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Optimal Configuration Scheme of Multi-Sensor Perception for Autonomous Vehicles based on Solid-State LiDAR*

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***Abstract*—Environmental perception is the first and most critical part of realizing autonomous driving. Solid-state LiDAR, as an important sensor in the perception layer of autonomous vehicles, gives the vehicles the ability to perceive beyond human eyes and guards the safety of people's travel. This paper proposes an optimal multi-sensor configuration method for autonomous vehicles based on solid-state LiDAR, camera, millimeter wave radar, and ultrasonic radar. The range of interests (RoIs) is divided into six zones and they are further classified into the core RoI and the extended RoI based on importance. The RoIs discretization mechanism is designed according to the functions and sensing range of various sensors. Considering the cost, coverage, and redundancy, a mixed integer programming model is built to determine the optimal number of sensors and placement positions. The optimal configuration scheme is obtained by using the IBM ILOG CPLEX solver. A model of a well-known vehicle brand is chosen to verify the effectiveness and feasibility of the proposed method. The solid-state LiDAR-based multi-sensor perception solution can meet the needs of environment perception for autonomous vehicles, and its coverage and redundancy are better than other control schemes, but its cost is relatively high due to the high cost of the solid-state LiDAR. The configuration scheme proposed in this paper will provide effective support for the design of an autonomous vehicle sensing solution.**

***Index Terms*—Optimal Configuration, Multi-Sensor Perception, Autonomous Vehicles, Solid-State LiDAR**

I. Introduction

In recent years, global shipments of self-driving vehicles at all levels and the scale of the self-driving market have been gradually expanding, and it is expected that global shipments of L1-L5 level self-driving vehicles will reach approximately 50 million by 2024. 2021 saw an explosion in the Chinese intelligent electric vehicle market, with sales reaching 2.382 million, and it is expected that sales in 2022 will exceed 4.4 million. Self-driving is an inevitable trend for the future of automotive development.

As a key technology for self-driving and autonomous vehicles, environment perception, through sensors such as LiDAR, camera, millimeter wave radar, and ultrasonic radar to sense the surrounding environment, real-time dynamic monitoring of changes, and decision-making judgment based on the information obtained, can provide support for autonomous vehicles path planning and navigation decisions [9], [11], [12] [13]. With the development of machine learning, especially the rise of deep learning technology, environment perception has received wide attention from industry and academia [7], [6]. There are two main routes of environment sensing technologies commonly used: one is a camera-led multi-sensor fusion scheme, and the other is a LiDAR-led solution with other sensors as auxiliaries. With the maturity of LiDAR technology and the significant reduction of cost, the LiDAR-led perception scheme has received more and more attention. The LiDAR has the advantages of higher resolution, stronger resistance to active interference, and good low-altitude detection performance. It is of great theoretical and practical significance to reasonably place multiple sensors, make up for the defects of a single type of sensors through sensor information fusion technology, and improve the safety and reliability of the whole intelligent driving system.

There is no doubt that the positions and number of sensors greatly affect the perceived performance of autonomous vehicles. How to optimize the multi-sensor configuration scheme has received some attention from researchers and engineers. A part of the group focused on the optimal configuration of a single type of sensor, such as LiDAR sensor [5], [8] and Ultrasonic sensor [4], and studied how to solve the environmental sensing problem for autonomous vehicles. To address the problem of lane change crashes caused by insufficient blind spot detection, Jamaluddin et al. [4] analyzed the effect of the ultrasonic radars' positions on the driver notification function. Meadows et al. [8] proposed a LiDAR placement optimization method for off-road autonomous vehicles. The AV Simulator was used to generate labeled LiDAR data, and the effects of different sensor poses on perceptual performance were analyzed based on a well-trained neural network by using these data. Kim and Park [5] proposed a genetic algorithm-based placement optimization (i.e., position and orientation) method of multiple 3-D LiDARs, considering the data density

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and blind spot.

