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Inter-vehicle Distance in Driver Behaviour Modelling

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Abstract— **The concept of traffic control in the future will be based on a fully managed planning, vehicles will be fully autonomous. Until that time traditional and autonomous cars will coexist on the streets. In this paper we describe a driver model concept, which allows for more accurate reflection of the drivers behavior and thus better prediction of their reactions in the situation where autonomous vehicles are moving with vehicles driven in the traditional way. We also present extension of our previously build platform which allows to measure distance between two cars using stereo cameras. We show that the distance measure while proceeding various maneuvers allows to distinct drivers.**

Keywords— driver behaviour mdel, distance measurement, intelligent vehicle

I. Introduction

Nowadays traditional vehicles are equipped with driver assistance systems, helping the driver in decision-making process. In the future they will be also equipped with various forms of communication mechanisms with the other vehicles. Cooperation between the traditional and autonomous vehicles used to movement planning may cause problems of planning uncertainty, therefore it will be necessary to take into account the traditionally controlled cars with varying degrees of autonomy, predictability and observability. For better anticipation and traffic planning we need to build models of drivers which will accurately describe their possible behavior in given circumstances. Autonomous vehicles in the future will be able to plan easily among themselves particular parts of their route. Each of them will know their destination and destinations of other autonomous vehicles. We can solve this planning uncertainty problem by using uniform dynamics model for every car, leaving a safety buffer, but this is far from optimal solution.

II. Existing solutions

The development of autonomous vehicle and self-driving car concepts have resulted in publications about communication between vehicles. Most of them describe communication between autonomous vehicles[1][2][3] forgetting about non-autonomous vehicles and communication with them.

Other articles[4] describe autonomous vehicles observing the environment and react to occurred obstacles, but without taking into account the specific models e.g. drivers models. By having information about the observed vehicle and the exact model of drivers behavior we would be able to plan movement more effectively.

Another approach[5] proposes to build a model of driver behavior, based on parameters collected only from the on-board computer connected via CAN bus. By adding environment parameters, such as distance to ahead car we would increase the accuracy of the discussed model.

We can also find publication that takes into account only vehicles model[6], their weight, maximum acceleration and deceleration. Such a models are valuable of course, but they ignore drivers characteristic such as aggressiveness (aggressive driver may behave less predictably then calm drivers)

There are also publications describing construction of expanded drivers models[7] and their classifications of driving style based on parameters such as: steering profiles, usage of pedals, speeding and getting out of the lane and road events. For the above mentioned classification authors used neural networks. This model would be more accurate, if authors took into account more information from the environment, such as the distance to the car ahead.

Some of the researches are created exclusively for the virtual world[8][9][10], experiments are conducted in the simulator, not on the vehicles moving in a real world, where every mistake can result in accident. Other approaches described in publications are making autonomous vehicles decisions without going into the details of individual driver's behavior[11].

III. Driver Behavior Model

We mentioned in the introduction about problems of planning uncertainty that may appear during movement planning between traditional and autonomous vehicles.

As a solution to this problem, we propose to use a model with some approximation to specify the behavior of traditional drivers and thanks to that provide better movement planning for autonomous vehicles.

To create such a model we need to carry out observation of movement of a group of drivers in urban traffic, in the presence of other vehicles. What we particularly needed is a continuous observation of the behavior of traditional cars. It will allow us to create and select the right model to perform prediction of the behavior of traditional cars, what will be used for autonomous vehicle traffic planning. Our subject of the observation in the experiment will be drivers and the environment in which they actually are. Observation of drivers will rely on the measurement of available parameters such as: gas pedal position, brake pedal position, clutch pedal position etc., which can be translate to other parameters such as: linear speed, engine speed, linear acceleration, centrifugal acceleration, and which can be finally translate into the actions which the driver takes: accelerate, slow down, turn, change the belt, etc. Environment observation will be based on the measurement of the distance to the preceding vehicle, measurement of the distance to the key destinations (e.g. stop line at traffic lights, the center of the turn, the center of the intersection), and determination of the current parts of the road (road straight, curve, intersection, etc.)

