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Monocular based Lane-Change on Scaled-down Autonomous Vehicles

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Abstract—**Lane-change is considered to be one of the toughest challenges in the field of autonomous vehicles. Any vehicles that are driving around the host vehicle may effect this operation. To ascertain the safety during the lane-change process, a comprehensive understanding of surrounding environments as well as a real-time decision is needed. Many researchers have proposed several approaches based on kinematics to perform this task. However, human drivers does not concerned too much about the kinematic parameters of vehicles, but try to control vehicles mainly based on the scenes from vision and experiences accumulated from long-time driving. From this perspective, we propose a more human-like lane-change system, whose sensors mainly based on five monocular cameras. Information from these sensors are fused into MOR(My Own Range) which means the drivable area for the vehicles. Finally, two fuzzy controllers are used to imitate expert behaviors and responses upon vehicle control. To verify the efficiency of the proposed lane-change system, a test platform, which includes ten scaled-down autonomous vehicles and a scaled model highway, is built. With this platform, tons of ideas or tests, especially of some dangerous tests, can be examined and implemented with a low cost later.**

I. INTRODUCTION

Lane Change is one of the most frequent and riskiest maneuvers in driving vehicles. Drivers have to change their traveling lanes not only for avoiding obstacles or overtaking slower vehicles in front, but also selecting the proper carriageway to make turns, merge to highways or take exit. During a lane-to-lane transition, drivers need to observe surrounding environment simultaneously while adjusting their cars into appropriate velocity and direction. Thus, the automation of lane-change is considered to be one of the toughest challenges in the development of autonomous vehicles [1].

Many researchers and projects have attempted to address the lane-change problems. Some tried to find the optimal trajectory for a safe lane-change. H. Jula *et al*. analyzed the kinematics of the vehicles and presented a general algorithm to calculate the minimum longitudinal spacing that vehicles to avoid collision [2]. In their experiments, they assumed all the vehicles kept a steady-state velocity during the changing maneuver except the changing vehicle. Furthermore, in their work, three different longitudinal acceleration scenarios were applied to the changing vehicle in order to determine the safe and unsafe regions as well as the minimum safety spacing between the changing vehicle and its surrounding vehicles. C. Hatipoglu *et al*. [3] proposed an equivalent virtual time optimal reference trajectory for lane-to-lane transition. A vehicle yaw rate controller was designed to make the vehicle track this reference. There are also some other relevant studies, which did not focus on automatic change but addressed safety assessment for a driver assistant system. R. Schubert *et al*. [4] presented a system that can perceive the vehicle's environment, assess the traffic situation, and give recommendations about lane-change maneuvers to the driver. Jin *et al*. [5] studied a typical scenario on highway. They considered that the vehicle runs into an adjacent lane with constant acceleration during initial lane-change phase and then adjusts self-velocity in the target lane. In 2007, an exhaustive literature review was accomplished by M. Tideman *et al*. to identify the current state of the art on lateral driver support systems [6].

As described above, most of these research works were based on the kinematic functions or hoped to find an optimal trajectory for lane-change. However, it is well established that human drivers pay no attention to acceleration or the exact yawing rate of their vehicles or surrounding vehicles. The information they use in controlling a car is mainly based on the scenes from vision and experiences accumulated from long time driving. Hence, we describe a more natural lane-change system in this paper, which does not rely on complex kinematic equations, but focuses more on the real-time states of autonomous vehicles and adjusts vehicles to a suitable position according to two fuzzy rules controllers. The main sensorial information used for decisions comes from five monocular cameras and one speedencoder. In short, we try to model a human driver's behavior to perform the lane-change [1]. Finally, a test platform is built to verify the efficiency of the outlined system. The test platform consists of ten scaled-down autonomous vehicles (SAVs) and a scaled model highway.

This paper is organized as follows. Section II introduces the scaled-down autonomous vehicles. Section III describes the system architecture of the algorithm. Details regarding senses, thinking and action will be given in sections IV to VI. The experimental results are presented in Section VII, and conclusions are made in Section VIII.

