Article

A design of the Autonomous Emergency Braking (AEB) system

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MENU

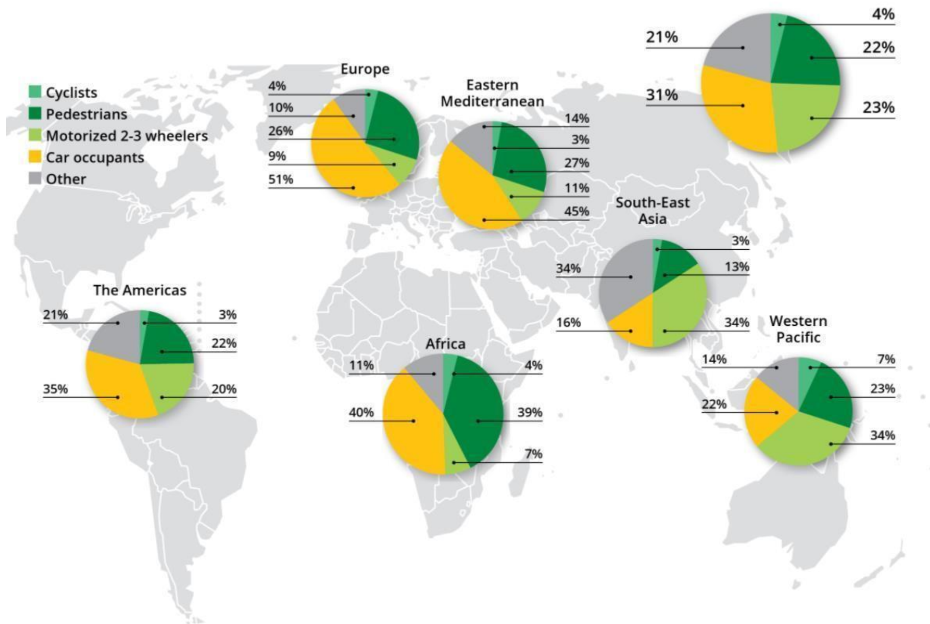
IMAGE

TABLE

I.ABSTRACT
1.1. Overview

The global economy's growth has led to a rise in vehicle numbers annually. WHO reports over 50 million injuries and about 2.5% fatalities from road accidents yearly. Around 90% of these accidents result from driver errors like inexperience, drunk, or fatigued driving. Often, drivers are unaware of collision risks or lack sufficient reaction

time to handle them effectively.



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1.2. Conclusion

Because of such yearly accidents, we choose AEB (Autonomous Emergency Braking) topic for our focused research. We hope that our proposed system could be effective and pratical for real system.

II. INVESTIGATION

2.1. Three levels of factors affecting the performance of AEB

2.1.1. Vehicle factor

The AEB system is primarily designed for low-to- medium speed traffic scenarios, with high-speed situations less frequently encountered. This limitation arises from the decreased effectiveness of the primary sensing equipment, namely cameras and radars, in adverse weather conditions and low-light environments such as sandstorms, fog, snow, and darkness. The field-of-view (FoV) angle of the sensor plays a pivotal role in determining the system's ability to avoid collisions.

System factors like system error, braking delay, maximum deceleration, and control strategy significantly influence the AEB system's collision avoidance effectiveness.
Among these factors, the choice of control strategy emerges as particularly crucial, directly impacting the overall performance of the AEB system. This aspect holds significance as the control strategy represents the core component of the system, shaping its ability to respond effectively to potential collision threats.

2.1.2. Driver Factor

Drivers can be categorized into three distinct types: radical, standard, and conservative. Once the driver style is identified, the implementation of varied control strategies and parameters tailored to each driver type becomes feasible. This approach aims to bolster the system's control accuracy and elevate driving comfort, thereby catering to the diverse preferences and behaviors exhibited by drivers on the road.

2.1.3. Environment Factor

Weather conditions encompass a range of states, from sunny and cloudy to rainy or severe weather. Road conditions, crucial for safe driving, are influenced by factors such as the road adhesion coefficient and slope. The road adhesion coefficient, impacted by variables like road type, wetness, tire properties, and air pressure, directly affects traction. Meanwhile, roads are typically categorized into ordinary, cross, and tee-section types. Additionally, road slope is classified into uphill and downhill gradients.

Light conditions play a significant role in visibility, with distinctions made between daytime and nighttime, further differentiated by the presence or absence of street lighting infrastructure.

