

An IoT-Assisted Semantic Road Incident Warning Framework Using GNSS-Enabled Smart Cones

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Abstract—Point-based road incident warnings, such as accident locations or map markers, are useful for notifying drivers that an incident has occurred. However, they do not describe the on-site traffic-control configuration, such as lane closure, taper guidance, restricted areas, or recommended driver actions. This paper proposes an IoT-assisted semantic road incident warning framework using GNSS-enabled smart cones. The proposed framework collects GNSS coordinates from deployed smart cones, analyzes their spatial configuration, infers semantic incident patterns, and generates lightweight warning messages for approaching drivers. A rule-based geometric inference method is designed to identify linear closure, taper guidance, polygonal blockage, and uncertain layouts. The inferred semantics are then encoded as structured warning messages and evaluated through prototype implementation and SUMO-based traffic simulation. The simulation results show that the proposed semantic-warning strategy reduces hard braking events, late lane changes, and maximum queue length compared with the no-warning baseline, while maintaining better traffic efficiency than the point-warning strategy.

Index Terms—GNSS smart cones, semantic road incident warning, intelligent transportation systems, IoT, work-zone safety, SUMO simulation

I. INTRODUCTION

Road traffic incidents can cause not only direct damage to the vehicles and passengers involved, but also secondary crashes, traffic congestion, and delays in the emergency response. With the development of intelligent transportation systems (ITS), Internet of Things (IoT) communication, edge computing, and mobile map services, road incident information can be disseminated to road users more efficiently than conventional manual notification. Recent IoT-based public-safety alert systems demonstrate low-latency dissemination of emergency information through edge/cloud and mobile notification channels, while connected-vehicle warning studies show that in-vehicle warnings can influence driver behavior when approaching downstream hazards [1], [2].

Many existing incident warning and emergency notification systems provide mainly point-based information, such as the location of an accident in the Global Positioning System (GPS), an event coordinate, or a marker on a digital map. Recent IoT-based accident detection systems commonly use GPS sensors or mobile devices to report the precise location

of the accident to emergency responders or road users [3], [4]. Similarly, vision-based or sparse-sensing traffic incident studies mainly focus on detecting, classifying, or localizing incidents from camera or traffic-sensing data [5], [6]. Our prior Wi-SUN FAN and MQTT-based prototype can also be viewed as an example of this point-based notification paradigm, where AI-detected accident locations are transmitted to mobile map clients [7]. However, such notifications do not describe the traffic-control configuration on-site, such as blocked lanes, taper guidance, restricted areas, or recommended driver actions.

In practical road maintenance and traffic incident management, traffic cones are commonly used to form lane closure boundaries, taper guidance, restricted areas, and temporary diversion zones. These cone layouts contain important traffic-control semantics. Connected temporary traffic control devices, including connected arrow boards and connected traffic cones, have been investigated to improve the accuracy of work-zone status and location information and integrate into traffic management operations [8]. Recent work-zone perception studies further indicate that temporary traffic control scenes require richer scene-level understanding than object-level detection [9], [10]. However, how to transform the spatial configuration of the smart cones enabled by the Global Navigation Satellite System (GNSS) into structured semantic driver warnings remains underexplored.

To address this gap, this paper proposes an IoT-assisted semantic road incident warning framework using GNSS-enabled smart cones. The key idea is to enrich conventional point-based incident notifications with cone-based scene semantics. After a road incident is detected or reported, the smart cones enabled by GNSS deployed at the incident site report their coordinates and status. The proposed system analyzes the geometric configuration of the cones, infers semantic incident information such as lane closure, taper guidance, polygonal blockage, or uncertain layouts, and generates lightweight structured warning messages for approaching drivers.

The main contributions of this paper are summarized as follows:

- We propose a semantic road incident warning framework that enriches point-based incident notifications, which may be generated by AI-based or IoT-based notification systems, with GNSS smart-cone-based scene information.

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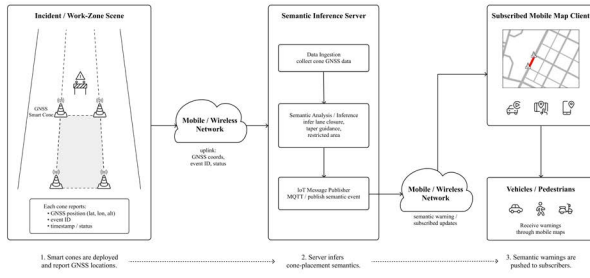


Fig. 1. System architecture of the proposed IoT-assisted semantic road incident warning framework.

