



# Machine learning for road active safety global dynamic drone assisted lane change maneuver for risk prevention and collision avoidance

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### Publications

1. J. Hao, R. Naja, D. Zeghlache, "GL-DEAR: Global Dynamic Drone Assisted Lane Change Maneuver for Risk Prevention and Collision Avoidance," accepted by ICC 2023

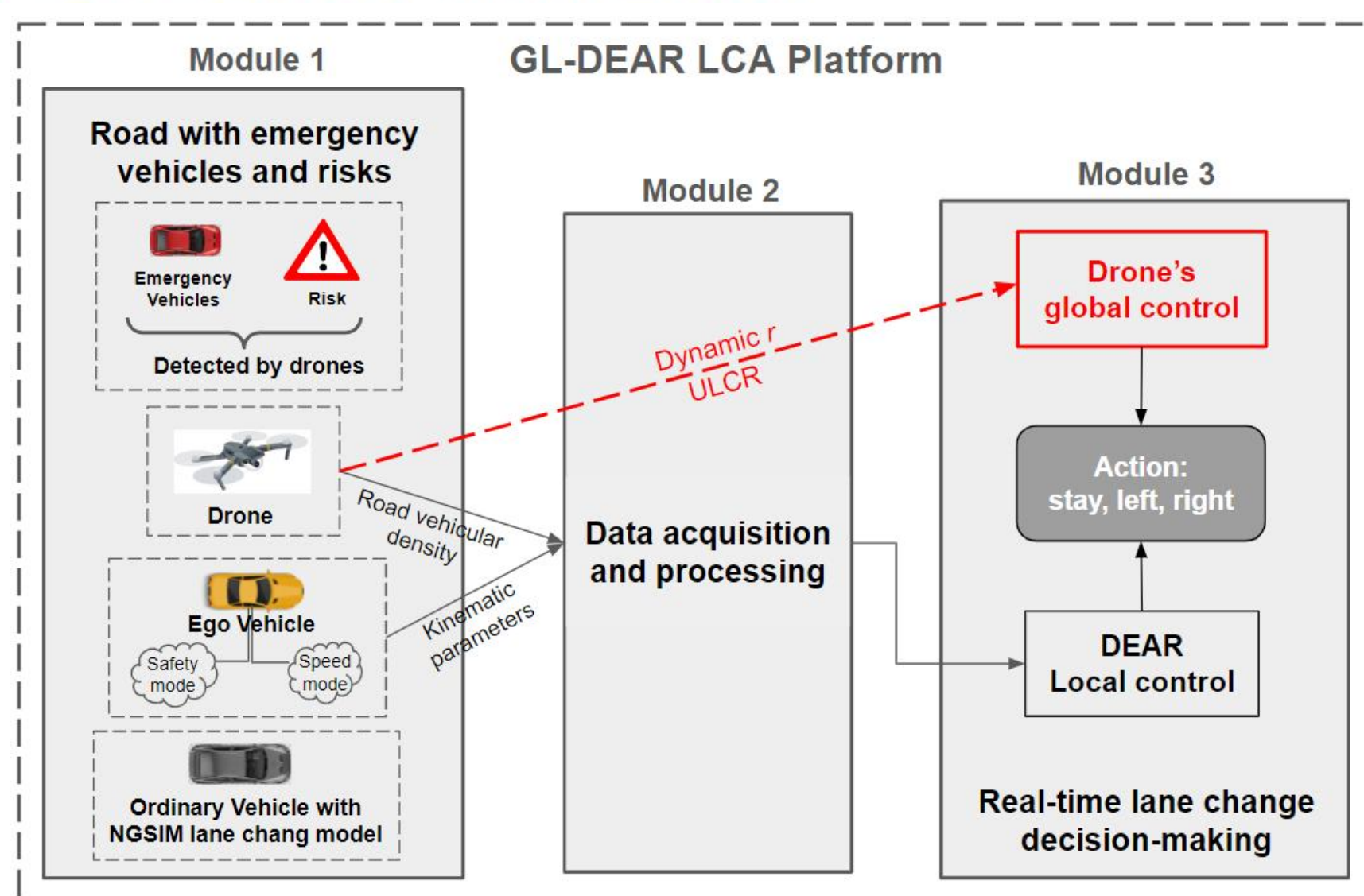
2. J. Hao, R. Naja, D. Zeghlache, "Drone-Assisted Lane Change Maneuver using Reinforcement Learning with Dynamic Reward Function," IEEE WiMob 2022, October, Greece

