind of operations. The framework is tested using the Waymo Open dataset. Results provide insights into the possibility of real-time traffic state estimation using AVs' data for traffic operations and management applications.

Keywords: Autonomous Vehicles, LiDAR, Traffic Management, Road Safety, Open Data.

Introduction:

Traffic State measurement is crucial to the operation of a transportation network. The traffic flow, density, and speed state variables are crucial inputs to different methods from aging and controlling traffic. Historically, traffic state estimation has been carried out by Reliable fixed sensors including induction loop detectors. Building autonomous vehicles (AVs) is a complex problem, but enabling them to operate in the real world where they will be surrounded by human-driven vehicles (HVs) is extremely challenging. The coexistence of AVs and HVs faces two main obstacles, which we have identified. First, an AV is unaware of the social preferences and unique character traits of a certain human driver, such as selflessness and aggression, and it is nearly impossible to infer these in real-time during a brief AV-HV contact. Second, unlike AVs, which are predicted to follow a policy, HVs are exceedingly unpredictable and do not always follow a stationary policy. We characterize the mixed-autonomy problem as a multi-agent reinforcement learning (MARL) problem and suggest a decentralized framework and reward function for training cooperative AVs in order to address the aforementioned difficulties.

The Waymo dataset displays three different coordinate systems: global vehicle, and sensor frames. Knowing these frames is essential to comprehendingtheAV'slocationandt heitemssurroundingitundervarious circumstances over space and time. The orientation and position of the AV with regard to Earth are described by the global frame. The automobile Regardless of mobility frame is related to the vehicle itself. Using the Cartesian coordinate system, the LiDAR Spherical coordinate system is within the frame of the LiDAR sensor.

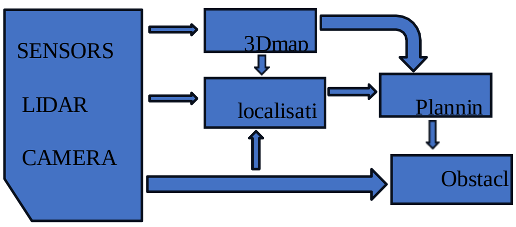
NOTATIONS AND ASSUMPTIONS:

The Waymo Open Data set comprises a 2Dcamera and 3DLiDAR data. In the proposed method, we use only. Table 1. Variables of interest.

LiDAR data to measure local traffic conditions in 2D imaging used for quality validation and comparison.

The coordinate system used is based on the vehicle frame where The x-axis is positive in the direction of travel, the y-axis is positive left and the z-axis is positive up.

Three types of coordinate systems are presented in the Waymo dataset including the global, vehicle, and sensor frames.



These frames are crucial in understanding the AV’s location and its surrounding objects in different contexts over time and space.

(X_i^j, Y_i^j)	Position of i^{th} sign in j^{th} frame detected by the AV
(x_i, y_i)	Position of i^{th} vehicle detected by the AV
s_i	Spacing from the i^{th} vehicle to its surrounding vehicle
h_i	Headway from the i^{th} vehicle to its preceding vehicle
v_i	Spot velocity of the i^{th} vehicle detected by the AV

Table 1 : Notations for the equations

Assumption1:

The proposed method is lane-based. Therefore, only vehicles moving in the same area in a frequency band such as AV are considered in the calculations.

Assumption2:

Detects AV band and locations all vehicles moving in the same lane, we assume an average road width is 3.7 meters.

Assumption3:

The proposed model assumes that AV is driving on a road section that is either straight or parallel to its constant curvature.

Assumption4:

AV is assumed to pass through a point in the middle of the road and go tangent to the road. Because we can't get information on this topic directly from detection outputs

DATE PRE-PROCESSING:

The data is initially pre-processed, where it is converted into a machine- and human-readable format, before doing traffic computations. The Natural Language Toolkit (NLTK) package was used to convert the data. All the factors that will be included in the tabular form are shown in Table 2. Data pertaining to identified bikers and pedestrians is eliminated. The only objects in the processed data frame are the automobiles and traffic signs that were detected.

AV SPEED, HEADWAY, AND DISPLACEMENT:

The AV velocity must be calculated relative to the nearby objects because it cannot be obtained directly from the dataset. As a result, fixed objects like traffic signs are used to determine how far the AV has moved between two frames.