- We design a cone configuration analysis method to infer semantic incident patterns, including lane closure, taper guidance, polygonal blockage, and uncertain layouts, from GNSS cone coordinates.
- We define a lightweight semantic incident message format and evaluate the traffic impact of the proposed semantic warnings using SUMO simulations under no-warning, point-warning, and semantic-warning scenarios.

II. SYSTEM MODEL AND PROBLEM FORMULATION

Fig. 1 illustrates the proposed IoT-assisted semantic road incident warning framework. The framework consists of four components: an incident event source, GNSS-enabled smart cones, a semantic incident processor, and a warning dissemination and evaluation module.

The incident event source provides a point-based road incident notification, which may be generated by AI-based accident detection, manual reporting, or an existing incident notification system. A point-based incident event is denoted as

$$E_p = \{e_{id}, l_e, t_e, s_e\}, \quad (1)$$

where e_{id} is the event identifier, $l_e = (lat_e, lon_e)$ is the incident location, t_e is the timestamp, and s_e is the event status.

After an incident is reported, GNSS-enabled smart cones are deployed at the incident site. The cone set is represented as

$$C_{gnss} = \{c_i \mid i = 1, 2, \dots, n\}, \quad (2)$$

where each cone is defined as

$$c_i = \{c_{id}^i, lat_i, lon_i, t_i, s_i\}. \quad (3)$$

Here, c_{id}^i , (lat_i, lon_i) , t_i , and s_i denote the cone identifier, GNSS coordinate, timestamp, and cone status, respectively.

For geometric reasoning, the GNSS coordinates are transformed into a local road coordinate system:

$$p_i = T(lat_i, lon_i) = (x_i, y_i), \quad (4)$$

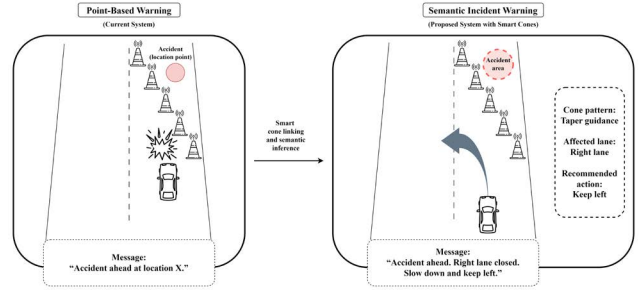


Fig. 2. From point-based incident warning to semantic incident warning based on cone configuration analysis.

where $T(\cdot)$ is the coordinate transformation function. The transformed cone set is denoted as

$$P = \{p_i \mid i = 1, 2, \dots, n\}. \quad (5)$$

Given E_p , P , and optional road context R , the semantic incident information is inferred as

$$S_i = f(E_p, P, R), \quad (6)$$

where

$$S_i = \{q, a, r, \gamma\}. \quad (7)$$

Here, q denotes the inferred cone configuration pattern, a denotes the affected road area or lane, r denotes the risk level, and γ denotes the confidence score.

The final output is a semantic driver warning:

$$W_s = g(S_i, E_p), \quad (8)$$

where

$$W_s = \{e_{id}, w_{type}, a, r, m\}. \quad (9)$$

Here, w_{type} is the warning type and m is a human-readable driver message.

Thus, the proposed problem is summarized as

$$E_p + C_{gnss} \rightarrow S_i \rightarrow W_s. \quad (10)$$

III. SMART-CONE-BASED SEMANTIC INCIDENT MODELING

This section presents the proposed method for converting GNSS smart-cone coordinates into semantic incident information and structured driver warning messages. As shown in Fig. 2, the proposed method transforms a conventional point-based warning into a semantic warning by analyzing the spatial configuration of deployed smart cones.

A. Cone Configuration Analysis

Given the transformed cone coordinate set $P = \{p_i \mid i = 1, 2, \dots, n\}$, where $p_i = (x_i, y_i)$, the system first analyzes the geometric relationship among cones to infer the cone configuration pattern q . In this paper, four basic patterns are considered: linear closure, taper guidance, polygonal blockage, and uncertain layout.