## I. MOTIVATION

### LANE CHANGE FOR DRONE-ASSISTED VEHICULAR NETWORKS

- Lane change (LC) leads to frequent car accidents
- There is an urgent need to timely LC decision-making
- We implemented a GL-DEAR platform
  - based on deep reinforcement learning method
  - assisted by drones to capture global view of the traffic
  - dealing with road potential risks and emergency vehicles

## II. GL-DEAR PLATFORM

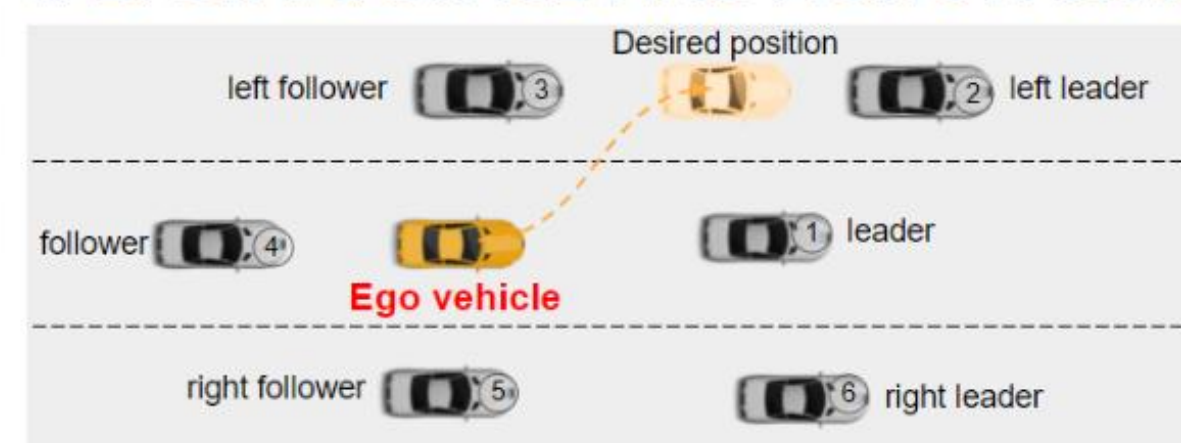


### II-1. DEEP Q-NETWORK BASED ON A DYNAMIC REWARD FUNCTION

$$R = w_{comf}R_{comf} + w_{eff}R_{eff} + w_{safe}R_{safe}$$

- $R_{comf}$  reduces sharp brakes and sudden accelerations
- $R_{eff}$  increases speed and reduces unnecessary lane changes
- $R_{safe}$  increases road active safety:
 
$$R_{safe} = R_{den} + R_{colli} + R_{risk} + R_{block}$$
  - $R_{den}$  is related to road vehicular density, which is calculated by drones
  - $R_{colli}$  is related to collision number, and is **dynamically adjusted by drones**
  - $R_{risk}$  and  $R_{block}$  consider road potential risks and emergency vehicles

### II-2. STATE SPACE AND ACTION SPACE



- Action space:  $a = \{0, 1, 2\}$ , representing
  - staying in current lane
  - LC to the right
  - LC to the left
- State space:  $o[j] = \{o_{ego}[j], o_1[j], \dots, o_6[j]\}$ , where:
  - $o_{ego}[j] = \{l_{risk}[j], x_{ego}[j], y_{ego}[j], v_{ego}[j], a_{ego}[j], l_{ego}[j]\}$  contains road risk label, kinematic parameters and current lane id of the ego vehicle at step  $j$
  - $o_i[j] = \{x_i[j], y_i[j], v_i[j], a_i[j], l_i[j], d_i[j], p_i[j]; i \in [0, 6]\}$  consists of the kinematic parameters, current lane id, distance to ego vehicle and vehicle priority of ego's  $i$ -th neighbor at step  $j$