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II. SCALED-DOWN AUTONOMOUS VEHICLE

Our SAV is based on a 1/12 scaled model chassis. Its propulsion is provided by a DC motor. Steering is controlled by a servo motor. In order to obtain the real-time velocity of the vehicle, a rotary encoder is mounted at the rear-right tyre.

All the other sensors equipped on the SAV are five monocular cameras. One of them is mounted in the front-left side of the car and pointed downward with a slightly right angle, in order to detect the lane markings, which we refer to as Tracking Camera (TC). The other four cameras, which point at left-front, left-rear, right-front and right-rear directions respectively, are used for environment perception, and we refer them as Environment Cameras (ECs).

The computational tasks in the vehicle are allocated to six ARM chips. Five of these chips are connected to the five cameras separately and the remaining chip is used as the control center. All these chips are connected with a CAN bus.

Since human drivers do not need the environmental information from all directions at one time, except for the information from the area which affects their driving maneuvers, we use publish-subscribe mechanisms to deal with the communications between the control center and other computational chips. This is more human-like, and also more efficient.

The other devices mounted on the vehicle are six signal lights, four for turning and two for emergency stop. These lights are used to tell the intention of the vehicle to its surrounding drivers. Fig. 1 shows the appearance of the SAV.

Fig.1. The appearance of the scaled-down autonomous vehicle.

III. SYSTEM ARCHITECTURE

The overall system architecture is depicted in Fig.2. According to [6], the general architecture of a lateral driver support system can be subdivided into three sub-functions: sense, think, and act. The difference in our system is the reduction of sensors both in type and number.

A. Sense

In this sub-function, sensors are used to capture the information of the surrounding environment as well as the velocity of the vehicle. Traditional information in image, such as lane markings, surrounding vehicles, and road shapes are detected with the environment perception algorithms. Moreover, more details such as turning signals and emergency stop signals, which are essential for safety in lane-change, are also detected. Finally, information is sent to "Think" sub-function through well defined asynchronous messages.

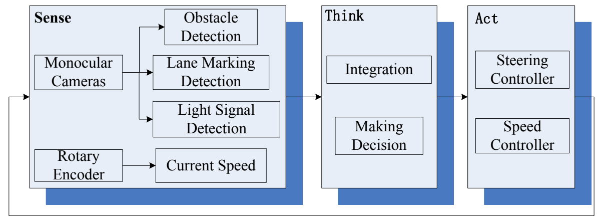


Fig.2. System architecture for lane-change

B. Think

The information from "Sense" sub-function will first be integrated into a thorough understanding of the surrounding environment. After a series of safety assessment, two kinds of decisions are made to maintain the car in a proper speed and direction

C. Act

Finally actions are performed on steering wheel and DC motor of the vehicle to implement the decision made by "Think" sub-function correctly.

IV. SENSE

For a lateral driver support system, there are two types of most relevant information: the position of the vehicle in the lane and the relative positions and velocities of surrounding vehicles and obstacles [6]. Beyond these, other details such as lane shape and light signals are also essential for safety. Since vehicles should have different speed on different types of roads. Furthermore lane-change should be forbidden in a sharp turn due to the limitation in visual field. Finally, although the importance of light signals in driving especially in lane-change is obviously known by all drivers, it has been rarely considered in autonomous car research nowadays.

For SAVs, their driving road nowadays is a scaled-down highway model, which is relatively simple to the real world. Thus, the algorithm used for vision is a little bit simple but well done in this context. And as a test platform, the key idea can also be used for the real world.

A. Obstacle Detection

Similar to most of the color vision tasks, the first step we need to do is to classify each pixel in the image into one of the specified color classes. To achieve this, thousands of labeled exemplars are used to train for a list of the K nearest neighbors. And then the pixel in new image can be classified according to the largest proportion of classifications of the neighbors. To accelerate the computing speed, a table which prestored all colors' class labels is created.