For linear closure detection, the cone points are fitted by a straight line. Let d_i denote the perpendicular distance from cone point p_i to the fitted line. The average fitting error is defined as

$$D_{line} = \frac{1}{n} \sum_{i=1}^n d_i. \quad (11)$$

If D_{line} is smaller than a predefined threshold θ_{line} , the cone set is considered to have a linear structure.

To distinguish between linear closure and taper guidance, the system compares the orientation of the fitted cone line with the road direction in the local road coordinate system. The positive x -axis of the local coordinate system is aligned with the road direction at the incident location, and the y -axis represents the lateral direction. Let $\mathbf{u}_c$ denote the unit direction vector of the fitted cone line and $\mathbf{u}_r$ denote the unit road-direction vector. Because a fitted line is directionless, $\mathbf{u}_c$ and $-\mathbf{u}_c$ represent the same cone-line orientation. The directionless angular difference is therefore computed as

$$\Delta\alpha = \cos^{-1}(|\mathbf{u}_c^\top \mathbf{u}_r|). \quad (12)$$

This formulation directly gives the minimum angle between the cone line and the road direction and bounds $\Delta\alpha$ within $[0, \pi/2]$.

If the cone set is approximately linear and $\Delta\alpha$ is smaller than a threshold $\theta_{parallel}$, the pattern is classified as linear closure. If the cone set is approximately linear but $\Delta\alpha$ falls within an oblique range, it is classified as taper guidance, indicating lane merging or traffic diversion. In the prototype, a valid linear or taper pattern must contain at least a minimum number of cones. For taper guidance, the oblique angle must fall within $[\theta_{taper}^{min}, \theta_{taper}^{max}]$, and the cone sequence must also satisfy minimum lateral-span and monotonic lateral-progression constraints. These additional checks prevent a small number of noisy or randomly scattered cones from being over-interpreted as a valid taper.

For polygonal blockage detection, the system computes the convex hull of the cone points and estimates the enclosed area A_{hull} . If the number of cones is sufficient and A_{hull} is larger than a predefined threshold θ_{area} , the cone set is classified as polygonal blockage. To avoid misclassifying elongated or sparse non-linear cone scatters as polygonal blockage, a compact local-closure constraint is additionally applied in the implementation. This pattern usually represents an incident core area or a restricted region.

If none of the above conditions is satisfied, the configuration is classified as an uncertain layout. This category is introduced to avoid over-interpreting ambiguous or incomplete cone deployments and may trigger manual confirmation. For the single-pattern inference evaluated in this paper, fragmented cone observations that form multiple disconnected clusters are also conservatively classified as uncertain rather than being forced into one of the valid traffic-control layouts.

TABLE I
CONE CONFIGURATION PATTERNS AND INCIDENT SEMANTICS

Pattern	Geometric Meaning	Incident Semantics
Linear closure	Collinear cones	Lane boundary / closure
Taper guidance	Oblique cone line	Lane merge / diversion
Polygonal blockage	Closed cone area	Restricted incident area
Uncertain layout	No clear structure	Manual confirmation

B. Incident Semantic Mapping

After the cone configuration pattern q is inferred, the system maps it to incident-scene semantics. The semantic mapping used in this paper is summarized in Table I. The goal of this step is not only to classify the geometric pattern, but also to interpret its traffic meaning in the incident scene.

The inferred semantic information is represented as

$$S_i = \{q, a, r, \gamma\}, \quad (13)$$

where q is the inferred cone pattern, a is the affected road area or lane, r is the risk level, and γ is the confidence score. In the current prototype, the affected area a is determined by comparing the cone configuration with the road direction and lane layout. The risk level r is assigned according to the inferred pattern and the degree of lane occupation.

C. Confidence Estimation

To account for GNSS positioning errors and incomplete cone deployments, the proposed method assigns a confidence score γ to each semantic inference result. The confidence score reflects the reliability of the inferred cone pattern.

For a linear or taper pattern, the confidence score is related to the line fitting error and the angular consistency. A smaller D_{line} indicates that the cone points form a clearer line structure. For polygonal blockage, the confidence score is related to the hull area and the number of cones forming the enclosed region. If the geometric evidence is weak, the confidence score decreases.