Collected data, described above, will be tagged and preprocess in purpose to extract the characteristics features that will describe the behavior of drivers.

After characteristic features extraction, data will be grouped by the type of road part (road straight, turn, etc.) and by the actions taken by the driver (following, taking over, braking, etc.) Each portion of data will be analyzed with use of methods of machine learning in order to classify individual drivers into bigger groups. Based on obtained data we will be able to propose various classes of drivers depending on their behavior (from aggressive drivers to moderate drivers).

Prepared classes will be used to create a model describing the full range of drivers behaviors.

With the knowledge gained during the observation we will know with which driver we are dealing with (moderate, aggressive) and what kind of maneuver is he proceeding at the moment (going straight through the intersection, turning left, braking). By having a proper driver model we will be able to predict driver behavior, and we will be able to better plan the behavior of autonomous vehicles.

IV. Experiment description

In the previous article[12] we described our extensible platform built for studying the behavior of drivers in urban traffic and one of the experiments which we conducted using the platform that we built. We analyzed left-turn maneuver performed by two drivers. Data acquired through OBDII and RaspbrryPi interfaces allowed us to obtain and store following parameters such as: measurement timestamp, GPS time, longitude, latitude, GPS speed, engine RPM, car speed, throttle position, trip distance, brake pedal and clutch pedal status.

The above parameters described well the behavior of the driver but did not described the state of the environment. It was not known if there is a car ahead to the test car and in what distance it is.

For this purpose, we enriched our laboratory measurements with information about the distance to the car in ahead of our test car.

In this paper, we focused on the distance measurement analysis during braking maneuver, while driving after the car, which was also performing the braking maneuver. For this purpose we had to measure the distance between those two cars. We assumed that the measurements have to be made within the range of 0 to 100 m in the front of the car and with a time resolution of at least few frames per second. We chose stereo cameras system[13] as a method to measure the distance between the cars.

To conduct the experiment we used two cars. In one of them we installed two parallel positioned WEB cameras connected to PC computer via USB. For calibration and image processing we used the OpenCV library.

The first step of the experiment was to calibrate cameras using a chessboard printed on paper [14][15]. After that we developed algorithms to detect the rear red lights of a car moving in front of a test car. Having red lights detected we were able to obtain common points in left and right camera for the distance calculation. Next we calibrated the distance estimation between two cars. Having the distance estimation we were able to conduct the experiment and exam drivers behaviors. The experiment was performed on three drivers during the iterative braking maneuver while real traffic. Then, results were analyzed in order to extract characteristics features of drivers. Finally we compared average values of those features for each driver and we received data that allowed us to distinguish one driver from another and that could be used in drivers behavior model.

V. Distance estimation

In the preceding section we wrote that we used two WEB cameras connected to the PC computer for the distance estimation experiment. We have to add that those cameras were fixedly mounted one to each other with a distance of 7 cm. We calibrated them by using a paper chessboard and then we implemented created algorithms to detect red rear lights of the car ahead.

Detection of a car moving ahead of the test car was based on the following image processing algorithm:

- Detect the red areas in the image (in Range filters concatenation)
- Discard detected areas, that do not have pairs on a similar Y distance from top (does not have corresponding light on the other side)
- Discard areas with significant differing surface areas (big red blobs e.g. house roofs)
- Discard areas having inappropriate width to height ratio

After comparing images from those two cameras we made the second algorithm:

- Discard areas not founded by both cameras at the similar Y distance from top
- Discard pairs of areas which are significantly different in length
- Discard pairs of areas which are intersecting at an angle greater than 5 degrees

Those two implemented algorithms allowed us to detect the rear red lights of a car moving in ahead of the test car – in a large majority of frames, with practically individual detection of areas that are not being rear red lights (false detection). The result of detection on a single frame was shown on Figure 1.

