Task-Specific Performance Evaluation of UGVs: Case Studies at the IVFC

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***Abstract*—Performance evaluation is considered as an important part of the unmanned ground vehicle (UGV) development; it helps to discover research problems and improves driving safety. In this paper, a task-specific performance evaluation model of UGVs applied in the Intelligent Vehicle Future Challenge (IVFC) annual competitions is discussed. It is defined in functional levels with a formal evaluation process, including metrics analysis, metrics preprocessing, weights calculation, and a technique for order of preference by similarity to ideal solution and fuzzy comprehensive evaluation methods. IVFC 2012 is selected as a case study and overall performances of five UGVs are evaluated with specific analyzed autonomous driving tasks of environment perception, structural on-road driving, unstructured zone driving, and dynamic path planning. The model is proved to be helpful in IVFC serial competition UGVs performance evaluation.**

***Index Terms*—Autonomy levels, comprehensive evaluation methods, driving tasks analysis, performance evaluation, unmanned ground vehicle (UGV).**

I. Introduction

PERFORMANCE evaluation is considered as an important part of the unmanned ground vehicle (UGV) research; it starts from UGV functions verification to overall performance assessment, helps to discover the research problems, and improves autonomous driving safety. Several previous work are good for reference, such as the DARPA Grand/Urban Challenge (DUC) and the European Land-Robot Trial robot competitions [1], [2], the "eVALUE" intelligent vehicles evaluation project [3], and recently the "Grand Cooperative Driving Challenge" [4]. These projects are dedicated to autonomously operating in a mock urban environment developing testing and evaluation methods for active vehicle safety and testing vehicles cooperative driving. The evaluation methodologies applied are traced back to the previous work on robotic autonomous levels definition of the NASA SMART project, MIT Automation Level Framework [5] and the NIST annual Performance Metrics for Intelligent Systems Workshop, which is devoted to the definition and testing of robot intelligence, intelligent systems benchmark, and autonomy of unmanned systems level (ALFUS) [7]. However, UGVs' testing in DUC similar games did not cover all the real traffic scenarios and certify safety driving, particularly when autonomous driving transited from constrained testing environment to real "scaling-up" traffic environment. When UGVs will have to move faster and deal with higher density traffic, how to manage the performance and collision risk is an important and urgent issue to make UGVs' safety travel in real traffic.

Further testing of UGV is now continued with Google's driverless car in public traffic [6], [40], German Technical University of Braunschweig autonomous car BLeonie tested in heavy traffic [8], and VisLab Intercontinental Autonomous Challenge starting from Italy to Shanghai Expo 2010 [9].

Since 2009, with the support of the National Natural Science Foundation of China, the Intelligent Vehicle Future Challenge (IVFC) has been annually held as a UGV competition event, which also aims to achieve autonomous driving in real traffic. The authors participated in the IVFC competition's proposal, organization, and judgment. Based on these practices and other related research studies [10]–[14], [31], [34], [44], [47], a task-specific UGV performance evaluation model is discussed in this paper. The first section is the related work introduction. The second section is the description of the task-specific UGV performance evaluation model. The third section is the methodologies analysis of UGV performance evaluation. The fourth section is the overview of UGVs performance evaluation at IVFC competitions. The fifth section is the case study of UGVs performance evaluation at IVFC 2012, including environment perception, structural on-road driving, unstructured zone driving, and dynamic path-planning tasks analysis. The final section is the conclusion and future work of UGVs performance evaluation.

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II. Task-Specific UGV Performance Evaluation Model

UGV autonomous driving functions mainly include environment perception, motion planning, mission execution, and mission planning [15]–[20]. A task-specific UGV performance evaluation model is in functional levels, avoiding the complexities of tremendous algorithms evaluation, similar to gray box testing, as shown in Fig. 1.

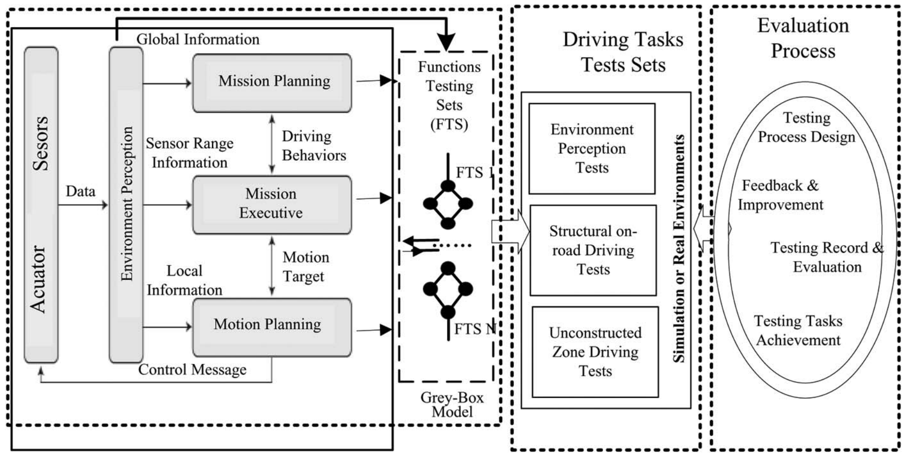

Fig. 1. UGV performance evaluation model based on driving tasks analysis.

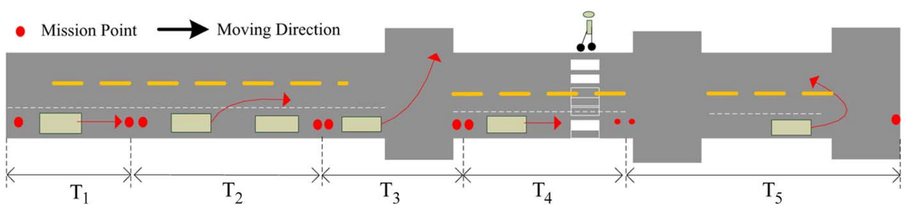

Fig. 2. UGV testing driving tasks design.