After classification, a Gaussian filter is applied to remove noise. The color and shape information of different regions are extracted based on the method proposed by CMVision [7]. Thus, lane markings, roads and vehicles in the frame can be identified based on their characteristics in terms of color and shape. However, the purpose of the obstacle detection is not only to find the obstacles, but also to get the range of drivable road. Hence, an Inverse Perspective Mapping (IPM) transformation is necessary to get the position of the detected vehicles.

B. Lane Markings Detection

Various vision-based lane markings detection algorithms have been developed during the past years. Most of these algorithms can be classified into two types: feature-based methods and model-based methods. The feature-based methods are mainly based on low-level features of lane markings such as painted lines or line segments [8], [9], etc. Thus, these methods are more suitable for a road which has clear lane markings. Due to the flexibility in feature definition, these methods may be applied in different types of lanes or lane markings. On the other hand, the model-based methods mainly use a few parameters to represent the lane models [10], which are much more robust against noise and missing data. However, as most defined lane models are only suitable for certain shapes of road, these methods may lack the flexibility in modeling arbitrary shapes of the road.

Because of the respective disadvantages of each method presented above, we combine the two types of methods in different areas of their expertise. On one hand, we use a model-based method for position adjustment. Since we just need a small patch of the lane markings to calculate the current position of a vehicle in lane, various shapes of markings (e.g. bend or straight) can appear as straight line approximately. And we can avoid the influence of noise or occlusion to a large extent. On the other hand, we use a feature-based method to identify large range lane markings for lane shape detection and also as the basis for obstacle position calculation. To enhance the robustness under different lighting conditions, the output from the former is used as an input for the latter.

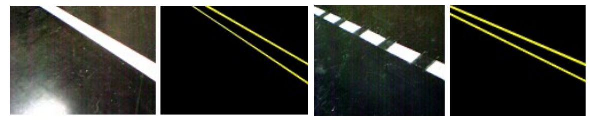
1)Model-based lane markings detection

In SAVs, model-based lane markings detection method is used to locate and adjust a car's position and direction relative to the road. Just as we have said before, only a small patch of the lane markings is enough. In this way, lane markings in TC can always be seen as a line approximately, regardless of whether the road is straight or curved. Furthermore, this method can be applied on gray image, which speeds up the computation as well as enhances the robustness under different lighting conditions.

A simple algorithm used to find out the line is Hough Transformation, which can be applied to the image after edge detection. The strongest peak line found in all candidate lines could be the lane marking. Then the IPM is also used to get the rotation (θ) and offset (d) of the lane marking according to the vehicle position. And vehicle can be adjusted to a good position according to the two parameters later. Fig.3 depicts two typical examples in lane markings detection.

2) Feature-based lane markings detection

Feature-based lane markings detection method is applied on frames captured by ECs. A series of preprocessing is performed as described in obstacle detection. After region extracting, color blocks with their details are obtained, although, color information can be delicate under different lighting conditions. Thanks to the fact that we have already obtained the lane markings information by model-based detection method, what is required to do next is just to extend the range. Thus, an adaptive computer vision algorithm can be built, which uses the pixel inside the lane markings that have been detected as its training data, and finds out the extended lane markings.



(a) (b) (c) (d)

Fig.3. (a) An image obtained by Tracking camera. (b) The yellow lines are the recognized edge of lane markings. (c) Another example of discontinuous lane markings. (d) Result is also good for this case.

The method we propose here is similar to the vision method in Stanley [11], who is the winner of the DARPA Grand Challenge. The difference lies in that the input information in Stanley is from laser analysis, which is a high-level sensor, while what we used here comes from a monocular camera.

To model the lane markings we have found, EM algorithm is used first to establish three Gaussian models in RGB space separately with the pixels in detected lane markings. Since the road color cannot change abruptly, color of lane markings in TC should be highly similar to the color in ECs. Thus color blocks from ECs, which have the similar color character in Gaussians and are also near or connected to the lane markings region, are classified as the lane markings.