2.2. AEB system framework

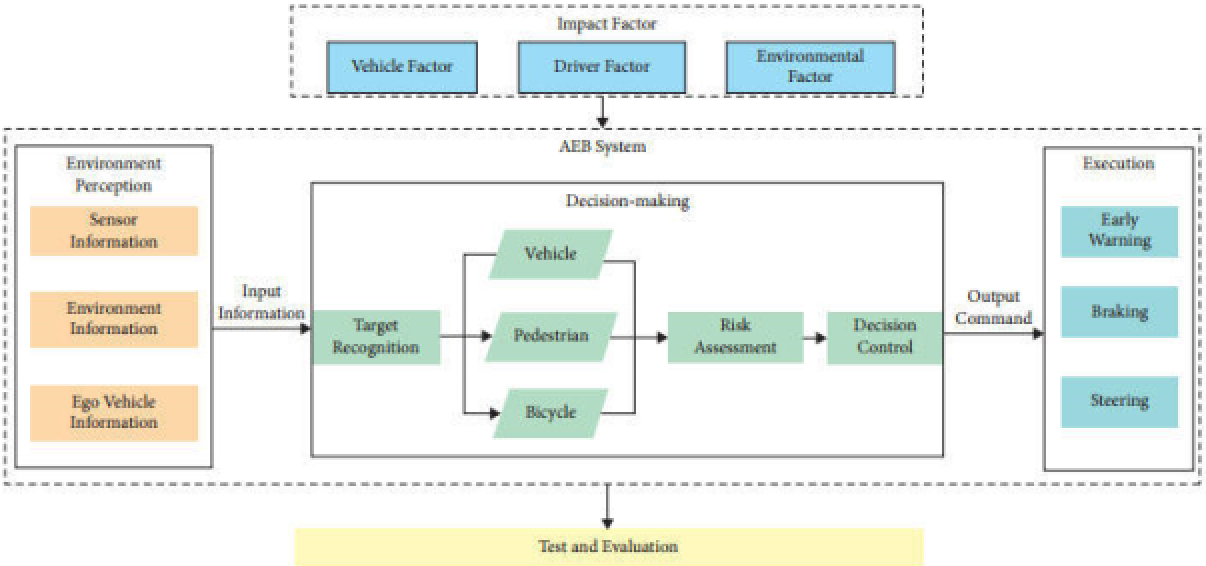


Figure 2: AEB system framework

The environment perception subsystem is to obtain the vehicle and surrounding road information through on-board sensors, such as cameras, radars, and thermal sensors, and send the information to the decision-making subsystem. Based on the received information, the decision-making subsystem judges the critical situation of the current road conditions and simultaneously determines whether early warning, braking, and other collision avoidance strategies (e.g., steering) must be implemented. The subsystem then transmits commands to the execution subsystem for executing the collision avoidance operation of the corresponding module.

The working process of the AEB system can be divided into the following three stages.

- Normal stage: the vehicle will not collide with the vehicle at the front or other obstacles (pedestrians, cyclists, etc.); the AEB system will not intervene in the driving behavior.
- Early warning stage: the AEB system will alert the driver immediately through visual or audial warning sign, or by tightening the safety belt.
- Braking stage: the AEB system uses a single-stage or multistage braking strategy (i.e., directly applies the maximum braking pressure or gradually increases the braking pressure) to avoid the collision.

2.2.1. Environment Perception Subsystem

The environment perception subsystem primarily comprises various sensors that collect information and identify targets. At present, the most commonly used sensors in AEB systems include 77 GHz millimeter-wave radar, lidar, mono-binocular cameras, and thermal sensors.

Table 1: Pros and cons of different sensors

	Pros	Cons
Radar	Better penetration and large detection range. Unaffected by light and weather.	Expensive Target recognition is difficult.
LIDAR	Response time of lidar is short. High ranging accuracy.	Expensive. Affected by weather.
Camera	Cheap. Effectively identify the target.	Detection range is short.

2.2.2. Decision-Making Subsystem

2.2.2.1. Target Recognition Strategy

AEB system recognizes objects into three categories: vehicles, pedestrians, bicyclists.

2.2.2.2. Risk Assessment Strategy

It is the judgment of the AEB system on the possibility of collision and severity of the accident under the current working condition, which provides a reference for the system to perform corresponding collision avoidance operations.

The widely used evaluation parameters are the safe distance and TTC (time-to-collision).

2.2.2.3. Decision-Making Control Strategy

Determines the corresponding collision avoidance operation according to the dangerous extent based on existing road conditions.