By analyzing UGV functions, lists of simple function test cases are selected and assembled into different testing processes [21], which are further abstracted as driving tasks sets. Environment perception is the basic function. UGV percepts and fuses data of structural road, unconstructed zone, traffic signals, and static and dynamic obstacles by vehicle-mounted cameras, radar, and lidar sensors [18], [45]. By analyzing specific driving tasks, UGV environment perception function can be evaluated [22]. Motion planning and mission execution are key functions that decide the UGV autonomous driving performance [23]. Structural on-road driving includes tasks set of straight and curved roads driving, car following, obstacle avoiding, lane changing, and overtaking. Unconstructed zone driving includes tasks set of intersections, parking lots and congested traffic driving, and other error states recovery. The mission-planning function consists of tasks set of path planning, traffic congestion and safety forecasting, and traffic laws complication.

Accordingly, UGVs driving task tests are carried out under different simulation or real environments. By a formal evaluation process, including tests design, recording and evaluation, and completion verification, all driving tasks completions are finally evaluated.

Driving tasks are defined as T_i, which can be further divided into subtasks $T_i = \{t_{1i}, t_{2i}, \ldots, t_{ni}\}$, $n \geq 1$. Each T_i is with different task complexity property, which is assessed according to the atomic sequences of autonomous maneuvers and evaluated under different environment complexities.

Driving tasks are always set along the test routes and divided by mission points (GPS coordinates in defined mission file); as an example, T_1 (On-road Driving), T_2 (Overtaking), T_3 (Turn Left), T_4 (Pedestrian Avoidance), and T_5 (U-TURN) are set along the competition route and divided by mission points, as shown in Fig. 2. The driving environments are rebuilt or modified according to the appropriate testing tasks.

TABLE I
OVERVIEW OF IVFC ANNUAL COMPETITIONS

Date & Loc	Teams	Mileages	Completion
June 4, 2009, XI'AN	6	2.6 km, Park Internal Road	Complete with heavy intervention
Oct 16, 2010, XI'AN	10	3.7 km, vehicles proving ground	2 teams completed with intervention
Oct 20, 2011,Odos	9	10 km, Urban Road	2 teams completed with intervention
Oct 31,2012, Chifeng	14	6.7 km, urban road, 16 km rural road	9 teams completed, urban road fastest 26 min, rural road 35 min

TABLE II
TESTING TASKS SETS OF IVFC 2009 TO IVFC 2012

Basic Tasks (Set A)	Simple Tasks (Set B)	Complex Tasks (Set C)
①Task starting ②Driving right side ③pass way-point; ④Lane keeping ⑤Speed control ⑥Emergence stop ⑦Obstacle avoidance ⑧Distance keeping ⑨Left and right turns ⑩Stop task	①Traffic sign and lane marks detection ②Traffic signals detection ③Lane changing, overtaking; ④U-turn execution ⑤Reversing ⑥Pedestrian avoidance ⑦Using lights	①Parking. /Parallel park, Roadside stop ②Driving through the intersection ③Roundabout driving ④Driving overpass ⑤ Freeway driving; ⑥Make way for emergency vehicles ⑦Driving into traffic ⑧Dynamic path planning.

IVFC Competitions Evaluated Tasks	2009:	2010:	2011:	2012:
	A,	A,	A,	A,
	B: 1,2,4	B: 1,2,3	B: 1,2,3,4	B: 1,2,3,4,6,7
	C: 1	C: 1,3	C: 1,2,7	C: 1,2,7,8

The task-completion levels are defined as G_i. Evaluated task complexity and environment complexity are synthesized as the weight W_i of each task completion levels G_i. With G_i and W_i, the overall UGV performance is evaluated.

Fig. 3. IVFC (a) 2009, (b) 2010, (c) 2011, and (d) 2012 competition routes and driving environments (urban).

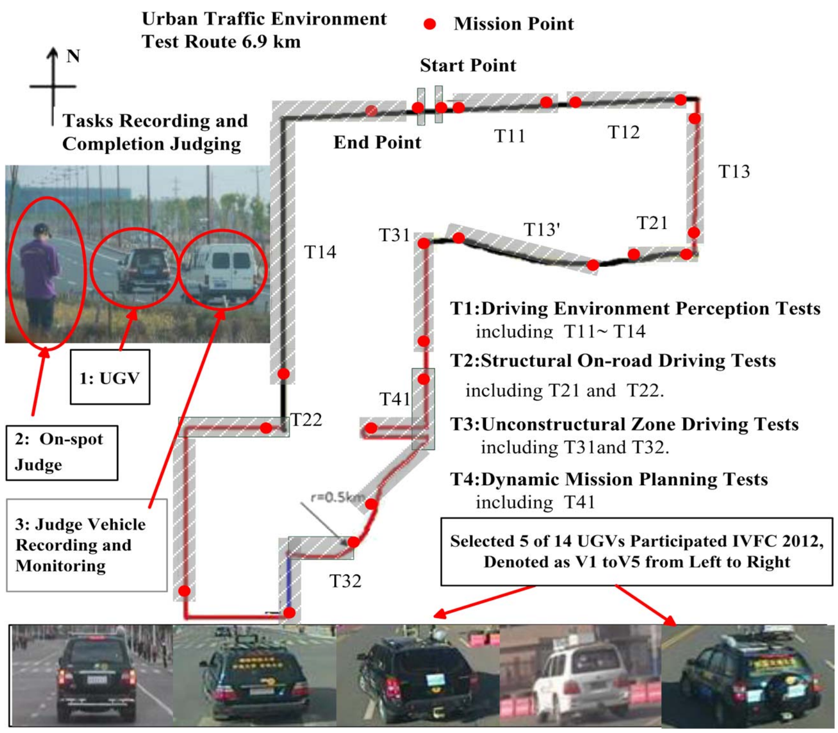

Fig. 4. IVFC 2012 overview.