The confidence score can be generally expressed as

$$\gamma = h(D_{line}, \Delta\alpha, A_{hull}, n), \quad (14)$$

where $h(\cdot)$ is a normalized confidence function. If γ is lower than a threshold θ_γ , the system classifies the result as uncertain and generates a warning that requires manual confirmation.

D. Semantic Warning Message Generation

The final step is to convert the inferred incident semantics into a structured driver warning message. The warning message is represented as

$$W_s = \{e_{id}, w_{type}, a, r, m\}, \quad (15)$$

where e_{id} is the event identifier, w_{type} is the warning type, a is the affected area, r is the risk level, and m is a human-readable driver message.

Table II shows examples of semantic warning generation. Compared with a point-based warning that only indicates the existence of an accident, the semantic warning provides more actionable information for approaching drivers.

TABLE II
EXAMPLES OF SEMANTIC WARNING MESSAGE GENERATION

Pattern	Semantics	Driver Message
Linear closure	Lane closure	Slow down and avoid the closed lane.
Taper guidance	Lane merge	Slow down and keep left/right.
Polygonal blockage	Restricted area	Do not enter the incident area.
Uncertain layout	Ambiguous scene	Slow down and follow on-site guidance.

An example lightweight JSON payload compatible with MQTT-style or other vehicular IoT communication mechanisms is shown below:

```
{
  "event_id": "E001",
  "type": "semantic_warning",
  "pattern": "taper_guidance",
  "lane": "right_lane",
  "risk": "medium",
  "message": "Slow down and keep left."
}
```

IV. PROTOTYPE AND EVALUATION

This section presents the prototype implementation and evaluation design of the proposed semantic road incident warning framework.

A. Prototype Implementation

The prototype consists of three modules: a smart-cone data emulator, a semantic incident processor, and a warning dissemination interface. The emulator generates cone identifiers, GNSS coordinates, timestamps, event identifiers, and cone status values to emulate GNSS-enabled smart cones deployed at an incident or work-zone site.

The semantic incident processor transforms GNSS coordinates into a local road coordinate system, applies the proposed cone configuration analysis method, and generates semantic incident information, including the cone pattern, affected area, risk level, confidence score, and recommended driver action. The warning dissemination interface encodes the result as a lightweight IoT message formatted for an MQTT-style event interface or SUMO-based traffic impact evaluation.

B. Cone Configuration Evaluation

Four representative cone configuration patterns are considered: linear closure, taper guidance, polygonal blockage, and uncertain layout. For each pattern, synthetic cone deployments are generated in a simplified road coordinate system. The generated cone coordinates are used as input to the semantic incident processor.

The classification accuracy is defined as

$$Acc = \frac{N_{correct}}{N_{total}}, \quad (16)$$

where $N_{correct}$ is the number of correctly inferred cone configurations and N_{total} is the total number of test cases.

TABLE III
GNSS NOISE SETTINGS FOR CONFIGURATION EVALUATION

Noise Level	Purpose
0 m	Baseline without positioning error
1 m	Low positioning uncertainty
2 m	Low-to-medium positioning uncertainty
3 m	Medium positioning uncertainty

TABLE IV
CONFIGURATION ACCURACY UNDER GNSS NOISE

Noise	Linear	Taper	Poly.	Uncertain	Avg.
0 m	100.0	100.0	100.0	100.0	100.0
1 m	100.0	73.4	87.4	100.0	90.2
2 m	91.6	44.2	66.4	99.6	75.5
3 m	58.4	25.4	45.6	98.6	57.0

To evaluate robustness under positioning uncertainty, Gaussian noise is added to each cone coordinate:

$$\tilde{p}_i = p_i + \epsilon_i, \quad (17)$$

where p_i is the original cone coordinate and ϵ_i denotes the simulated GNSS positioning error. The noise levels are set to a 0 m baseline and 1–3 m positioning uncertainty, as summarized in Table III.

Table IV summarizes the configuration classification accuracy under different GNSS noise levels. All patterns are correctly identified without positioning error, and the average accuracy remains 90.2% under 1 m noise. As the noise level increases to 2–3 m, the accuracy of linear closure, taper guidance, and polygonal blockage decreases because GNSS perturbations distort line orientation, lateral progression, and convex-hull geometry. In contrast, the uncertain-layout class remains stable, showing the fail-safe behavior of rejecting ambiguous layouts.