The calculation is performed on all traffic sign pairs from the 3D LiDAR point cloud within two frames in order to maximize accuracy. Denote M as the number of stationary traffic signs identified, and X^j and Y^jas the x and y coordinates of traffic sign i in the j^{th} frame.

For a single vehicle, its spacing is the linear distance to its preceding vehicle as expressed in Equation:

$$spacing = s_i = \sqrt{(x_{i-1} - (x_i))^2 - (y_{i-1} - (y_i))^2}$$

The vehicle's headway is estimated as the time taken for the vehicle to reach the current position of the preceding vehicle, which is expressed in Equation: $headway = h_i = \frac{s_i}{v_i}$

Therefore, the positional change of the AV between two successive frames is estimated using immovable objects like traffic signs. To achieve maximum precision, the computation is done for every pair of traffic signs from the 2D LiDAR point cloud in three dimensions

$$x\ displacement = \Delta x_{avg} = \sum_{i=1}^{M} x_i^{j=1} - x_i^j \quad (1)$$

$$y\ displacement = \Delta y_{avg} = \sum_{i=1}^{M} y_i^{j=1} - y_i^j \quad (2)$$

$$displacement = d_{avg} = \sqrt{(\Delta x_{avg})^2 - (\Delta y_{avg})^2} \quad (3)$$

Now denote the time-step of detection as t(0.1s), the AV speed and heading are computed with Equations (4) and (5).

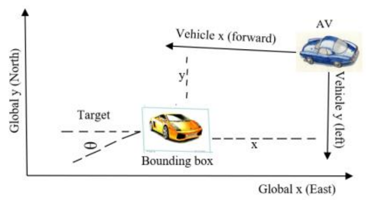
$$\text{Speed} = v_{avg} = \frac{d_{avg}}{\Delta_t} \quad (4)$$

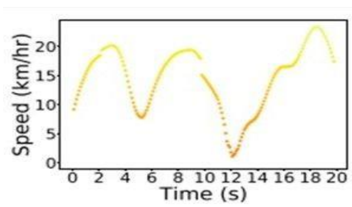
$$\text{heading change} = \Delta\theta_{avg} = \tan^{-1}\left(\frac{\Delta y_{avg}}{\Delta x_{avg}}\right) \quad (5)$$

LANEPOSITIONAL CONSTRAINTS:

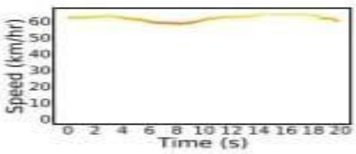
utilizing pre-established positional and directional limits, vehicles in all other lanes are identified and removed from the traffic estimation. It is assumed for both constraints that the AV is traveling down the middle of the lane, matching the tangent there. The positioning constraint may limit the number of vehicles to those whose center coordinates are inside the defined lane boundaries. Each detected vehicle is monitored at its x and y locations as indicated by the AV. The radius of curvature can be either "positive" or "negative" depending on whether the AV is traveling clockwise or anticlockwise

TRAFFIC FLOWMEASUREMENTS:

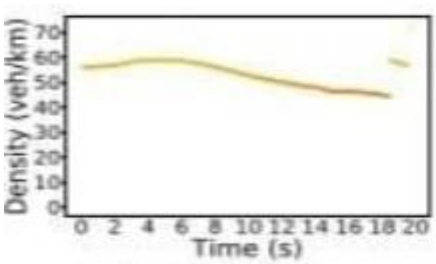




(d) Speed-time diagram



(d) Speed-time diagram



(c) Density-time diagram

STUDY LIMITATIONS :

The effective detection range of the AVs' LiDAR sensors often vary depending on the sensor type and weather conditions. In this section, we test how LiDAR detection range affects the estimation of traffic states. We use data from Video 1 with detection radii of 60 meters and 40 meters. The slight temporal aggregation in the traffic metrics that are displayed is what causes the fluctuations that are observed. These restrictions may have an impact on the number of cars that are identified, which may therefore have an impact on how representative the measured local traffic conditions are. As mentioned in Section III-D, reducing the number of vehicles might increase the effects of detection errors on the measured outputs because the traffic calculations rely on arithmetic and harmonic means. Long-range radar (LRR) data can be utilized to gather farther-reaching information in order to address this problem. The purpose of LRR, which has a 200-meter range, is to find additional cars traveling in the same direction as the projected volume, speed, and density.

