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بسم الله الرحمن الرحيم

مركز الشبكات وتكنولوجيا المعلومات

قسم التوثيق الإلكتروني



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جامعة عين شمس

التوثيق الإلكتروني والميكروفيلم

قسم

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Cairo University

TESTING AUTONOMOUS VEHICLES USING REINFORCEMENT LEARNING TO GENERATE FAILURE SCENARIOS IN COMPLIANCE WITH STANDARDIZED TESTS

By

Nagy Mohamed Salah Mohamed Ali Abotaleb

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
in
Electronics and Communications Engineering

FACULTY OF ENGINEERING, CAIRO UNIVERSITY
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Under the Supervision of

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Title of Thesis:

**Testing Autonomous Vehicles Using Reinforcement Learning To
Generate Failure Scenarios In Compliance With Standardized Tests**

Key Words:

Artificial Intelligence; Reinforcement Learning; Autonomous Vehicles; Deep Reinforcement Learning;

Summary:

This thesis proposes a design for a reinforcement learning framework to test specific autonomous vehicle components according to standardized tests of EuroNCAP. It shows how reinforcement learning algorithms are being used in real-world applications, in different testing domains outside the autonomous vehicle testing, and how to make use of reinforcement learning algorithms for autonomous vehicle testing rather than the popular topic of usage in driving autonomous vehicles. In addition, it presents a complete reinforcement learning formulation for the framework including environment description, reward function design, model training, and model testing procedures. Moreover, the proposed framework was able to generate automatic failure scenarios that were applied on autonomous vehicles covering two EuroNCAP scenarios; approaching a stationary car and approaching a slower car. The proposed framework controls parameters such as velocity, position and time, and generates more accurate failure scenarios to happen in real-life situations. Our failure scenarios are generated using q-learning and deep reinforcement learning algorithms causing real accidents for the designed scenarios. Hence, our reinforcement learning framework proves its validity to generate failure scenarios for autonomous vehicle components improving the safety of autonomous vehicle components and reducing both the costs and time required for testing autonomous vehicle components.

Disclaimer

I hereby declare that this thesis is my own original work and that no part of it has been submitted for a degree qualification at any other university or institute.

I further declare that I have appropriately acknowledged all sources used and have cited them in the references section.

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Table of Contents

Disclaimer	i
Acknowledgements	ii
Table of Contents	iii
List of Tables	vii
List of Figures	viii
List of Symbols and Abbreviations	xi
List of Publications	xii
Abstract	xiii
1 INTRODUCTION	xiv
1.1 Autonomous Vehicle Testing	1
1.2 EuroNCAP [8, 9]	3
1.3 Carla Simulator [10]	3
1.4 Thesis Contribution	4
1.5 Thesis Organization	5
2 REINFORCEMENT LEARNING ALGORITHMS IN LITERATURE	6
2.1 Reinforcement Learning Problem Structure and Components	8
2.1.1 Agent	9
2.1.2 Environment	9
2.1.3 Reward	10
2.1.4 Observation State	10
2.2 Q Learning [14, 15]	10
2.3 Deep Reinforcement Learning [16]	12
3 TESTING USING REINFORCEMENT LEARNING IN LITERATURE	17
3.1 Testing Anti-Ransomware with Reinforcement Learning [17]	18

3.1.1	Reinforcement Learning Formulation	18
3.1.1.1	Action Space	18
3.1.1.2	Learning Algorithm	18
3.1.1.3	Reward Function	19
3.1.2	Results	20
3.2	Generating Performance Testing Pattern using Reinforcement Learning [18, 26]	21
3.2.1	Reinforcement Learning Formulation	21
3.2.1.1	Action Space	23
3.2.1.2	State Space	23
3.2.1.3	Learning Algorithm	23
3.2.1.4	Reward Function	24
3.2.2	Results	24
3.3	Penetration Testing using Reinforcement Learning [20, 21]	26
3.3.1	Reinforcement Learning Formulation	26
3.3.1.1	State Space	26
3.3.1.2	Action Space	27
3.3.1.3	Learning Algorithm	27
3.3.1.4	Reward Function	28
3.3.2	Results	28
3.4	Test Cases Generation using Reinforcement Learning for Software Testing [22]	31
3.4.1	Reinforcement Learning Formulation	31
3.4.1.1	State Space	31
3.4.1.2	Action Space	31
3.4.1.3	Learning Algorithm	32
3.4.1.4	Reward Function	33
3.4.2	Results	33
3.5	Test Cases Generation using Reinforcement Learning for Hardware Verifi- cation[24]	34
3.5.1	Reinforcement Learning Formulation	34
3.5.1.1	State Space	34