C. SUMO Simulation Setup

The Simulation of Urban MObility (SUMO) platform is used to evaluate the traffic impact of semantic incident warnings. A 3-km one-way highway segment is constructed with three lanes and a speed limit of 110 km/h. Lane 0, i.e., the rightmost lane, is blocked from 1500 m to 1525 m. Background traffic is generated with a demand rate of 2700 vehicles/hour, random departure lanes, and maximum departure speed.

The warning zone is set from 1200 m to 1500 m, while local speed and late lane changes are measured within the 1400–1525 m analysis range. For fairness, all scenarios use the same road network, traffic demand, blocker configuration, and random seed list. The point-warning and semantic-warning scenarios use the same advance deceleration target of 20.0 m/s over 15 s, while the semantic-warning scenario additionally applies affected-lane merge guidance derived from the semantic payload. Three scenarios are compared: no warning, point warning with only incident-location information, and semantic warning with affected-lane, cone-pattern, risk-level, and recommended-action information.

D. Evaluation Metrics and Results

The evaluation uses five metrics: local average speed, average travel time, maximum queue length, hard braking events, and late lane changes. The local average speed is measured within the 1400–1525 m analysis range, and the average travel time is computed over the full 3-km segment. The maximum queue length represents the detected distance from the blockage to the upstream-most halted vehicle before the blockage.

Hard braking events are defined based on the acceleration threshold. Let the hard-braking acceleration set be

$$\mathcal{A}_{hard} = \{\alpha \mid \alpha \leq -4.5 \text{ m/s}^2\}, \quad (18)$$

for the k -th simulation run, the hard braking count is defined as

$$E_k = \sum_{i=1}^{N_{hb,k}} \mathbf{1}(a_i^{hb} \in \mathcal{A}_{hard}), \quad (19)$$

where $N_{hb,k}$ is the number of detected braking events in the k -th simulation run, a_i^{hb} is the acceleration of the i -th braking event, and $\mathbf{1}(\cdot)$ is the indicator function.

Similarly, for the k -th simulation run, the late lane change count is defined as

$$L_k = \sum_{i=1}^{N_{lc,k}} \mathbf{1}(x_i^{lc} \in \mathcal{Z}_{late}), \quad (20)$$

where $N_{lc,k}$ is the total number of lane-changing events, x_i^{lc} is the longitudinal position of the i -th lane change, and $\mathcal{Z}_{late}$ denotes the late lane change analysis range.

For event-based metrics, the reported values are averaged over multiple simulation runs. The reported hard braking and late lane change values are defined as

$$\bar{E} = \frac{1}{N_{seed}} \sum_{k=1}^{N_{seed}} E_k, \quad (21)$$

and

$$\bar{L} = \frac{1}{N_{seed}} \sum_{k=1}^{N_{seed}} L_k, \quad (22)$$

respectively, where N_{seed} is the number of random seeds.

Table V summarizes the 1000-seed average results under the fair baseline setting. Compared with the no-warning scenario, the semantic-warning scenario reduces hard braking events from 113.0 to 49.2, late lane changes from 145.3 to 91.0, and maximum queue length from 48.95 m to 33.55 m. Compared with the point-warning scenario, semantic warning further reduces hard braking events, late lane changes, and queue length while maintaining higher local average speed and shorter average travel time. These results indicate that lane-specific semantic guidance can reduce reactive near-blockage lane-changing behavior and provide a better safety-efficiency balance under temporary lane-blocking conditions.

TABLE V
TRAFFIC IMPACT EVALUATION RESULTS (1000-SEED AVERAGE)

Scenario	Local Avg. Speed (km/h)	Avg. Travel Time (s)	Max Queue (m)	Hard Braking	Late Lane Changes
No-warning	73.42	108.39	48.95	113.0	145.3
Point-warning	58.33	111.55	38.40	56.4	146.5
Semantic-warning	61.37	110.94	33.55	49.2	91.0

V. CONCLUSION

This paper proposed an IoT-assisted semantic road incident warning framework using GNSS-enabled smart cones. The framework converts GNSS cone coordinates into semantic incident patterns and lightweight driver warning messages. Prototype and SUMO evaluation results show that the proposed method can infer cone-based semantics under low GNSS noise and reduce hard braking, late lane changes, and queue formation compared with no-warning and point-warning baselines. Future work will address lane-level road context and field validation.

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