The existing decision control models include:

- Hierarchical control
- Brake steering control
- Acceleration control
- Brake pressure adaptive models

III. SYSTEM DESIGN PROPOSAL

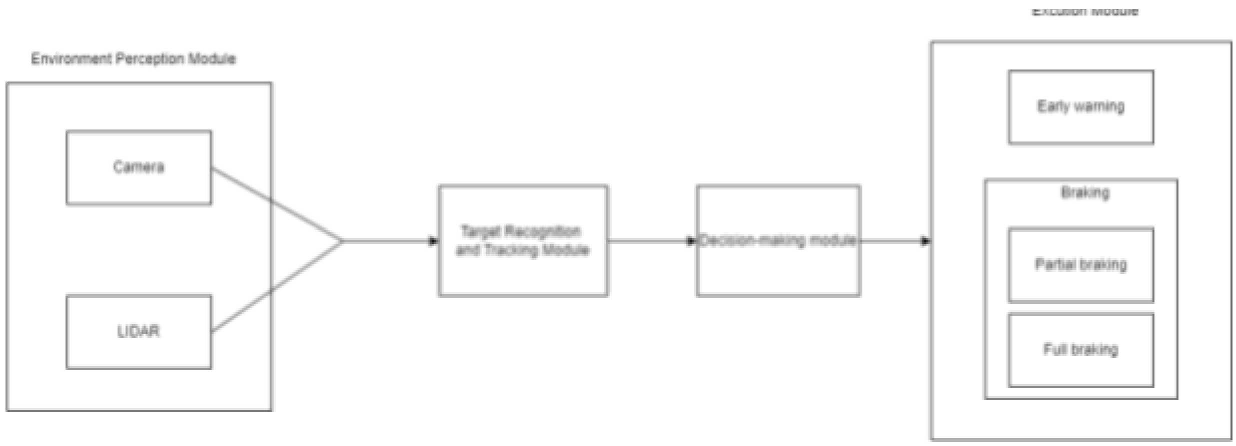


Figure 3: System Design Proposal

3.1. Environment Perception Module

Figure 4: Device Setup

We propose using one LIDAR, which is Velodyne HDL-64E LIDAR and one camera, which is AVT F200C camera.

The LIDAR sensor has a 30° vertical field of view, as well as a 360° horizontal field of view, and the 16 planes represent an angular resolution of 2° in the vertical directiona and is installed in the front of the car. The monocular camera is installed in the front of the car but on top of the car, which has a 135° field of view.

3.2. Target Recognition and Tracking Module

The tracking system consists of three modules: mask generation, depth estimation, and re-tracking mechanism

1. An arbitrary rectangle bounding box in the first frame of the color image sequences captured by the monocular camera
2. The mask generation module tracks the selected object and generates a binary segmentation mask that expresses whether or not a pixel belongs to the target during the tracking process. The generated mask provides pixel-level information for the depth estimation module.
3. Based on the results of the joint calibration between monocular camera and LIDAR, we project the LIDAR point cloud onto the image plane to obtain the sparse two-dimensional depth map. According to the segmentation results of the target, the spatial position of the target is estimated from the sparse depth map.