C. Light Signals Detection

When driving on road, light signals are one of the important languages between vehicles. Accidents can be largely avoided if we know the intentions of other cars, whether to change direction or slow down. Therefore, perceiving and interacting with the light signals of other cars are necessary for a safe driving.

In fact, after obstacle detection, we have identified different regions in image, such as lane, lane markings and vehicles. Hence, we can try to find out lights on the vehicles' region directly. To alleviate the influence of noise, the shape, luminance, and position information of an illuminated light can also be used.

Fig.4 illustrates the process in finding out the left turn indicator light. We first find out the car region above drivable road like Fig.4(c). If this region exists, a round shape, yellow color and illuminated object within this region will be recognized as a lamp. To correctly distinguish the left or right lamp of the car, a middle line is simulated according to the bottom of the car. Fig.4(e) shows the result. Furthermore, a particle filter algorithm is then used to track such a flash object over time to validate whether it is really a direction indicator.

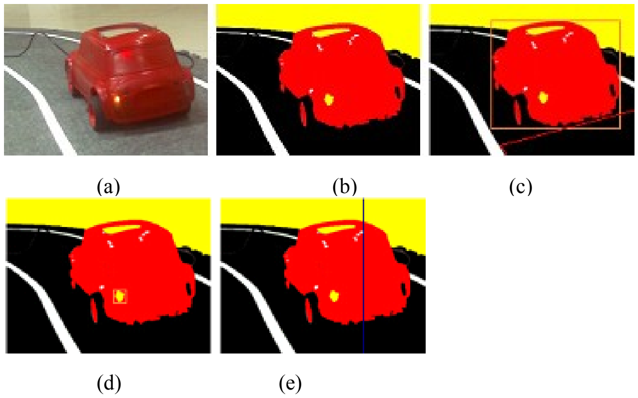


Fig.4. (a) Image from right-front camera. (b) The classified image. (c) The car region is found out above drivable road. (d) Lamp is found out within car region. (e) The simulated middle line of car

V. THINK

In this sub-function, we are going to create a decision-making module, whose mission is to think and decide what the vehicle needs to do next, such as changing lane or staying in the same lane.

As discussed in the previous section, three types of information around the vehicle have been interpreted and sent through CAN bus, i.e., safety area, light signals, and lane shape. First, we will integrate this information into drivable areas around us, and we would like to call these areas as My Own Ranges (MORs), which refers to the space belonging to our vehicle that we could move to. The difference between a safety area and a drivable area is that a safety area is an area where no obstacle currently exists, while a drivable area is safe during the whole time when we moves to this area with the current speed.

In this way, we divide sub-function Think into two steps, first is integration, then making decision.

A. Integration

The road model we set for SAVs is a three-lane, one-way highway. Thus, there are three possible drivable areas for the host vehicle, which are forward, left or right lane relative to the current position. And we divide its surrounding environment into six regions, which are front, behind, left-front, left-rear, right-front, and right-rear. Then the space for the host vehicle in the six directions can be presented as:

$$D_\theta=\min\{ S_i(0)+ \Delta v \bullet T_v \} \tag{1}$$

where θ represents the direction; Δv is the speed difference between the host vehicle and the vehicles involved in the direction θ. What we should notice is that vehicles involved in this direction not only contain vehicles already in this position relative to the host vehicle, but also vehicles that have the intention to move to this position, which means the vehicles have signaled to this position. When the involved vehicle is in front of the host vehicle, Δv can be presented as v_i-v, otherwise it will be presented as v-v_i, where v is the velocity of the host vehicle and v_i is the velocity of an involved vehicle; $S_i(0)$ is the initial space between the two vehicles; T_v is the required time to complete a lane changing with current speed v, which is an experiential value. One of the special cases is that, there is no road in one side of the host vehicle, and then we simply set both the two D_θ on this side to *zero*.