III. Overview of UGVs' Performance Evaluation at the IVFC Competitions

A. IVFC Competitions Overview

The overview of the IVFC 2009 to IVFC 2012 serial competitions is shown in Table I.

The evaluated driving tasks are classified into Basic Tasks, Simple Tasks, and Complex Tasks (sets A, B, and C, respectively), as shown in Table II.

The annual competition urban routes with different environment complexities are shown in Fig. 3, in which IVFC 2009 and IVFC 2010 are constrained roads, and IVFC 2011 and IVFC 2012 are open urban road, with slight artificial modifications.

B. IVFC 2012 as a Study Case

In this paper, IVFC 2012 is selected as a study case and five UGVs are chosen from a total of 14 UGVs as analysis objects, which are denoted by V1–V5. A judge vehicle runs behind each UGV, which is responsible for the preceding UGV emergency stop, traffic laws following observation, and evaluation metrics measurement. On the critical evaluation road sections, there are on-spot judges responsible for metrics (time, velocity, and distance), recording, and measurement.

As shown in Fig. 4, IVFC 2012 evaluation tasks are classified into T1–T4. Every task completion is evaluated by several metrics. Some metrics can be measured by the instrumental devices installed on the closely following judge vehicles. Vehicle odometer and wheel encoder are for long-range measurement of UGV driving distance. Calibrated cameras are for short-range distance estimation. A speedometer is for vehicle speed estimation and a timer is for recording the time to complete the task. Some metrics are difficult to measure. They should be observed and recorded by the on-spot judges or obtained by analyzing the recorded video after the competition.

Some metrics cannot be directly measured. They should be acquired by comprehensive methods, such as discussion with judges and analyzing the recorded videos.

IV. Methodologies of UGV Performance Evaluation

UGV performance evaluation methodologies consist of metrics preprocess, metrics selection, weights computing,

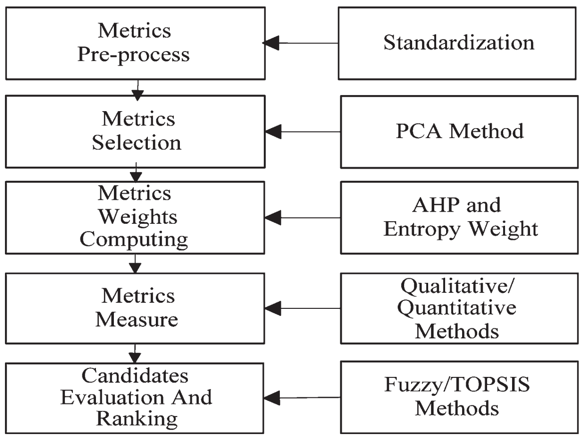

Fig. 5. UGV performance evaluation methodologies.

measurement, and UGV candidates' comprehensive evaluation and ranking, as shown in Fig. 5, in which principal component analysis (PCA), analytic hierarchy process (AHP), fuzzy comprehensive, and technique for order of preference by similarity to ideal solution (TOPSIS) methods are applied. With these methodologies, UGV performance is evaluated.

A. Evaluation Decision Matrix Representation

The evaluation decision matrix X is denoted by

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{pmatrix} \end{array}.$$

x_{ij} represents the score of evaluated candidates $A_i = \{x_{i1}, x_{i2}, \ldots, x_{in}\}$ under evaluation metric C_i, and $x_{ij} \geq 0$ $(1 \leq i \leq M, 1 \leq j \leq N)$. Its weight is set to be w_j and $\sum_{j=1}^{n} w_j = 1$.

B. Evaluation Metrics Preprocessing

The UGV performance evaluation metrics can be classified into max type (benefits, larger is better) and min type (cost, smaller is better). All the evaluation metrics should be standardized as max type with (1) or min type with (2), i.e.,

$$x_{ij}^* = \frac{x_{ij} - \min_i(x_{ij})}{\max_i(x_{ij}) - \min_i(x_{ij})}, \quad 1 \leq i \leq M, 1 \leq j \leq N \tag{1}$$

$$x_{ij}^* = \frac{\max_i(x_{ij}) - x_{ij}}{\max_i(x_{ij}) - \min_i(x_{ij})}, \quad 1 \leq i \leq M, 1 \leq j \leq N. \tag{2}$$

In preprocessing, we standardize the evaluation metrics as max type with (1).

C. Evaluation Metrics Selection

When there are too much metrics of task completion G_i, we need to find out the most effective metrics and exclude the redundant and secondary metrics vectors by linear transformation. PCA is a well-studied method for reducing the dimension in multivariate data and it is applied to be practically used in many fields [36], and the principle metrics are computed as the following simplified steps.

Get the decision matrix metric correlate coefficient and construct a matrix $R = [r_{ij}]_{p \times p}$, where

$$r_{ij} = \frac{1}{n-1} \sum_{t=1}^{n} r_{ti} \times r_{tj} (i, j = 1, 2, \ldots, p). \tag{3}$$

Get the characteristic roots of matrix R and sort in decreased order, i.e., $\lambda_i^* (i = 1, 2, \ldots, p)$. Select the top m metrics as $\lambda_i^* (i = 1, 2, \ldots m)$. Get the λ_i^* related eigenvectors matrix, i.e., P_1. Decision matrix of principal metrics is presented as $X' = (XP_1)_{n \times m}$.