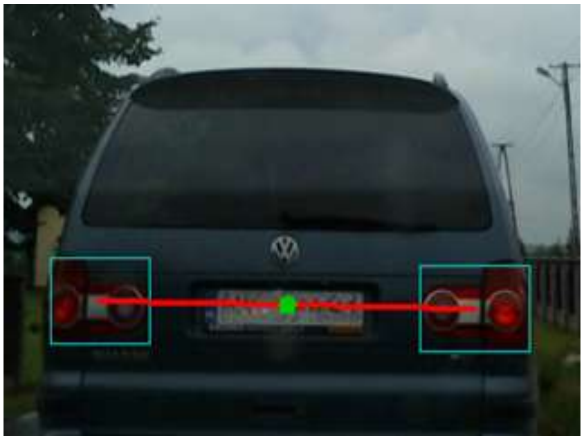

Figure 1. Result of rear red lights regions (left and right) detection, line connecting them as a pair and center of the car (for disparity calculations).

We also compared HaarCascdes[16] method of detection, however due to the large change of distance (0 m to 100 m) and the size of the car on single frame (far distance compared to close distance), they acted worse than the algorithms described above.

After that, we perform a distance calibration which was made according to the procedure described below. Two cars were set one ahead another in a distance of 1 m. We measured the distance between cars by using a measure tape and taking a camera snapshot of the car ahead at the same time. Than we were increasing the distance between cars and we were measuring the distance again. We repeated the procedure few times, until we reached 100 m distance between the cars.
After the experiment, data collected form the pictures were processed using described above algorithms. We obtained following parameters:

- The difference of the characteristic points in the stereo image (center of the car)
- The difference between the left and right rear light previously detected Figure 2.

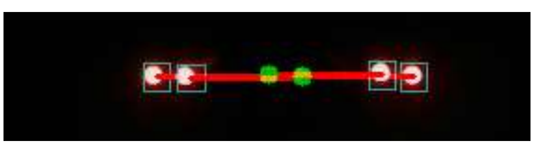

Figure 2. Lights detection and their disparity in stereo image.

On this basis, we developed two methods of car distances measurement:

- Based on the stereo image, shown on Figure 3.
- Based on the distance between the detected rear red lights (left and right) Figure 4.

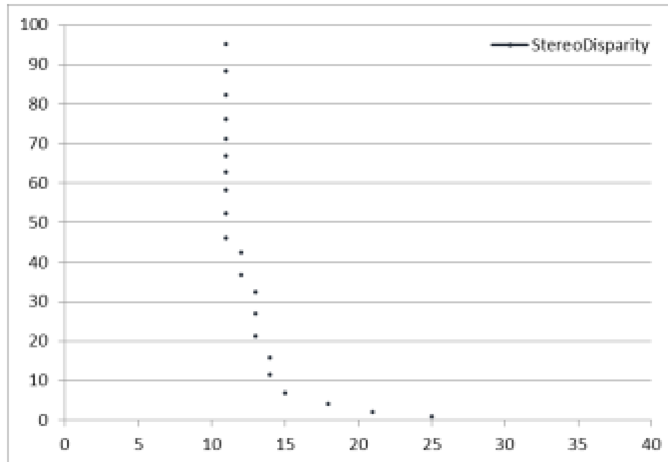

Figure 3. Stereo disparity distance (X in pixels) against car ahead distance (Y in m).