Chen et al. [1] proposed a laser and camera-based cooperative sensing design scheme for autonomous vehicles to detect road curbs, lane lines, and recognize traffic signs. The vehicle assembled with multi-sensors according to the cooperative scheme won the 2010 Future Challenge. Dey et al. [2] proposed a so-called VESPA framework to obtain the optimal configuration scheme of four different types of sensors on vehicles, including the camera, LiDAR, radar, and ultrasonic. With this framework, the optimal placement and orientation of heterogeneous sensors can be acquired. Hartstern et al. [3] constructed a simulation-based evaluation method for sensor placement of automotive vehicles in an attempt to realize the conceptual design of the sensor systems, where the effects of sensors' placement locations on surround-view coverage and object detection are analyzed through virtual testing. Pramanik et al. [10] proposed two formulations for optimal multi-sensor configuration on vehicles based on variational quantum algorithms, while one is the fixed sensor-count-based formulation and the other is the approximate set-coverage-based formulation. Four regions of interest (RoIs) of the vehicle (front, left, right, and back) are considered separately to compare the performance, i.e., coverage and cost, of the classical and universal quantum models.

In this paper, we propose an optimal configuration method for multiple source sensors based on quantitative calculation, which can improve the safety and reliability of the whole intelligent driving system by ensuring coverage and redundancy while reducing the cost, thus improving the shortcomings of the existing sensors' placement scheme.

The remainder of this paper is organized as follows: Section II presents the framework of optimal configuration for a multi-sensor perception system; Section III formulates the optimal configuration problem with a multi-sensor perception system; Section V performs a case study to study the effects of the optimal configuration scheme; and Section VI concludes this paper.

II. Framework of Optimal Configuration for Multi-Sensor Perception System

The framework of optimal configuration for a multi-sensor perception system is shown in Fig. 1.

1) Determining the size and parameters of the autonomous vehicle's solid-state LiDAR, camera, millimeter wave radar, and ultrasonic radar, such as field of view (FoV) and range, according to their models

2) Dividing the range of interests (RoIs) according to the vehicle model, with the RoIs composed of core and extended RoIs, requiring the coverage and redundancy of the core RoIs to be higher than the extended RoIs.

3) Designing a RoIs discretization mechanism according to the functions and sensing range of various sensors and proposing a feasible sensor placement area division method applicable to this vehicle model

4) Considering the cost, coverage, and redundancy, determining the quantitative optimal configuration scheme of multi-source sensors and constructing a mixed integer programming model to obtain the optimal number of sensors and placement positions.

5) Setting the parameters in the objective function and constraints, solving the formulated problem based on the IBM ILOG CPLEX solver, and outputting the optimal multi-sensor configuration scheme.

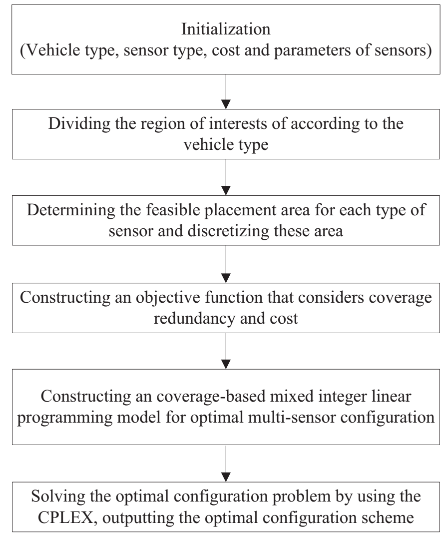

Fig. 1. Framework of optimal configuration for multi-sensor perception system.

Based on the basic parameters determined by modules (1)-(2) in the above process, the objective function and model are constructed by dividing the feasible placement area of sensors according to modules (3)-(4), and the CPLEX solver is applied to generate the optimal multi-sensor configuration scheme.