D. Evaluation Metrics' Weights Computing

The evaluation metrics' weights are interfered by subjective deviations when they are directly assigned. When applying the AHP method [41], the weights can be mathematically achieved from the relative importance matrix that is obtained by the pairwise comparison between the factors according to the relative importance assigned by the UGVs evaluation judges. Therefore, the deviations can be decreased.

1) AHP Metrics' Weights: The pairwise comparisons matrix is denoted by $A = [a_{ij}]_{n \times n}$ (a_{ij} represents the importance of metrics c_i and c_j to the higher level). The maximum eigenvalue $\lambda_{\max}$ and eigenvector $\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$ are computed. Random consistency ratio is calculated with $\lambda_{\max}$ and the inconsistent degree of matrix A is checked for acceptation. Eigenvector $\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$ can be accepted and normalized as α', which is considered as the weights of the selected metrics.

2) Entropy Metrics' Weights: To further decrease the subjective preferences, we proposed a combination of AHP and entropy weights method [43], which can reflect both the subjective and objective properties of the evaluation and more easily distinguish the metrics difference.

The entropy weights are determined by the amount of objective information provided by each metric's value. When the differences of elements in a given metric vector are much bigger, the amount of objective information and its entropy are greater.

The entropy weight $\beta = \{\beta_1, \beta_2, \ldots, \beta_n\}$ can be calculated through the following steps.

Calculate the entropy value e_j of metric β_j, i.e.,

$$e_j = -k \sum_{i=1}^{m} f_{ij} \ln f_{ij}, \quad j = 1, 2, \ldots, n \tag{4}$$

where $f_{ij} = x_{ij} / (\sum_{i=1}^{m} x_{ij})$, $k = 1/\ln m$; when $f_{ij} = 0$, $f_{ij} \ln f_{ij} = 0$.

Calculate the degree of diversity of metric β_j, i.e.,

$$d_j = 1 - e_j, \quad j \in [1, n]. \tag{5}$$

Calculate the weight of metric β_j, i.e.,

$$\beta_j = \frac{d_j}{\sum_{i=1}^{n} d_j} = \frac{1 - e_j}{n - \sum_{i=1}^{n} e_j}, \quad j \in [1, n]. \tag{6}$$

Finally, the multiply results of the multiply combination of AHP weights $\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$, $\alpha_i > 0$, and entropy weights $\beta = \{\beta_1, \beta_2, \ldots, \beta_n\}$, $\beta_i > 0$, are denoted by

$$\omega_j = \frac{\alpha_j \beta_j}{\sum_{j=1}^{n} \alpha_j \beta_j}, \quad (j = 1, 2, \ldots, n). \tag{7}$$

E. Comprehensive Evaluation

In this paper, fuzzy and TOPSIS comprehensive methods are used to integrate the evaluation metrics. The fuzzy method is very convenient in a comprehensive evaluation [42], [43]. There are many studies of this method for solving the qualitative and quantitative complex problems with fuzzy concepts. The TOPSIS method is one of the well-known methods for classical multicriteria decision making, based on the concept of the positive ideal solution (PIS, maximizes the benefit criteria and minimizes the cost criteria) and the negative ideal solution (NIS, reverse of PIS) [37]. The basic principle of TOPSIS is that the chosen alternative should have the shortest distance from the PIS and the farthest distance from the NIS. The computation involved is simple, as shown in the following.

1) Fuzzy Comprehensive Evaluation: In the two-level model of the fuzzy comprehensive evaluation method, the decision matrix is denoted by $R = (R_1, R_2, \ldots, R_m)^T$ and the weights of the metrics set are denoted by $W = \{\omega_1, \omega_2, \ldots, \omega_m\}$, where $\sum \omega_i = 1$. Fuzzy operator * transforms W and R to Y, i.e., $Y = W^* R$.

2) TOPSIS Comprehensive Evaluation: Decision matrix R combines with weight ω_j and builds the standardized decision matrix Z, which is denoted by

$$Z = (z_{ij})_{m\times n} = \begin{pmatrix} \omega_1 x_{11} & \omega_2 x_{12} & \ldots & \omega_n x_{1n} \\ \omega_1 x_{21} & \omega_2 x_{22} & \ldots & \omega_n x_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ \omega_1 x_{m1} & \omega_2 x_{m2} & \ldots & \omega_n x_{mn} \end{pmatrix}. \tag{8}$$

The sets of the positive ideal point (PIP, z^+) and the negative ideal point (NIP, z^-) of the evaluated object, respectively, are

$$\begin{aligned} z^+ &= \{z_1^+, z_2^+, \ldots, z_n^+\} \\ &= \left\{ \left(\max_{1\le i\le m} z_{ij} \,|\, j \in J_1 \right), \left(\min_{1\le i\le m} z_{ij} \,|\, j \in J_2 \right) \right\} \end{aligned} \tag{9}$$

$$\begin{aligned} z^- &= \{z_1^-, z_2^-, \ldots, z_n^-\} \\ &= \left\{ \left(\min_{1\le i\le m} z_{ij} \,|\, j \in J_1 \right), \left(\max_{1\le i\le m} z_{ij} \,|\, j \in J_2 \right) \right\} \end{aligned} \tag{10}$$

where J_1 and J_2 are max-type and min-type metrics, respectively.