Since a vehicle on highway is always moving forward, the speed in changing lane can be determined by the longitudinal space with vehicles ahead. However, the space between the host vehicle and vehicles behind is only used for making safety decision. In this way, MORs can be obtained by integrating the front and behind D_θ in the same lane, as well as the lane shape.

$$MOR_{front}=D_{front} \tag{2}$$

$$MOR_{left}=\begin{cases} D_{left-front}, \text{ while } D_{left-back}>D_0 \\ \quad\quad \text{and road shape is straight} \\ 0, \quad\quad \text{otherwise} \end{cases} \tag{3}$$

where D_0 is a minimum safety distance for lane changing. And MOR_{right} has the similar form to MOR_{left}.

After these transformations, MORs are no more concerned with the current speed of the host vehicle, but transformed to a normalized distance for a relatively stationary vehicle.

B. Making Decision

With the integrated information from sensors, we get a comprehensive understanding of the surrounding environment. Since all the decisions we make have to be executed by speed motor or steering, two types of basic decisions—speed and steering need to be made. Each of the decisions is divided into several driving states, and two finite state machines (FSM) are used to switch between these states.

For the system in this paper, the steering decision states contain LaneKeep, LaneChangeLeft and LaneChangeRight, each of them corresponds to a driving mode.

- LaneKeep: This state corresponds to lane keeping or forward driving. And this is the common state of vehicle.
- LaneChangeLeft: This state is invoked when current lane is jammed, while the left lane is better for driving.
- LaneChangeRight: This state is invoked when both the current lane and left lane are jammed, while the right lane is better for driving.

The speed controls of a vehicle can generally be classified into three types-- cruising, accelerating, and decelerating. Considering the emergency condition, state of stop is added to guarantee the safety in driving.

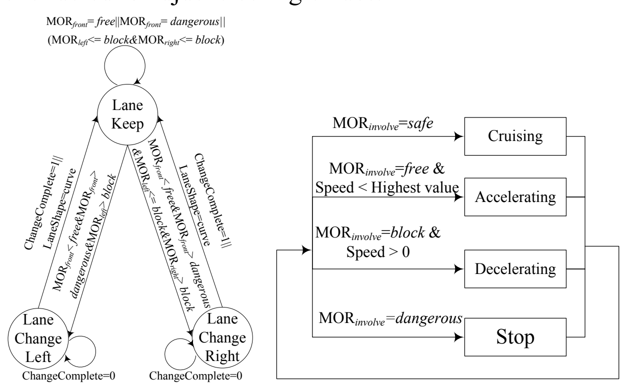
- Cruise: This state means the current speed is appropriate, vehicle will go on to keep the speed.
- Accelerating: This state is invoked when the target MOR has sufficient space for speeding up, and vehicle will accelerate to its preferred speed.
- Decelerating: This state is invoked when the target MOR is lower than the set threshold. Vehicle will slow down its speed for a safety driving. One special condition is to decelerate till an occupant space for lane changing. This will occurred when the contiguous lane is satisfied for lane-change, while the longitudinal space from vehicle in front is not enough.
- Stop: In this state, vehicle will make an emergency brake

till stop.

In order to evaluate the transition conditions between these states, MORs are divided into four levels—free (i.e. there are no vehicles within the perceptual distance), safe (i.e. the distance to the closest vehicle in this direction is safe for current speed), cautions (i.e. the closet vehicle in this direction is within a distance, but outside the critical range) and dangerous (i.e. the closet vehicle in this direction is within a critical range). The corresponding states transition diagrams are shown in Fig.5. in which MOR$_{involve}$ means the MOR in the direction of where the vehicle will pass through. For example, if the vehicle will change to left lane, both the directions in front and left are involved, thus MOR in both directions are MOR$_{involve}$.