3.2.1. Mask Generation

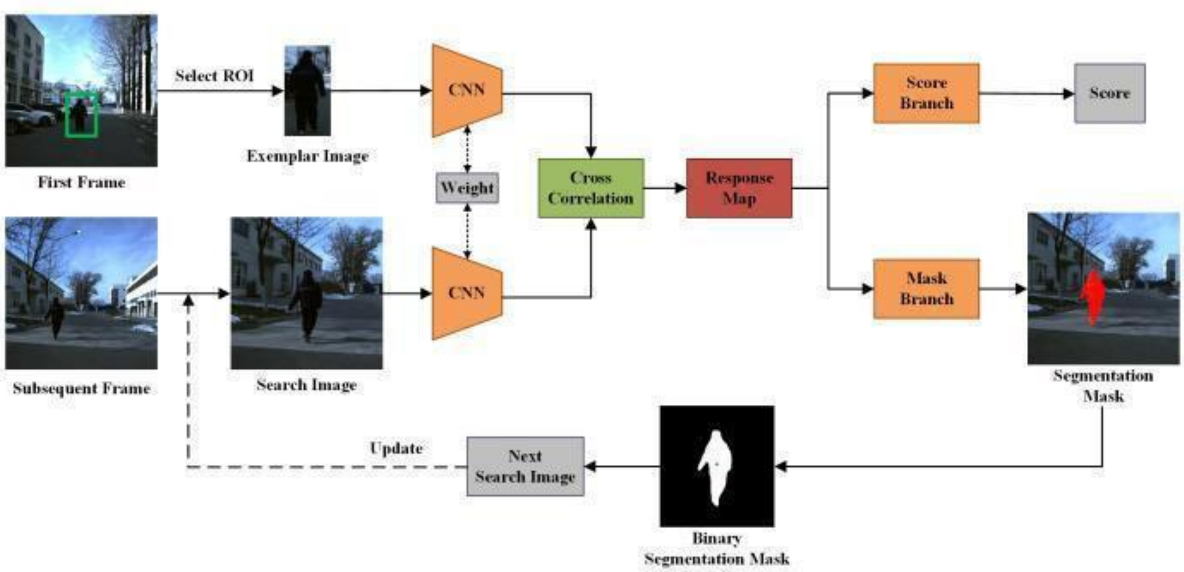


Figure 5: The mask generation and object tracking network architecture

1. Putting an exemplar image X1 and a search image X2 into the fully-convolutional Siamese network.
2. Two feature maps are generated and combined with a cross-correlation layer, which is a cross correlation operator between two feature maps, to generate a response map.

3. Using a multitask learning method called SiamMask to predict:
    a. object score : outputs the score of tracking results, which can be used to judge whether the target is lost.
    b. segmentation mask : output a binary segmentation mask, which is used to express whether or not a pixel belongs to the target object within the search image.

    Both the binary segmentation mask and the object score are implemented by a two-layer CNN.

4. After obtaining the segmentation mask, the center position of the search image X2 in the next frame can be inferred and updated. The update strategy takes the last estimated position of the target as the center of the search image X2, that is, the center point of the binary segmentation mask.

3.2.2. Depth Estimation

In this section, we describe how to estimate the spatial position of the target object with respect to the self-driving car from the binary segmentation mask and the LIDAR point clouds.

Figure 6: Depth Estimation Pipeline

It is necessary to know the transformation matrix between the corresponding coordinate systems of both sensors to provide redundant information in the same reference system. With the above calibration pipeline, the LIDAR point clouds can be projected into the camera frame:

$$\mathbf{p}_C = \mathbf{R}_{CL}\mathbf{p}_L + \mathbf{t}_{CL}$$

where:

- $p_L = [x_L, y_L, z_L]$ denotes the 3D coordinates of the point clouds in the LIDAR frame.
- $p_C = [x_C, y_C, z_C]$ denotes the 3D coordinates in the camera frame.

According to the pinhole camera model, there is a mathematical relationship between the coordinates of a point in the threedimensional space and its projection onto the image plane:

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \frac{1}{z_C} \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_C \\ y_C \\ z_C \end{bmatrix} = \frac{1}{z_C} \mathbf{K} \mathbf{p}_C$$

Where:

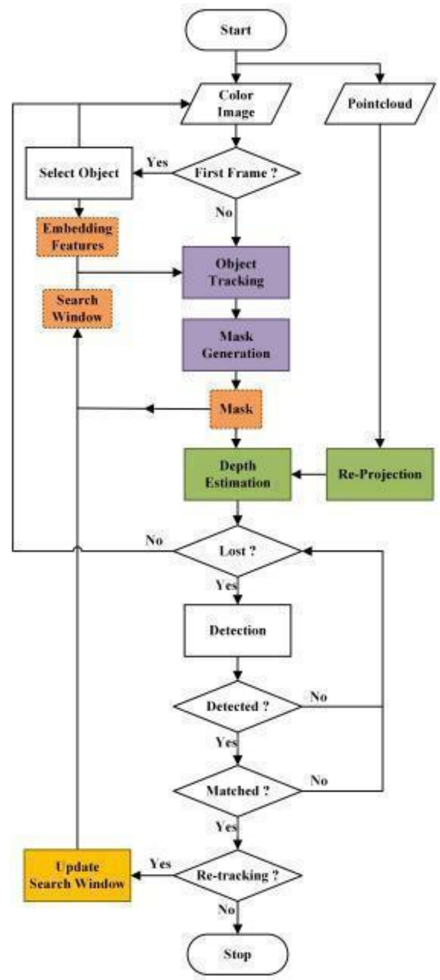
- K indicates the camera intrinsic matrix.
- $p_i = [u, v]$ indicates the coordinates of a point on the image plane.