Another limitation is the dependency of the developed framework on the accurate detection of stationary objects to estimate the motion of the AV. This impedes the application of the methodology in road segments with no such stationary objects. The issue can be resolved with self-sensing techniques, including odometer and gyroscope. Finally, the presented estimation method is limited to simple road geometries, namely straight and continuously curved lanes. If the AV turns left or

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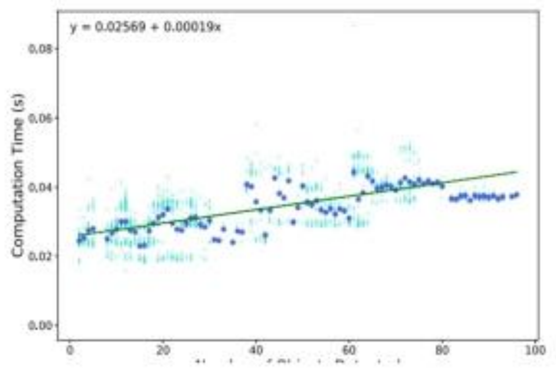
right or changes lanes, additional steps are required to correct the traffic state estimations. To estimate the lane profile, the AV is assumed to be traveling at the center of the lane, and the radius of the road curvature is selected manually through an analysis of the AV travel path before conducting the calculations. To improve the practicality of the presented method, other location-based techniques could be investigated. Avs use a combination of sensors such as GPS, GNNS, inertial measurement units, and cameras for localization

RESULTS:

The developed approach is iteratively applied to the frameworks in four different sample videos collected from the Waymo Open observation data training set Dataset. All tests are done on the desktop a computer with an Intel Core i7-10700K@ 3.80 GHz × 16 processor, 3200 MHz 2 x 16 GB RAM. The programming language used is Python3.8.8.Table3 mentions the four examples of videos used in our analysis, two of which represent direct path sand the two permanently indicate curved sections of road. Directly tea samples have a duration of 20 seconds the duration of curved road samples is less than 20 seconds. Constantly winding roads are rare in Waymo Open the dataset. Curved road samples are excerpts of full-length sample videos. Four graphs are illustrated for each sample, including space- time, flow-time, density-time and velocity-time profiles(Figures2-5). Blue on space-time diagrams dotted lines represent the AV trajectory, while red dotted lines represent the trajectories of other vehicles same band as AV. Vertical extension of blue AV The figure shows the LiDAR detection range of the AV, which is the assumed default value is 80 meters in all directions. The color of the extensions determines the AV rate where green means higher speed and red means lower speed. Traffic flow, density and speed calculated in Part II-F, is also shown on a red-green scale with smaller values to the red color and higher values associated with the green color. Note gaps and random breaks with in the plot. These are caused by vehicles appearing and disappearing while traveling near the edge of the LiDAR detection area. In the future, the study could explore different ways to include vehicles moving near the boundaries of the LiDAR detection zone and AV lane entry and exit in real-time traffic mode assessment.



CONCLUSION:

In this study, we proposed a spatial measurement of local traffic A method based on LiDAR data from AV. fitness method is presented using the Waymo Open Dataset. The U.S. The goal was to develop a simple evaluation technique for real-time local traffic state variables that provide immediate information on congestion relief and vehicle routing for optimization.

Another limitation of the LiDAR data is the fixed detection boundary, which can cause in consistent inclusion of the same vehicles. Vehicles traveling on the edge of the detection range can be included in some time frames and excluded in others. This inconsistency can result in discontinuities in the time series diagrams. For instance, the leading vehicle in Figure 2 is included in some frames (0-9.9s) while excluded in others. The impact is especially severe when the vehicles driving on the detection edge have significantly different speeds and spacings.

With a higher penetration rate in the future, AVs may complement fixed sensors to detect traffic. All study different areas of traffic situation assessment, we the study investigated the estimation of basic traffic variables in real-time. The accuracy of the proposed framework remains specified as ground truth traffic status information not available Thus, as a future research direction the accuracy of the model can be verified using simulation-based techniques, while this paper focuses on feasibility using real data from the proposed method. In addition, The current approach can be extended to measure multi-lane traffic and eventually develop processes to control traffic data aggregation, imputation and forecasts using real-time AV datasets. The recognition ability of AVs can also be analyzed and their reliability as mobile sensors in different traffic and environmental conditions. If we mainly focused on the use of LiDAR sensors in Avs in this study, future work can ensure the feasibility of traffic estimation using other AV sensors including cameras and radar. By combining data collected from multiple sensors, the accuracy of traffic measurements should improve.

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