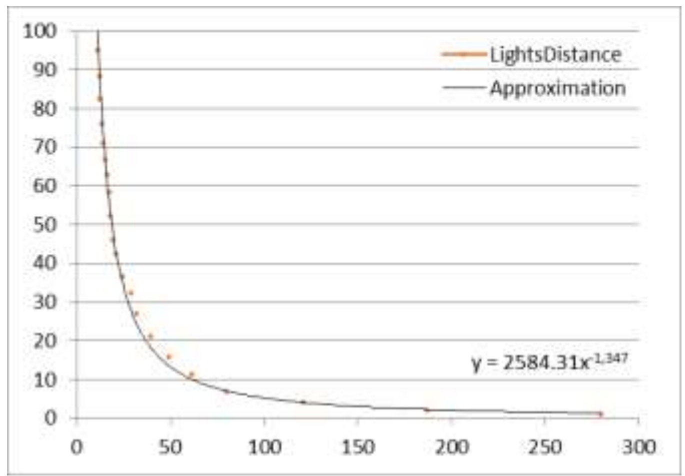

Figure 4. Rear brake lights distance (X in pixels) against car ahead distance (Y in m).

Approximating the graph in Figure 3. we created a formula (1) describing the relations between the car to car distance and to the left and right rear red light distance (where D is a real distance between car to car and LD is a distance between detected lights ahead car measured in pixels).

$$D[m] = 2584.31 * LD[pixels]^{-1,347} \quad (1)$$

After analyzing above graphs, we concluded that the measurement of the distance between 0 m and 100 m based on stereo images gives us a not enough accurate measurements [17]. Wider spacing of the cameras would improve measurement resolution in the range of 50 m to 100 m but it would be impossible to measure distance in range of 0 m to 10 m, because both cameras will not be able cover the entire car ahead.
Taking into account the above problem we chose to measure the car distance based on the distance between the rear red

lights (left and right), which gives us a more accurate measurement.

VI. Drivers behavior result and analysis

The experiment of drivers behavior with distance measurement between the cars was carried out while driving on a real road. While driving a car, braking maneuvers were performed for each of the drivers and they were repeated 4 to 5 times. Braking maneuvers were initiated at a speed of about 60 km/h.

The whole route was constantly recorded with a speed of 5 frames per second and resolution 640x480 pixels for each camera. After completion of the experiment, the images were perform to analyze to isolate individual braking maneuvers and their characteristics for each driver.

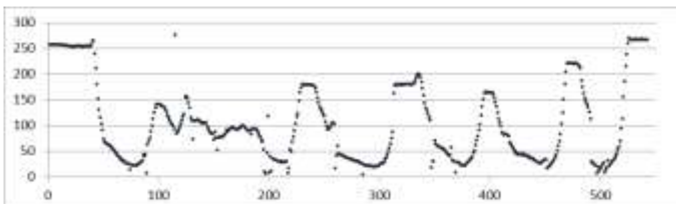

Figure 5. Rear lights distance in pixels during the trip (X axis contains number of samples).

Chart of rear lights distance while driving after the car was presented in Figure 5. It can be noticed that there are values that cause discontinuity in the chart. This values were caused by false lights detection of ahead car. These false values were filtered out during data processing. For comparison, the distance of the stereo disparity is shown in Figure 6. We can see that the resolution of the data (10 px to 25 px) is much lower than the rear lights distance data (10 px to 260 px).

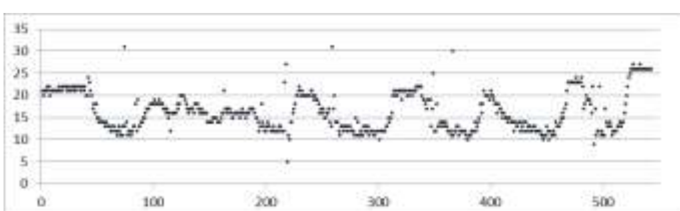

Figure 6. Disparity distance in pixels during the trip (X axis contains number of samples).

The next step was to combine data with distance between the vehicles with data obtained from OBDII and data obtained from RaspberryPi, based on the samples timestamp, Figure 7. We can notice there is a correlation between the speed and the distance to the car ahead of us. What is more important, each driver keeps different distance at a given car speed.