Given p_c, K, p_i is known, we can easily compute depth of target object, z_c.

3.2.3. Re-tracking mechanism

Generally, most target loss occurs when the target makes a quick turn and disappears from the camera's field of view. When the lost target returns to the camera view, RTM can deal with the tracking recovery problem. universal fast object detection framework YOLO is used to output a rough target detection on the input image.

When target loss begins to occur, RTM records the target category selected in the first frame (e.g. pedestrians, vehicles) and the direction angle θl of the target with respect to the self-driving car. RTM keeps running the YOLO detection algorithm according to the recorded category to detect whether the specified object category appears again in subsequent images. When the target of the specified category is detected again, RTM calculates a target azimuth in the LIDAR data according to the depth estimation module and compares it with the azimuth of the target when it is lost to determine whether the re-detected target is in the vicinity. Besides, RTM crops a temporary search image according to the position of the target in the current image and re-inputs it into the fully convolutional Siamese network.



Given a certain score threshold and neighboring azimuth threshold, RTM determines whether the previously tracked object reappears. If the re-detected target satisfies the conditions of similarity score judgment and adjacent azimuth judgment at the same time, RTM resumes tracking and updates the search window based on the bounding box of the detected object. When the next image frame appears, the system continues to track the specified target based on the updated search window.

3.3. Decision-making module and Execution module

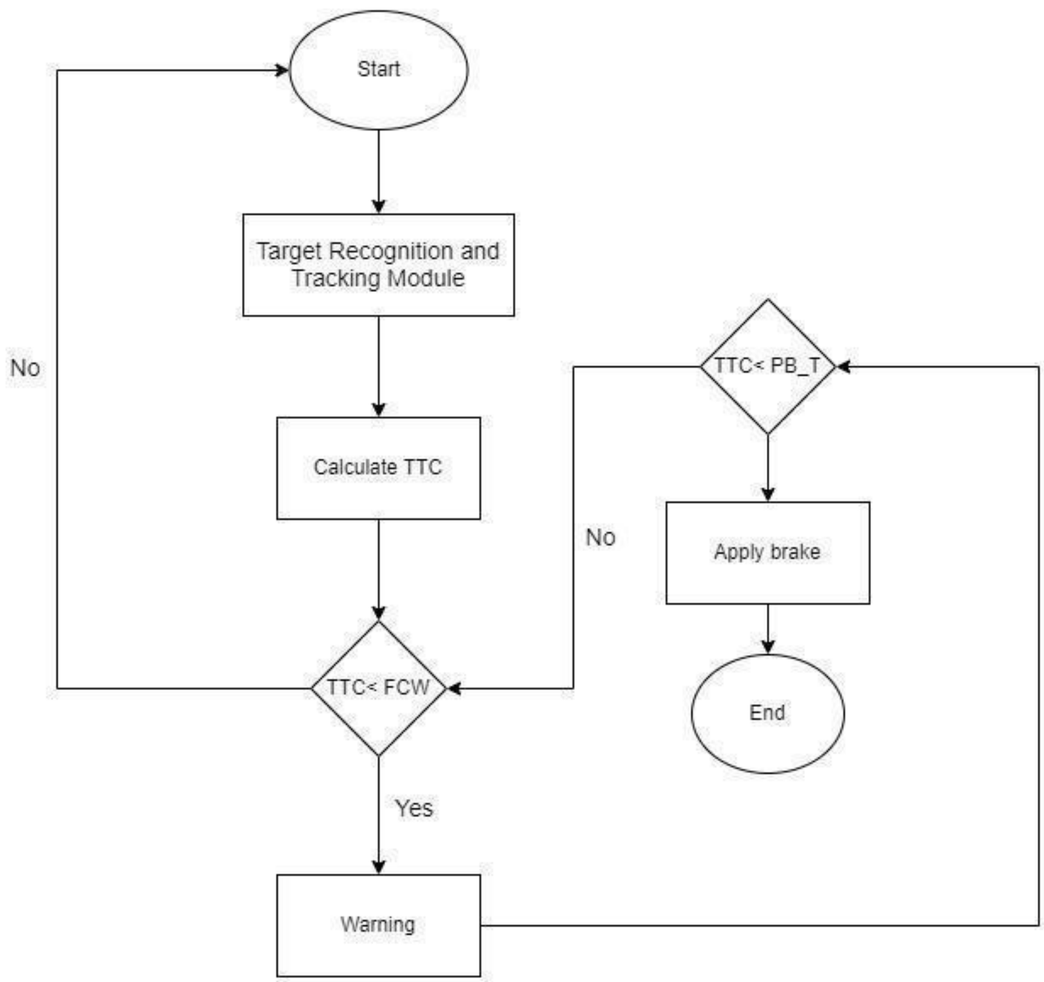


Figure 7: Flow chart of AEB with detailed Design-making module and Excution module