The weighted Euclidean distances of (D_i, D^+) and (D_i, D^-) are respectively computed as

$$\begin{aligned} D_i^+ &= \sqrt{\sum_{j=1}^{n} \left(z_{ij} - z_j^+\right)^2} \\ &= \sqrt{\sum_{j=1}^{n} (z_{ij} - \omega_j)^2} \quad (i = 1, 2, \ldots, m) \end{aligned} \tag{11}$$

$$\begin{aligned} D_i^- &= \sqrt{\sum_{j=1}^{n} \left(z_{ij} - z_j^-\right)^2} \\ &= \sqrt{\sum_{j=1}^{n} (z_{ij})^2} \quad (i = 1, 2, \ldots, m). \end{aligned} \tag{12}$$

Compute the relative closeness of each alternative to the ideal solution. The relative closeness of the alternative D_i with respect to D^+ is defined as

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad i = 1, 2, \ldots, m. \tag{13}$$

Rank the alternatives according to the relative closeness to the PIS. The best alternative is the one with the greatest relative closeness to the PIS.

V. Case Study of UGVs' Performance Evaluation at IVFC 2012: Environment Perception Tests

Environment perception is the basic autonomous driving function, which includes structural road, traffic signals, dynamic and static obstacles detection, and position estimation by vehicle-mounted cameras, radar, and lidar sensors, and UGV percepts and fuses data of different environments [18], [45]. Therefore, by analyzing UGV driving tasks with specific metrics, UGV environment perception function can be evaluated [22]. UGVs performances in IVFC 2012 are shown in Fig. 6(a)–(d).

A. Structural Road Detection Tests

The road is always presented as a curve model in UGV perception module, i.e.,

$$s(t) = [x(t), y(t), \varphi(t), C_0(t), C_1(t), W(t)]. \tag{14}$$

$[x(t), y(t), \varphi(t)]$ represents the origin and orientation of the base of the curve, $C_0(t)$ is the curvature of the road, $C_1(t)$ is the rate of curvature, and $W(t)$ is the road width.

A Taylor series representation of a clothoid is used to generate the actual curve, which is denoted by

$$y(x) = \tan[\varphi(t)]\, x + C_0 \frac{t}{2} x^2 + C_1(t) \frac{t}{6} x^3. \tag{15}$$

The difficulties of structural road tests lie in detection of sudden changes of road shape and slope and detection of road lane, curb, and concave obstacles, which need good algorithms and prediction models [20], [23], [26], [29]. The goodness of

Fig. 6. UGVs environment perception tests analysis (IVFC 2012). (a) Structural road detection. (b) Traffic signs detection. (c) Static obstacles detection. (d) Dynamic obstacles detection.

fit between the clothoid and the actual road curve is as an important metric to the algorithms; and the accuracy of the detection of road shape, curb, and other obstacles also reflects the perception system performance.

However, it is more convenient to select the offset between UGV trajectory and real lane center as a metric of the former road model, which can be presented as in (16), where N is the measuring point number, P_i is the measurement point to the lane center line distance, and pc_i is the real projection point of the lane model center line, i.e.,

$$e_L = \frac{1}{N}\sum_{i=1}^{N} |(p_i - pc_i)| . \tag{16}$$

The UGV is proposed to be in the middle of lanes and the lane width is known as 2.8 m in IVFC 2012. In straight road sections, UGVs trajectory and real lane center offsets are sampled and measured by the on-spot judges and through analysis of the recorded video, as shown in Fig. 6(a).

B. Traffic Signals and Obstacles Detection Tests

1) Traffic Signals Detection Testing: It is a challenge to achieve robust real-time detection of the traffic lights and traffic signs in urban environment. Complex lighting conditions, varied changed shapes, coverage, and wear out of the traffic signs also increased the difficulty of the traffic signs detection. Many methods are applied to enhance the robustness [30]. Several camera-based methods are used to detect traffic light real-time states, such as combining vehicle localization and assuming prior knowledge of traffic light location and then applying a template-matching algorithm [32]. The laser-based sign detector is combined with trained support vector machine algorithm to detect all signs of all types around the car and locate the position and orientation of all signs.

Therefore, traffic signs detection is evaluated by the accuracy rate and with the consideration of UGV speed, detection distance, etc. As shown in Fig. 6(b), UGVs are required to slow down before "Speed Limit" and "Pedestrians" traffic signs.

2) Obstacles Detection Testing: Lidar and radar sensors are used to detect/track moving obstacles, which are always presented as a list of object hypotheses and characteristics to the tracking system [24], [33], [46]. The UGV classifies the moving obstacles status into box or point model according to the reliabilities of the sensor data. The predictions of the moving objects' shape and motion description are filtered, and their position and velocity state variable are tracked with a list of validated features, which are extracted from the combination of road geometry and obstacle map, and updated the object hypotheses list and the estimated object states.

The accuracy of moving obstacles validated extracted features is an important evaluation metric, which includes the obstacles' distance, moving direction, speed, and other estimated states, including the statistics results of the obstacles' amount and shape.

As shown in Fig. 6(c), UGVs are required to pass through a specific road under construction, which simulates static obstacles, and through a crosswalk with simulated pedestrian, which simulates dynamic obstacles detection.

C. UGV Position Estimation System Tests

Due to the road map error, lane detection error, GPS discontinuous errors (such as position jumps), and GPS continuous errors (such as slowly position drift), the position estimation system should minimize the accumulated error by data fusing. For example, UGV fuses GPS, inertial, and wheel encoder data and measurements of road lane markers with an annotated road map and then transforms the pose provided by the GPS-based pose estimation system into a smooth coordinate frame registered to a road network [35]. The position and attitude estimation system should be evaluated by analyzing the position error to the structural road lines, even in situations in which GPS quality is insufficient or, otherwise, localized within a lane.