III. Formulation of Optimal Configuration Problem with Multi-Sensor Perception System

A. Solid-State LiDAR

In this paper, the solid-state LiDAR with the model of RS-LiDAR-M1 from RoboSense was chosen to study the optimal configuration of multi-sensors. The LiDAR is stable, reliable, and up to automotive-grade standards for passenger and commercial vehicles. The main specifications of the RS-LiDAR-M1 are shown in Table I.

B. Scenario Description

In order to describe the optimal configuration problem of multi-source sensors for autonomous vehicles, a certain car model is selected and its top view is shown in Fig. 2.

The region of interest (RoI) is divided according to the vehicle model, and the self-driving vehicle RoI is divided into the core RoI and the extended RoI, with the coverage and redundancy requirements of the core RoI being higher than those of the extended RoI, as shown in Fig. 3. The RoI of an autonomous vehicle is $P_Z = P_1 \cup P_2 \cup P_3 \cup P_4 \cup P_5 \cup P_6$.

TABLE I
THE MAIN SPECIFICATIONS OF THE RS-LIDAR-M1.

Paramenter	Value
Laser Wavelength	905 nm
Range	200 m (150 m @10% $NIST$)
Horizontal FoV	120^o (-60^o $+60^o$)
Vertical FoV	25^o (-12.5^o $+12.5^o$)
Accuracy (Typical)	± 5 cm ($1sigma$)
Frame Rate	10 Hz
Blind Spot	$\leq 0.5m$
Horizontal Resolution	0.2^o ($Average$)
Vertical Resolution	0.2^o ($Average$)
Power Consumption	15 W

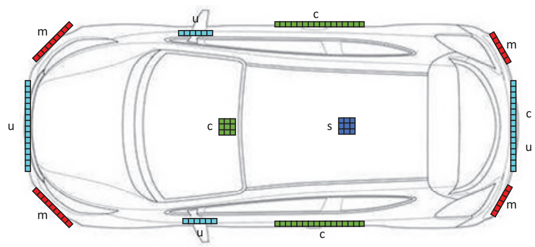

Fig. 2. Top view and feasible placement area division of the autonomous vehicle.

The core RoI is $P_1 \sim P_4$ and its area is S_{core}. The extended RoI is $P_5 \sim P_6$ and its area is S_{extend}.

The horizontal FoVs and ranges of four types of sensors are shown in Fig. 4. The parameters of the camera, millimeter wave radar, and ultrasonic radar, such as FoV and range, are determined, as shown in Table. II.

TABLE II
THE MAIN PARAMETERS OF THE CAMERA, MILLIMETER WAVE RADAR, AND ULTRASONIC RADAR.

Sensor	horizontal FoV	Range
Camera	60^o (-30^o $+30^o$)	150 m
Millimeter wave radar	120^o (-60^o $+60^o$)	100 m
Ultrasonic radar	120^o (-60^o $+60^o$)	2.5 m

According to the functions and sensing ranges of various sensors, a sensing area discretization mechanism is designed, as shown in Fig. 5, to discretize the sensing area of the intelligent vehicle into a square area of size $l \times l$. In order to simplify the computational complexity caused by the irregularity of the sensor coverage area, an approximate calculation method is proposed, and when the covered square area is larger than $\frac{1}{2}l^2$, the covered area is recorded as l^2, otherwise, it is recorded as 0.

This paper proposes a method of dividing the feasible arrangement area of sensors applicable to this vehicle model, as shown in Fig. 2. For different types of sensors, the feasible arrangement area is set considering their features, $s \in \{1,2,\ldots,S\} = \mathbf{S}$, $c \in \{1,2,\ldots,C\} = \mathbf{C}$, $m \in \{1,2,\ldots,M\} = \mathbf{M}$, and $u \in \{1,2,\ldots,U\} = \mathbf{U}$, indicating the feasible arrangement location variables of solid-state LiDAR, camera, millimeter wave radar, and ultrasonic radar, respectively. S, C, M, U are positive integers.