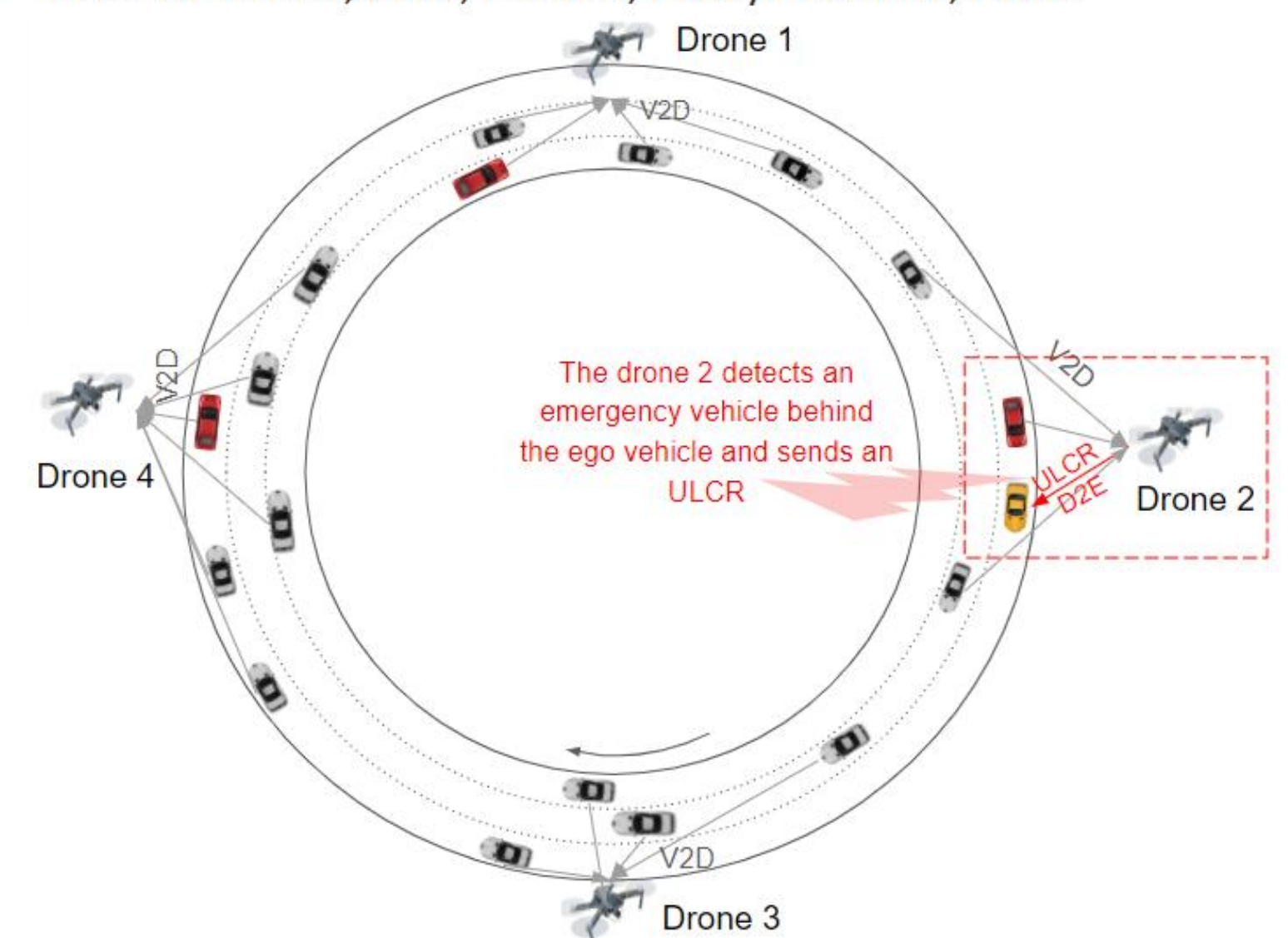
### II-3. DRONES PLAY AN IMPORTANT ROLE IN RISK PREVENTION AND COLLISION AVOIDANCE