Similar to structural road detection tests, we use the vehicle's bumper position to the stop line of intersection as a metric of UGV position estimation system tests.

D. Synthetic Results of Environment Perception Tests

UGVs environment perception tests performances in IVFC 2012 are shown in Fig. 6(a)–(d).

TABLE III
DYNAMIC/STATIC OBSTACLES DETECTION TESTS RESULTS

Metrics	*Candidate UGVs*					*Weights*
	V1	*V2*	*V3*	*V4*	*V5*	
R	0.67	1.0	1.0	0.67	1.0	0.6
D (m)	0	1	0.088	0.324	0.765	0.2
V (m/s)	0.167	1	0.333	0	0.208	0.2
Synthetic Results	0.435	1.000	0.684	0.467	0.795	

TABLE IV
SYNTHETIC RESULTS OF ENVIRONMENT PERCEPTION TESTS

Metrics	*Candidate UGVs*					*Weight*
	V1	*V2*	*V3*	*V4*	*V5*	
Structural Road Detection	0.927	1	0	0.210	0.606	0.4
Traffic Signals Detection	0.435	1.000	0.684	0.467	0.795	0.3
Position Estimation	0.202	0.601	1	0	0.549	0.3
Synthetic Results	0.562	0.880	0.505	0.224	0.645	

The average lane detection error result of V1–V5 is

$$\mathrm{LD}_{\mathrm{err}} = \{9.32, 5.69, 55.35, 44.92, 24.26\}.$$

As discussed in the previous section, all the metrics should be standardized as max types with (1) in preprocessing. Then we get

$$\mathrm{LD}'_{\mathrm{err}} = \{0.927, 1, 0, 0.210, 0.606\}.$$

The metrics of Traffic Signals and Dynamic/Static Obstacles are the same, which are simplified as detection rate (R), detection distance (D), and vehicle speed (V). The synthetic results of V1–V5 are computed with multiplying the weights to the values of R, D, and V. The results are shown in Table III.

The UGV position estimation system tests average sampling results of V1–V5 in five intersections tests are

$$\mathrm{PE}_{\mathrm{err}} = \{3.48, 2.1, 0.72, 4.18, 2.28\}.$$

After standardization as max types with (1), we get

$$\mathrm{PE}'_{\mathrm{err}} = \{0.202, 0.601, 1, 0, 0.549\}.$$

The weights of Structural Road Detection, Traffic Signals Detection, and Position Estimation tests are directly assigned as $W = \{\omega_1, \omega_2, \omega_3\} = \{0.4, 0.3, 0.3\}$.

By multiplying the weights to the values of the three perception tasks, the synthetic results of V1–V5 environment perception tests are computed, as shown in Table IV.

VI. CASE STUDY OF UGVS' PERFORMANCE EVALUATION AT IVFC 2012: AUTONOMOUS DRIVING TESTS

By autonomous driving tasks testing, UGVs' environment perception, motion planning, mission execution, and vehicle control key functions can be benchmarked. In this paper, we select structural on-road driving, unconstructed zone driving, and dynamic path planning as main autonomous driving tested tasks. The selected UGVs' performances in Structural On-road Driving Tests, Unconstructed Zone Driving Tests, and Dynamic Path Planning Tests are shown in Fig. 7(a)–(c), respectively.

A. Structural On-Road Driving Tests

During on-road driving, the motion planner constructs a curve along the center line of the desired lane. The constrained trajectory generation algorithm determines the control parameters set that drives the difference between these target boundary state constraints and the integral of the model dynamics (the endpoint of the computed vehicle trajectory) to be zero [20].

Structural on-road autonomous driving tests include several scenarios, as shown in Fig. 8. Lane-changing and overtaking are typical scenarios of structural on-road driving tests [38], [39]. Each branch of the tests case tree is covered according to different traffic scenes.

A simple lane-changing driving example is shown in Fig. 9. The feasibility of changing lanes is based on the ability to maintain proper spacing (x_u) with the surrounding vehicles $(V_1 - V_3)$ and to reach a target point (x_t) in the lane to merge into while meeting the velocity constraint (compare v_u with v_1, v_2, and v_3). If proper spacing is met, check whether the other vehicle's velocity can be matched by acceleration or deceleration after the merge without proper spacing being violated.

The former steps should be repeated for all n obstacles in the merge-to lane. Finally, the UGV will accomplish the lane changing with the following: 1) reached the desired position both in longitudinal and lateral directions within the required time (e.g., 8 s); 2) generated trajectory and speed are smooth both in the longitudinal and lateral directions; 3) vehicle lateral and longitudinal accelerations are relevantly small and avoid the rough lane changing; and 4) in addition to the lateral direction, the longitudinal acceleration, and the speed are required to be reasonable and are best to be kept uniform.

B. Unconstructed Zone Driving Tests

Within unstructured driving environments, the motion planner generates a trajectory that moves the vehicle toward the goal point from the initial state. Several quickly replanning search algorithms are used to generate a path consisting of a sequence of highly feasible maneuvers that are collision free [20], [25], [27], [28]. The unconstructed zone driving tests include intersections, parking lots, congested traffic driving, and other error states recovery.

Taking the case of driving through an intersection without traffic lights as an example, UGV precedence should be estimated, and stop signs and lines should be detected; a simplified scenario is shown in Fig. 10.

A UGV with initial state (x_u, v_u, and a_u) will be responsible for merging into or across moving traffic from a stop $(V_1 - V_3)$ while a virtual lane is created, and moving traffic should be considered. When the UGV stops at the lines, watches, and waits for the timing to cross the intersection, a required temporal window should be computed for each yield lane, which includes the time to traverse the intersection and get into the target lane and the minimum required temporal spacing between vehicles, i.e., D_{safe}.