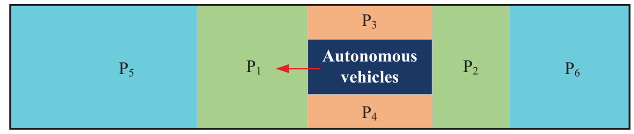

Fig. 3. Regions of interest (RoIs) division: Core RoIs (P1-P4) and extended RoIs (P5-P6).

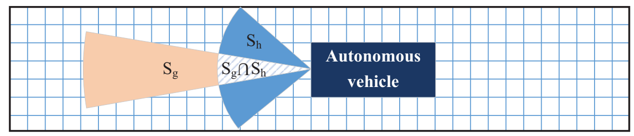

Fig. 5. Effective FoV calculation for autonomous vehicle (top view).

C. Assumptions

The following assumptions are made to facilitate the problem formulation.

1) The variation of sensor placement angle is not considered in this paper. The sensors are placed at an angle perpendicular to the surface of the vehicle.

2) Placement positions of sensors on the vehicle surface are mapped to the horizontal direction.

D. Decision variables

The optimal configuration of multi-source sensors is determined quantitatively by considering the cost, coverage, and redundancy. A mixed integer programming model is built to obtain the optimal number of sensors and their placement positions. Four binary decision variables were first defined to determine the location of each of the four sensor arrangements.

$$\alpha_s = \begin{cases} 1, & \text{If a solid state LiDAR is assigned to } s \\ 0, & \text{Otherwise} \end{cases} \tag{1}$$

where $s \in \{1,2,\cdots,S\}$, the value of α_s is 1 if position s is arranged with a solid-state LiDAR, otherwise is 0.

$$\beta_c = \begin{cases} 1, & \text{If a camera is assigned to } c \\ 0, & \text{Otherwise} \end{cases} \tag{2}$$

where $c \in \{1,2,\cdots,C\}$, the value of β_c is 1 if position c is arranged with a camera, otherwise is 0.

$$\chi_m = \begin{cases} 1, & \text{If a millimeter wave radar is assigned to } m \\ 0, & \text{Otherwise} \end{cases} \tag{3}$$

where $m \in \{1,2,\cdots,M\}$, the value of χ_m is 1 if position m is arranged with a millimeter wave radar, otherwise is 0.

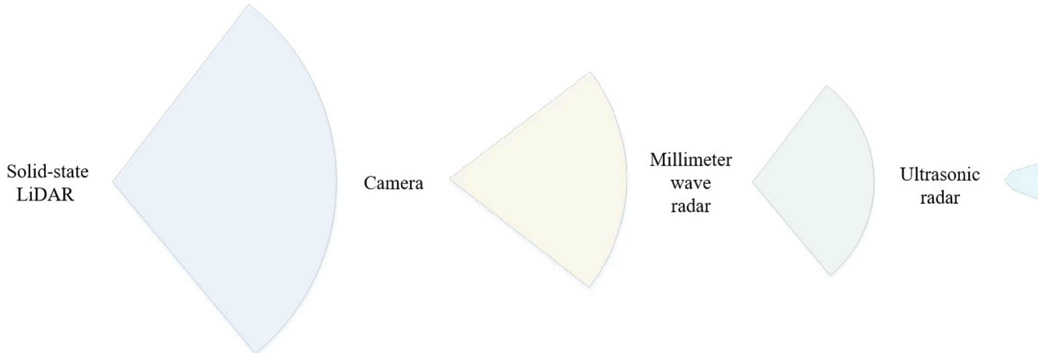

Fig. 4. The schematic for horizontal FoVs and ranges of four type of sensors.

$$\delta_u = \begin{cases} 1, & \text{If a ultrasonic radar is assigned to } u \\ 0, & \text{Otherwise} \end{cases} \quad (4)$$

where $u \in \{1, 2, \cdots, U\}$, the value of δ_u is 1 if position u is arranged with a ultrasonic radar, otherwise is 0.