At the start, Target Recognition and Tracking Module detect and track objects near the ego vehicle. When an ego vehicle approaches a leading vehicle, the sensor measures the ego vehicle's distance from the leading vehicle, calculates the speeds of both vehicles, calculates the time to collision, activates the forward collision warning (FCW), and then calculates the stopping distance. When the lead vehicle's TTC is less than the TFCW, the FCW alert is activated. Due to distractions, the driver may fail to engage the brakes; in this situation, the AEBS operates autonomously to avoid or lessen the impact.

Here, TTC is calculated by the following formula:

$$\mathrm{TTC} = \frac{\mathrm{h} - \mathrm{L}}{\mathrm{V_P} - \mathrm{V_F}}$$

where:

- h: the distance between the preceding and following vehicles,
- V_F and V_P: the speed of the following and preceding vehicles
- L: the length of the preceding vehicle

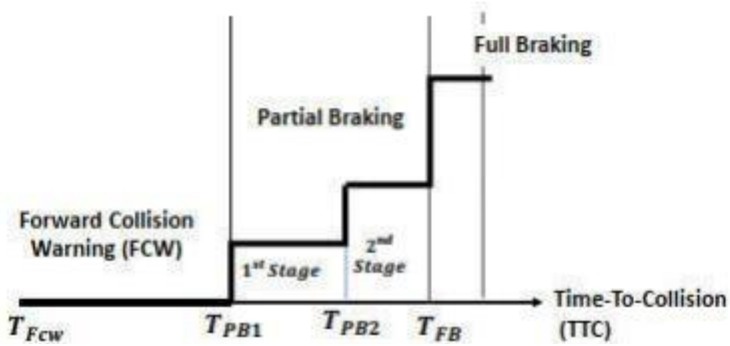


Figure 8: The AEB system's cascaded braking

The two stages of partial braking (PB) and full braking (FB) make up the cascaded braking. When TTC is in first stage and second stage, AEB system activate partial braking in respective deceleration. After that T_{FB}, ego vehicle doesn't stop, full braking comes into use.

When a pedestrian cross the road or ego vehicle takes turn, we need to concern more specifically.

When a self-car is close enough to a pedestrian, the AEB-P system may be in off, ready to work, or active state, which is mainly based on the pedestrian status as a reference indicator.

If the pedestrian is in the BCG or EFH area, and $v_1 = 0$ or $v_2 = 0$, the AEB system will be in a ready working state. If a pedestrian is in the AECGH area, the AEB-P system will be activated regardless of the sporting state of a pedestrian. In this case, the risk assessment model will issue a pedestrian collision warning or an automatic emergency braking signal.

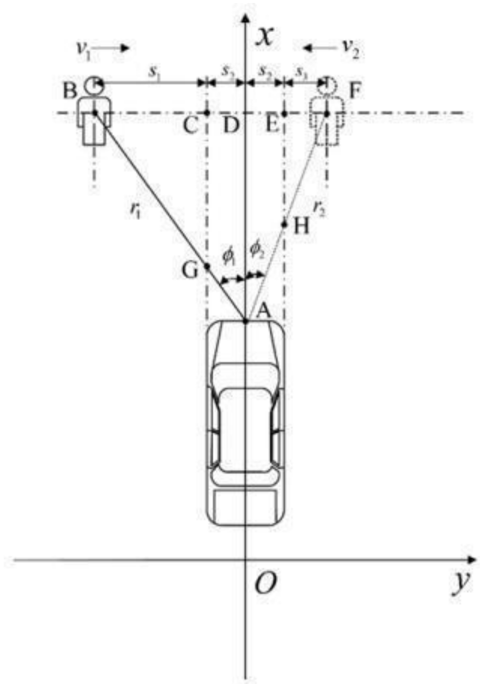


Figure 9: mstesyAEBehtofnoivisidareaginrkoW

IV. KEY MILESTONES AND ASSIGNING

4.1. Key milestones

- Set up device (i.e. camera and LIDAR)
- Solving proposed Perception module
- Solving porposed Decision-making module

4.2. Assigning tasks

- Hao, Thao: Perception module
- Minh: Decision-making module

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