Fig. 7. UGVs performances in autonomous driving tests (IVFC 2012). (a) Structural on-road driving tests. (b) Unconstructed zone driving tests. (c) Dynamic path-planning tests.

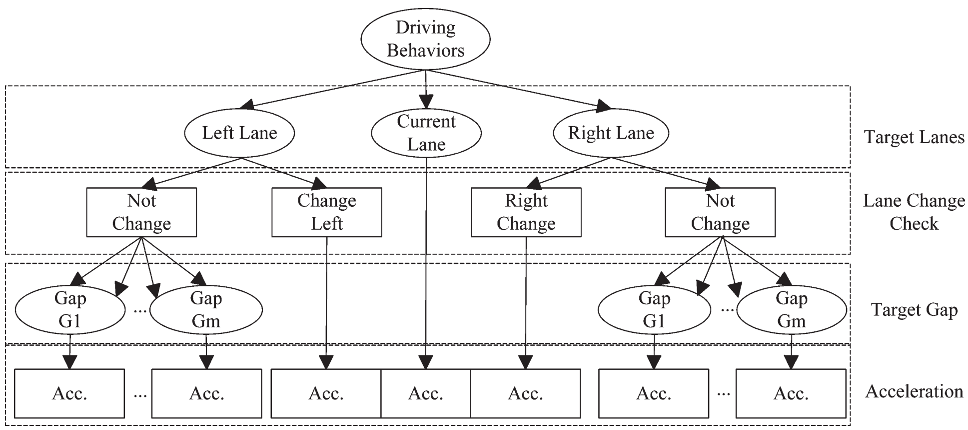

Fig. 8. UGV on-road driving tasks scenarios.

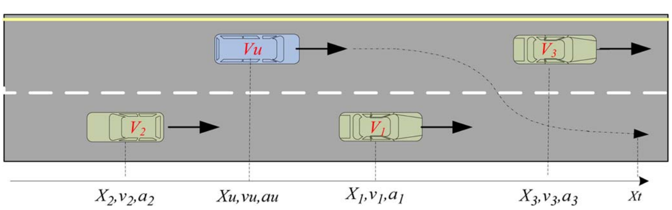

Fig. 9. Typical structural road overtaking scenario.

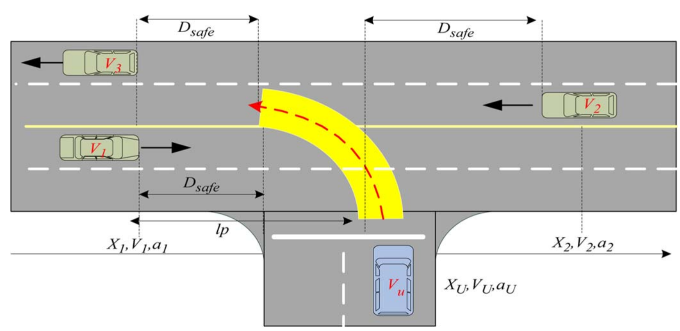

Fig. 10. Intersections autonomous driving scenario.

There are almost no multivehicles yielding across the intersection at IVFC 2012, and the evaluation is conducted by one UGV passing across the intersection with traffic lights. Evaluation metrics include the following: 1) detection rate of traffic light; 2) UGV yielding timing; 3) UGV reasonable trajectory; and 4) UGV space keeping and speed control (velocity and acceleration).

C. Dynamic Path-Planning Tests

UGV's dynamic path planning consists of path planning, traffic congestion and safety forecasting, and traffic laws complication. The road network is always presented as a directional graph, whose edges are counted based on the distance and the expected travel time of the edge, as well as the traffic environment complexity. Dynamic programming-like algorithms (such as A*, D*, and hybrid A*) compute the cumulative costs of moving from the current location to the goal point and decide which lanes and roads to navigate.

The mission planner should update its graph to incorporate newly observed information such as road blockages and regenerate a new route to its goal. The dynamic cost of position A to B is noted as a cumulative function, i.e.,

$$V(x) \leftarrow \min_u c(x,u) + \sum_y p(y|x,u)V(y). \tag{17}$$

When the planned road is observed to be blocked, the time and the risk cost function $c(x,u)$ are rapidly increased, the path is replanned and a U-turn is executed with the consideration of the transition probability $p(y|x,u)$. Therefore, the UGV high-level mission plan system can be evaluated by the road blockage in a temporary or a permanent manner to test whether the UGV can make U-turn driving, as shown in Fig. 11.

Dynamic path-planning tests are included in IVFC 2012 as a road blockage and U-turn execution. The road-blockage detection rate, execute U-turn delay, reasonable trajectory, and reasonable velocity and acceleration are regarded as metrics.

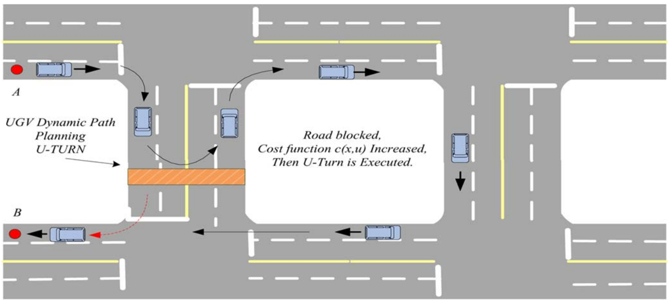

Fig. 11. Dynamic mission planning testing scenario.