E. Scheme formulation

A mixed integer programming model is constructed with the goal of minimizing the cost and maximizing the covered area and redundancy area of multi-source sensors. To ensure the consistency of the sum optimization objective, we define three sub-objectives, i.e., the cost, coverage, and redundancy. The multi-objective optimization function is designed as follows.

$$O = \min(\psi_1 O_1 + \psi_2 O_2 + \psi_3 O_3) \quad (5)$$

where O_1, O_2, and O_3 denote the cost, coverage and redundancy, respectively. ψ_1, ψ_2, and ψ_3 indicates the weights of the three sub-objectives.

The cost is determined by the price of the sensors, which is defined as follows.

$$O_1 = \omega_1 \sum_{s=1}^{S} \alpha_s + \omega_2 \sum_{c=1}^{C} \beta_c + \omega_3 \sum_{m=1}^{M} \chi_m + \omega_4 \sum_{u=1}^{U} \delta_u \quad (6)$$

where $\sum_{s=1}^{S} \alpha_s$, $\sum_{c=1}^{C} \beta_c$, $\sum_{m=1}^{M} \chi_m$, and $\sum_{u=1}^{U} \delta_u$ represent the total number of solid-state LiDAR, camera, millimeter wave radar and ultrasonic radar, respectively. ω_1, ω_2, ω_3, and ω_4 indicate the price of each of the 4 types of sensors, respectively.

Coverage is defined as the weighted sum of the core sensing area coverage and the extended sensing area coverage.

$$O_2 = \sigma_1 \frac{S_{core}}{F_{eff}} + \sigma_2 \frac{S_{extend}}{F_{ext}} \quad (7)$$

where F_{eff} and F_{ext} denote the FoVs of effective core RoIs and extended RoIs, respectively, and σ_1 and σ_2 denote the importance of the two types of coverage, and usually σ_1 is larger than σ_2.

The effective FoV of N_{sum} sensors is defined as follows.

$$\begin{aligned} F_1 \cup F_2 \cup \cdots \cup F_{N_{sum}} = & \sum_{1 \le i \le N_{sum}} F_i - \sum_{1 \le i \le j \le N_{sum}} F_i \cup F_j \\ & + \sum_{1 \le i \le j \le k \le N_{sum}} F_i \cup F_j \cup F_k - \cdots \\ & + (-1)^{N_{sum}-1} F_i \cup F_j \cup \cdots \cup F_{N_{sum}} \end{aligned} \quad (8)$$

where F_* represents the FoV of a sensor $* \in \{\mathbf{S}, \mathbf{C}, \mathbf{M}, \mathbf{U}\}$.

Redundancy is the ratio of the total RoIs to the redundant FoVs of multiple source sensors, which is defined as follows.

$$O_3 = \nu \cdot \frac{S_{core} \cup S_{extend}}{\bigcup_{g \ne h} (S_g \cap S_h)} \quad (9)$$

where $S_{core} \cup S_{extend}$ is the area of the RoIs of the autonomous vehicle, F_g and F_h represent the FoV covered by sensors g and h. $F_g \cap F_h$ corresponds to the area of the redundant FoV covered by two sensors, as shown in Fig. 5, and $\bigcup_{g \ne h} (F_g \cap F_h)$ represents the sum of the effective redundant areas covered by all sensors.

The constraints to be satisfied are as follows.

$$S_{core} \times \gamma_1 \le F_{eff} \quad (10)$$

where $\gamma_1 \in [0, 1]$. It indicates that the effective core FoVs of the multi-source sensor cannot be less than γ_1 times the core RoIs.

$$S_{extend} \times \gamma_2 \le F_{ext} \quad (11)$$

where $\gamma_2 \in [0, 1]$. It indicates that the effective extension FoVs of the multi-source sensor cannot be less than γ_2 times of the extended RoIs.

$$(S_{core} \cup S_{extend}) \times \gamma \le \bigcup_{g \ne h} (F_g \cap F_h) \tag{12}$$

where $\gamma \in [0,1]$. It indicates that the redundancy of FoVs cannot be less than γ times the total RoIs.