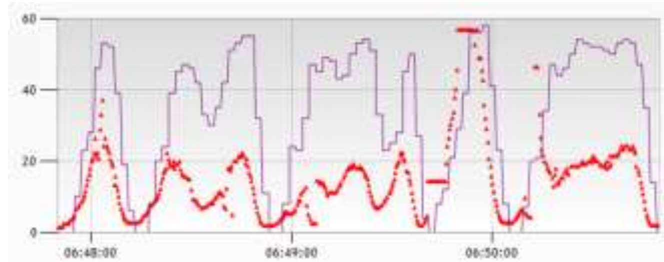

Figure 7. Speed [km/h] – continuous line and distance [m] – triangles against trip time.

We used combined and analyzed data in order to detect the braking maneuvers Figure 8. After that we extracted characteristic features of single maneuvers. Those features helped us to distinguish the drivers based on their behavior.

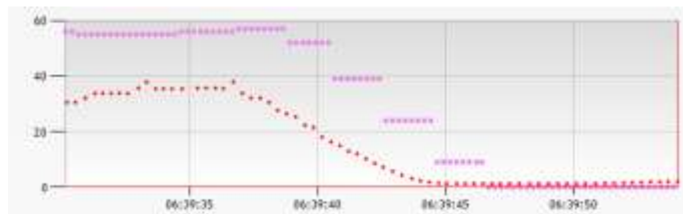

Figure 8. Braking maneuvers for one driver. Speed [km/h] - squares and distance [m] – diamonds against braking time.

During the braking maneuver we extract the following characteristic features:

- Speed before braking maneuver
- Distance between cars while driving
- Distance between cars after stopping
- Braking distance
- The minimum distance to ahead car
- The average distance to ahead car
- Average speed
- Clutch press time before stopping
- Last brake press time before stopping
- Time to stop from max speed
- Distance to ahead car divided by speed
- Average deceleration

VII. Conclusions and further works

In this paper we presented an extension for our previously build platform for studying the behavior of driver in urban traffic. We also described a driver behavior model, that we are going to develop in further experiments. We also presented an extension that allowed us to measure the distance to car ahead us by using two simple WEB cameras.

We described an experiment which compares drivers behaviors during the braking maneuver.

The average values of the characteristics features calculated for each driver during braking maneuver are shown in TABLE I.

TABLE I. THE AVERAGE VALUES OF THE CHARACTERISTICS FEATURES FOR EACH DRIVER

Feature	Driver 1	Driver 2	Driver 3
Speed before braking maneuver [km/h]	54	54,2	54
Distance between cars [m]	30,841	25,258	16,620
Distance between cars after stopping [m]	1,514	2,478	2,851
Braking distance [m]	83,6	67,7	58,0
The minimum distance to ahead car [m]	1,528	2,474	2,300
The average distance to ahead car [m]	11,754	9,822	7,43
Average speed [km/h]	29,08	24,450	29,533
Clutch press time before stopping [s]	6,952	7,314	7,970
Last brake press time before stopping [s]	6,514	3,356	6,867
Time to stop from max speed [s]	8,508	6,852	6,549
Distance to ahead car divided by speed	0,404	0,390	0,259
Average deceleration [m/s^2]	1,813	2,438	2,455

After analyzing the above summary of features of three drivers, we can notice that they differ from each other. On this basis, we can conclude that more drivers will also have different values of features, but they will have a similar orders of magnitude. This will allow us in the future to develop a driver model containing both: the lower and upper range of values of features. Such a model will allow autonomous vehicles for more accurate reflection of the drivers behavior and thus better prediction of their reactions while moving with vehicles driven in the traditional way.

In future experiments, we would like to examine more maneuvers and carry out research on a larger amount of drivers. More drivers and maneuvers will serve to create a final driver behavior model. Eventually created model will be used in microscale traffic simulation with use of mobile robots. We believe that we will be able to prove that the use of the model proposed by us will optimize the process of movement planning.

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