TABLE V
SYNTHETIC SCORES OF LANE CHANGING AND OVERTAKING TESTS

Metrics	*Candidate UGVs*					*Weight*
	V1	*V2*	*V3*	*V4*	*V5*	
d (m)	1	0	0.4	0.5	0.6	0.3
Reasonable lateral-V & a	1.0	0	1.0	0.5	0.5	0.3
Reasonable longitud-V & a	0.84	0.4	1	0	0.8	0.3
Reasonable trajectory	1.0	0.25	0	0	0.25	0.1
Synthetic results	0.952	0.145	0.720	0.300	0.595	

TABLE VI
UNCONSTRUCTED ZONE DRIVING TESTS RESULTS

Metrics	*Candidate UGVs*					*Weight*
	V1	*V2*	*V3*	*V4*	*V5*	
Detection Rate of red light	1.0	1.0	1.0	1.0	1.0	0.2
Green light and Staringt Delay (s)	0.130	0.348	0	1	0.203	0.2
Reasonable trajectory	0.556	0.926	0.926	0	1	0.3
ReasonableV&a	0.25	0.75	1	0	0.75	0.3
Synthetic Results	0.468	0.772	0.778	0.400	0.766	

TABLE VII
DYNAMIC PATH-PLANNING TESTS RESULTS

Metrics	*Candidate UGVs*					*Weight*
	V1	*V2*	*V3*	*V4*	*V5*	
Road blockage Detection Rate	1.0	1.0	1.0	1.0	1.0	0.2
Execute U-TURN Delay(s)	0.33	Fail/0	1.0	Fail/0	0.67	0.2
Reasonable trajectory	0.96	Fail/0	0.82	Fail/0	1	0.3
ReasonableV&a	0.92	Fail/0	0.85	Fail/0	1	0.3
Synthetic Results	0.830	0.200	0.901	0.200	0.934	

TABLE VIII
V1–V5 DECISION MATRIX OF FOUR TESTING TASKS

Alternatives	*Tasks*			
	Environment Perception	*Structural On-road Driving*	*Unconstructed Zone Driving*	*Dynamic Path Planning*
V1	0.5619	0.952	0.4678	0.830
V2	0.8803	0.145	0.7724	0.200
V3	0.5052	0.720	0.7778	0.901
V4	0.2241	0.300	0.4000	0.200
V5	0.6456	0.595	0.7656	0.934

TABLE IX
SYNTHETIC WEIGHTS OF FOUR TESTING TASKS

e_j	0.9520	0.9025	0.9774	0.8898
g_j	0.0480	0.0975	0.0226	0.1102
β_j	0.1724	0.3503	0.0811	0.3961
AHP Weights	0.2	0.2	0.3	0.3
Synthetic Weights	0.1392	0.2829	0.0982	0.4797
D+	0.0503	0.2795	0.0623	0.2716
D-	0.2570	0.0723	0.2482	0.0319
Ci	0.8364	0.2054	0.7992	0.1051

D. Synthetic Results of Autonomous Driving Tests

In structural on-road driving tests, UGVs are required to change lanes and overtake without collision. All UGVs successfully maneuver changing lanes and overtaking. Weights of the metrics are directly set as $W = \{0.3, 0.3, 0.3, 0.1\}$. Synthetic results of V1–V5 are computed by multiplying the weights to the values of metrics, as shown in Table V.

In unconstructed zone driving tests, UGVs are required to stop at the traffic light and run through the intersection with reasonable trajectory. The performances of selected UGVs V1–V5 are shown in Fig. 7(b). All UGVs stop at the traffic light, make a left turn, and successfully run through the intersection. The averages of the five tests results are shown in Table VI.

In dynamic path-planning tests, UGVs are required to execute a U-turn before the blockage. The performances of selected UGVs V1–V5 are shown in Fig. 7(c). The synthetic results are shown in Table VII.

E. Synthetic Results of Overall Performance

The overall performance decision matrix is composed of the synthetic results of Environment Perception Tests, Structural On-Road Driving Tests, Unconstructed Zone Driving Tests, and Dynamic Path Planning Tests, as shown in Table VIII.

The weights of four testing tasks are synthetically assigned as $\alpha = \{0.2, 0.2, 0.3, 0.3\}$; the entropy weights and the synthetic weights are computed, as shown in Table IX.

Rebuilding the decision matrix R with combination weight ω_j according to (10), we get the standardized decision matrix $Z = (z_{ij})_{m\times n}$. In the TOPSIS model, with (11) and (12), the PIP and the NIP are computed. With (13) and (14), the weighted Euclidean distances between D^+ and D^- are computed. With (15), the relative closeness of the alternative D_i with respect to D^+ is computed, as shown in Table IX. Rank the alternatives V1–V5 according to the relative closeness to the PIS. The sorted order is V1, V3, V5, V2, V4 (which is the same as the on-spot judgment).

VII. CONCLUSION

UGV is a highly complex system and the evaluation of it is also very complicated. The task-specific performance evaluation model of UGVs presented in this paper is one of the efforts to improve the evaluation work, which is based on the IVFC serial competitions' practices; it contributes to the evaluation work in several aspects, such as autonomous driving tasks analysis, evaluation metrics selection and processing, and comprehensive evaluation methods selection and discussion. With these works, several UGVs in IVFC are evaluated. However, this work is done only in IVFC-constrained traffic environments and the discussed evaluation model is relatively simple. They all needed to be pushed further in the future. As far as the evaluation of UGVs in a real environment with high-density traffic is concerned, there still is much work to be done. The most important ones are how to make full-cover functional tests, prove the functional technologies' maturity, and, finally, assure the safety of real traffic autonomous driving. Therefore, the UGV functions evaluation metrics and the test cases are needed to be more detailed, with more accurate quantity assurance. Furthermore, the interference of UGV to the human drivers should be analyzed in mixed traffic.

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