$$N_s^{min} \le \sum_{s=1}^{S} \alpha_s \le N_s^{max} \tag{13}$$

where N_s^{max} and N_s^{max} are constants. Considering the high cost of solid-state LiDAR, its number should be in the range of $(N_s^{\min}, N_s^{\max})$. For the solid-state LiDAR-free scheme, the values of these two parameters are set to 0.

$$N_m^{\min} \le \sum_{m=1}^{M} \chi_m \le N_m^{\max} \tag{14}$$

Considering the limited optional placement locations of millimeter wave radar, its number should be in the range of $(N_m^{\min}, N_m^{\max})$.

$$N_c^{\min} \le \sum_{c=1}^{C} \beta_c \le N_c^{\max} \tag{15}$$

The number of camera should be in the range of $(N_c^{\min}, N_c^{\max})$.

$$N_u^{\min} \le \sum_{u=1}^{U} \delta_u \le N_u^{\max} \tag{16}$$

The number of ultrasonic radars should be within the range of $(N_u^{\min}, N_u^{\max})$. Generally, ultrasonic radars are installed on the front and rear bumpers of a vehicle to measure obstacles and enable automatic parking assist systems.

$$\alpha_s \in \{0,1\}, \beta_c \in \{0,1\}, \chi_m \in \{0,1\}, \delta_u \in \{0,1\} \tag{17}$$

F. Solution procedure

The formulated optimization problem in the previous section is a typical 0-1 integer linear programming problem. The IBM ILOG CPLEX solver is used to solve the problem and generate the optimal multi-sensor configuration scheme.

IV. CASE STUDY

In this section, we choose a model of a well-known vehicle brand to verify the effectiveness and feasibility of the method proposed in this paper. The parameters of the vehicle are as follows: the length, width, and height are 4930 mm, 2004 mm, and 1776 mm respectively, and the wheelbase is 2975 mm.

At first, we designed two control schemes: one is an empirically determined multi-sensor configuration scheme (also called the baseline scheme) and the other is a solid-state LiDAR-free multi-sensor configuration scheme.

(1) Baseline scheme: Solid-state LiDAR*1, Camera*4, Millimeter wave radar*3, Ultrasonic radar*4.

(2) Solid-state LiDAR-free scheme: Camera*6, Millimeter wave radar*4, Ultrasonic radar*4.

The parameters of the sensors used in this paper are shown above section. The model parameters are set as follows. $\omega_1 = 30000$, $\omega_2 = 2000$, $\omega_3 = 2000$, $\omega_4 = 400$, $\sigma_1 = 10000$, $\sigma_2 = 8000$, $\nu = 10000$, $\gamma_1 = 99.5\%$, $\gamma_2 = 99\%$, $\gamma = 50\%$, $\psi_1 = 0.25$, $\psi_2 = 3$, $\psi_3 = 2.5$.

The FOVs of an autonomous vehicle under the solid-state LiDAR-based multi-sensor configuration scheme are shown in Fig. 6. This solution has a high level of coverage and redundancy. In this scheme, two solid-state LiDARs are placed on the top of the autonomous vehicle, with one directed to the front and the other to the back. Two cameras are placed in the front windshield and the back of the vehicle, and millimeter wave radars are placed in the front and sides of the vehicle. Finally, four ultrasonic radars, which are usually used for parking assistance, are placed on the four corners.