VI. ACT

To execute the intention determined in "Think" sub-function, two partially decoupled tasks are performed. One is speed adjusting and the other is steering. In our system, a classical PID method is used to control the velocity controller, whereas two Fuzzy Logic Controllers (FLCs) are constructed to adjust steering values.



(a) (b)

Fig.5. Finite State Machines that govern the vehicle

A. Speed controller

As mentioned above, there are four states in speeds adjusting, and each of the states corresponds to a desired speed value, denoted as $v(state)$. The current speed of the vehicle measured by rotary encoder is denoted as $v(t)$. Thus the PID controller can be constructed with the difference between two process variables in speed:

$$e(t) = v(state) - v(t) \tag{4}$$

$$u(t) = K_p e(t) + K_d \frac{d}{dt} e(t) + K_i \int_0^t e(\tau) d\tau \tag{5}$$

here $e(t)$ is the control error, K_p, K_d and K_i are tuning gains that are fine tuned by studying the effect of this value on the system response, and $u(t)$ is the controller output.

B. Steering Controllers

There are two basic modes in steering control—lane following and lane changing (including left change and right change). To smoothly adjust the direction of vehicle in different modes, two FLCs are used separately. In this way, we do not try to find a specific trajectory for the vehicle, but to adapt the different conditions in a more natural way.

FLC for Lane-Following: The inputs for the lane-following FLC are *rotation* θ and *offset* d of the current vehicle position to the right lane marking. Three fuzzy linguistic values, namely **left**, **center** and **right** are associated with the two input variables. The output variable of the controller is *steering angle* δ, whose linguistic labels are (**strong left**, **left**, **center**, **right** and **strong right**). The rule base used to reflect human driver's knowledge in lane-following can be given in the following form, for example:

"IF *offset* is **right** and *rotation* is **center**, THEN *steering angle* is **left**."

The complete fuzzy IF-THEN rules for the lane-following FLC are given in Table I. These rules show that we have simply translated the usual human reasoning in lane following to a fuzzy control strategy.

TABLE I
THE PREDICATE BOX FOR FUZZY STEERING IN LANE-FOLLOWING

Offset	Rotation (θ)		
(d)	Right	Center	Left
Right	Strong left	Left	Center
Center	Left	Center	Right
Left	Center	Right	Strong right

FLC for Lane-Changing: During the process in lane changing, vehicle will transfer from one lane to another. And we simply break down this maneuver into three steps (here, we take left-change as an example):

--First, turn direction: adjust the vehicle direction into the target lane, as showed in Fig. 6(a)

-- Second, hold direction: maintain the direction and going forward, till the vehicle arrives in the target lane, as showed in Fig. 6(b)

-- Third, keep lane: following the current lane, and try to drive in the middle, as showed in Fig. 6(c)

From the analysis above we note that, the aim of the first two steps is to guide the vehicle into the contiguous lane as quickly as possible, while the third step is to adjust the vehicle drive well within the lane. Thus the third step can be achieved with the same method of lane following. And since the purpose of the first two steps is to turn the vehicle into the right direction, only *rotation* of the current vehicle is enough for FLC input. Thus, the rule base for lane-changing can be given in the following form, for example:

"IF *rotation* is **right**, THEN *steering angle* is **strong left**."

The complete fuzzy rule base for left lane-changing is shown in Table II. And the rule base for right lane-changing is symmetrical. The output variable *steering angle* also has five linguistic labels (**strong left**, **left**, **center**, **right**, **strong right**).

Finally, to aggregate all the fuzzy sets and combine them into a single fuzzy set, the Mamdani's inference method is used, and centroid calculation is employed to get the crisp output value in steering angle.

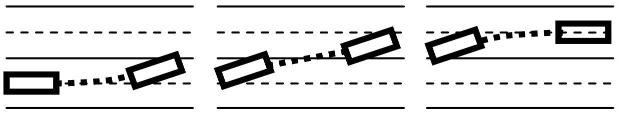


Fig. 6. (a) The step of turn direction in lane-changing. (b) The step of hold direction (c) The step of keep lane.