- The drones
  - calculate the road vehicular density
  - dynamically adjust  $R_{colli}$  according to the collision rate
  - sends urgent lane change requests (ULCRs) to recommend the ego vehicle to perform a LC when a risk or an emergency around ego vehicle is detected



## III. SIMULATION SCENARIO

- 4-km circular highway with maximum allowed speed equals 100 km/h
- Authentic dataset: Next Generation Simulation Vehicle Trajectories and Supporting Data
- Krauss mobility model for longitudinal control for all vehicles
- GL-DEAR LC model for the ego vehicle and NGSIM LC model for ordinary vehicles
- Simulator: SUMO (Simulation of Urban MObility)
- Baselines: KNN, DNN, LC2013, Policy Gradient, DEAR



V2D: vehicle-to-drone communication  
D2E: drone-to-ego communication

## IV. RESULTS

TABLE I  
PERFORMANCE TEST RESULTS IN SPARSE TRAFFIC

Model	KNN	DNN	LC2013	PG	DEAR	GL-DEAR
Collision Number	0	0	0	0	0	0
LC Request	0.6	23	31.5	544	353.3	477
Avg Speed (km/h)	29.9	46.3	60.9	60.8	65	58.6
$t_r$ (s)	26.1	22.8	14.4	19	5.6	4.7
$t_b$ (s)	83.3	22.8	66.4	100.4	68.7	50.1

TABLE II  
PERFORMANCE TEST RESULTS IN MEDIUM TRAFFIC

Model	KNN	DNN	LC2013	PG	DEAR	GL-DEAR
Collision Number	0	0	0	0	0	0
LC Request	69	34.7	44.2	782.5	284.3	516
Avg Speed (km/h)	33.8	47.3	60	61.6	67.1	53
$t_r$ (s)	29.1	29.6	25.1	46	10.9	7.7
$t_b$ (s)	131.6	66	166.8	172	116	83

TABLE III  
PERFORMANCE TEST RESULTS IN DENSE TRAFFIC

Model	KNN	DNN	LC2013	PG	DEAR	GL-DEAR
Collision Number	0	0	0	0	0	0
LC Request	44.3	65.5	202.2	717	296.8	466
Avg Speed (km/h)	44	47.1	56.5	55.4	65	49.4
$t_r$ (s)	46.2	38.7	20.7	26.4	19.9	8.1
$t_b$ (s)	248.2	178.3	82	315.6	106.5	75.8

TABLE IV  
PERFORMANCE WITH DIFFERENT  $n_{safe}$

Vehicle Number, nv	50			150			250		
$n_{safe}$	1	3	5	1	3	5	1	3	5
Avg Speed (km/h)	56	58.6	60.7	52.5	53	55.3	45.9	49.4	49.6
Risky Time (s)	5.2	4.7	18.5	41.7	7.7	13.8	5.6	8.1	9.2
Blocking Time (s)	47.3	50.1	64.4	65.6	83	90.9	94.4	75.8	85.9

$n_{safe}$  in TABLE IV is a predefined threshold, according to which the ego vehicle switches between safety mode and efficiency mode

## V. CONCLUSION AND PROSPECTS

1. We implemented a GL-DEAR LCA platform which:
  - enhances road active safety
  - takes into account risky roads and emergency vehicles with different traffic densities
2. LC decision should be made in a tight time window
  - We envision to adopt Federated Learning distributed on clients and controlled by the drones