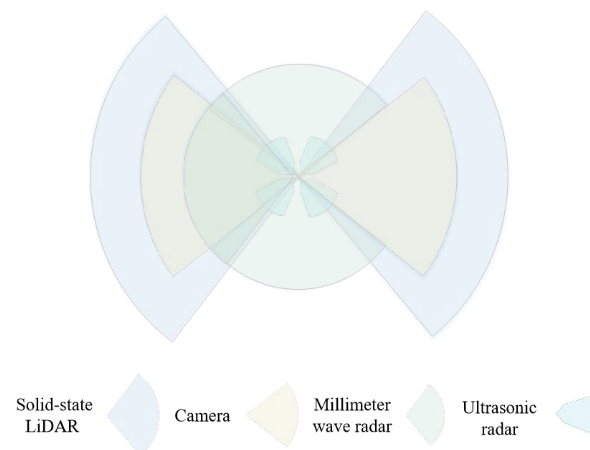

Fig. 6. The FoVs of autonomous vehicle under the multi-sensor configuration scheme.

Next, we compare the coverage, cost, and redundancy of three different configuration schemes. The results are shown in Table III. The overall cost of the optimal scheme is higher than that of the other two schemes due to the higher cost of solid-state LiDAR, but its coverage and redundancy can be guaranteed. The coverage rates under the three schemes are almost similar, with values above 18,000. On the contrary, the value of redundancy under the optimal scheme is the smallest, which is more than 40,000 lower than that of the solid-state LiDAR-free scheme. This is because the redundancy in this paper is defined as the ratio of the total RoIs to the redundant FoVs of multiple source sensors, so the better the performance, the smaller the value of the redundancy.

Then, the effect of the number of solid-state LiDARs on the perception performance of the autonomous vehicle is shown in Fig. 7. The optimal value of the objective function decreases with the increasing number of solid-state LiDARs

TABLE III
THE COMPARISON OF COVERAGE, COST AND REDUNDANCY UNDER THREE CONFIGURATION SCHEMES.

	Opt_Scheme	**Emp_Scheme**	**No_LiDAR_Scheme**
Coverage	18130	18466	18210
Cost	71600	45600	21600
Redundancy	16130	18860	21740

for the given parameters. Obviously, the cost also increases dramatically with the number of solid-state LiDARs. This is because the cost of solid-state LiDARs is much higher than that of cameras and other radars. Due to the large field of view of solid-state LiDARs, the redundancy and coverage under the solution with two solid-state LiDARs are higher than other solutions. Overall, the solid-state LiDAR-based multi-sensor perception solution proposed in this paper can meet the needs of environment perception for autonomous vehicles, and its coverage and redundancy are better than other schemes, but its cost is relatively high.

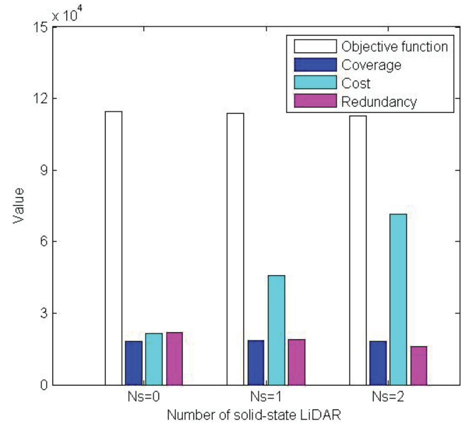

Fig. 7. Effect of the number of solid-state LiDAR on perception performance of the autonomous vehicle.

V. CONCLUSION

An efficient environment perception system can provide downstream modules with rich information, such as the location, shape, category, and speed of obstacles, as well as the semantic understanding of some special scenarios. The rational arrangement of the location of sensors according to their characteristics is one of the most important concerns of the perception system. This paper proposed an optimal multi-sensor configuration method for autonomous vehicles based on solid-state LiDAR, camera, millimeter wave radar, and ultrasonic radar. Considering the cost, coverage, and redundancy, a mixed integer programming model was built to determine the optimal number of sensors and placement positions. The optimal configuration scheme was obtained by using the IBM ILOG CPLEX solver. We chose a model of a well-known vehicle brand to verify the effectiveness and feasibility of the proposed method. The results show that the redundancy and coverage under the multi-sensor perception solution with two solid-state LiDARs are higher than other solutions. This can improve the safety and reliability of the whole intelligent driving system by ensuring coverage and redundancy.

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