TABLE II
THE PREDICATE BOX FOR FUZZY STEERING IN LEFT LANE-CHANGING

Rotation (θ)	Steering angle (δ)
Right	Strong left
Center	Left
Left	Center

VII. EXPERIMENT RESULT

The experiment data presented here was collected on the scaled-down model highway, whose road width is 30cm. Two SAVs are used to complete a left lane-change. At the beginning of the experiment, the host vehicle is stationary, and the other vehicle is cruising at a constant speed about 2.5 km/h ahead. According to the scale in size, this speed corresponds to the speed about 30*Km/h* in real world. The first set of experiment data, shown in Fig.7, indicates the offset and rotation of the SAV to the right lane marking during the lane-change process. Since during the change process, the origin left lane marking will become the new right reference lane marking, a peek value appears during the transition process. Fig.8 shows the relative position between the host vehicle and vehicle ahead. The sampling frequency is 10Hz. The triangle located at the origin of coordinate denotes the overtaken vehicle. Speed variation of the host vehicle during the whole lane-change process is shown in Fig.9.

VIII. CONCLUSION

In this paper, we present a system that is capable of performing automatic driving and lane-change based on monocular cameras. To alleviate the influence by different lighting conditions, two kinds of lane marking detection methods are used complementarily. More details such as turning signals and emergence stop signals are considered as important decision factors for safe driving. In this system, information from all sensors is integrated into MORs in different directions, which helps the vehicle to make decision in a way natural to human drivers. Furthermore, two fuzzy controllers are used to integrate the expert knowledge in driving. Thus no specific reference trajectory and complex kinematic equations are required. Vehicles can adjust their position simultaneously according to the information from cameras and fuzzy rule bases. In this way, a more human-like lane-change system is established. Finally the system is implemented in a test platform, which consists of ten scaled-down autonomous vehicles and a scaled model highway. The test results demonstrated the feasibility preliminarily. Furthermore, with this platform, tons of ideas and tests can be examined and implemented in a low cost later.

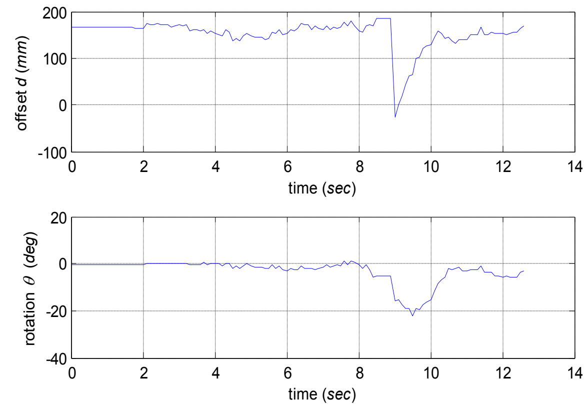


Fig.7. The offset and rotation to the right lane markings in a left lane-change

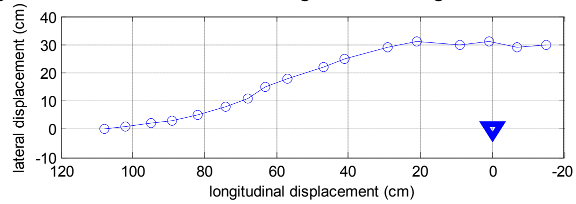


Fig.8. The relative position between the overtaking and overtaken vehicles

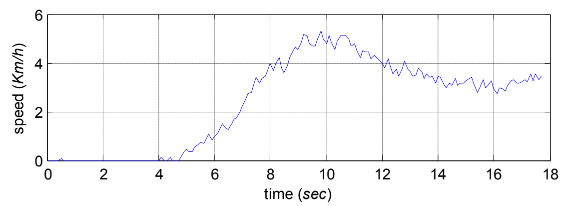


Fig.9 Speed variation during a left lane-change

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