3.5.1.2	Action Space	35
3.5.1.3	Learning Algorithm	35
3.5.1.4	Reward Function	35
3.5.2	Results	35
3.6	Summary	37
4	AUTONOMOUS VEHICLE TESTING USING REINFORCEMENT LEARNING IN LITERATURE	38
4.1	Generating Failure Scenarios for Autonomous Vehicles [1]	40
4.1.1	Reinforcement Learning Formulation	40
4.1.1.1	Action Space	40
4.1.1.2	Learning Algorithm	40
4.1.1.3	Reward Function	41
4.1.2	Results	41
4.1.3	Criticism of proposed approach	42
4.2	Generating Scenarios for Lane Switching Systems using Reinforcement Learning [29]	44
4.2.1	Reinforcement Learning Formulation	44
4.2.1.1	State and Action Spaces	44
4.2.1.2	Learning Algorithm	45
4.2.1.3	Reward Function	45
4.2.2	Results	46
4.3	Other methods for automated testing of AVs	47
4.3.1	Estimating the Possibility of Street Accidents [30]	47
4.3.2	Generating Unpredictable Street Scenarios from Available Streets Data-sets [31]	47
4.4	Summary	48
5	THE PROPOSED FRAMEWORK FOR AUTONOMOUS VEHICLE TESTING USING REINFORCEMENT LEARNING	49
5.1	Carla Simulator	50
5.1.1	Autopilot System [34]	50
5.1.2	Environment Selection	51

5.2	Approaching a Stationary Car Test	53
5.2.1	Reinforcement Learning Formulation for Approaching a Stationary Car Test	53
5.2.2	Training Reinforcement Learning Model for Approaching Stationery Car Scenario	56
5.2.3	A look into the Q-Learning Model Training for Approaching Stationery Car Test	57
5.3	Approaching a Slower Car Test	60
5.3.1	Simulation Environment Description for Approaching a Stationary Car	60
5.3.2	Vehicle Agent Class Built to Track the Simulation	62
5.3.3	Reinforcement Learning Formulation for Approaching a Slower Car Test	65
5.3.3.1	Actions	66
5.3.3.2	Episode Description	68
5.3.3.3	Reward Function	69
5.3.4	Deep Reinforcement Learning Model for Approaching Slower Car	70
6	THE RESULTS AND DISCUSSION OF THE OUTCOMES OF THE PROPOSED DESIGN	73
6.1	Experiment (I) Approaching a Stationary Car Test Results	74
6.2	Experiment (II) Approaching a Slowing Down Car Test Results	80
7	CONCLUSION AND FUTURE WORK	84
7.1	Conclusion	85
7.2	Future Work	86
	References	87

List of Tables

3.1	Different ϵ selections and the generated workload for the reinforcement learning model compared to normal performance testing approaches. [18]	25
3.2	A breakdown of the challenges that the RL model is trained on in [21].	27
3.3	The actions used to train the model in [21].	32
3.4	The benchmarking results of the trained model against various data sets. [21].	33
3.5	The purpose of the components used in fig. 3.12 in the experiment presented in [24].	35
3.6	Comparison between RLG vs MTG models using a timestamp and coverage percentage. [24].	36
5.1	The criteria used to evaluate termination condition and return reward value.	55
5.2	The parameters used for training the Q Learning model for approaching a stationary car test.	57
5.3	State to action mapping for values available in matrix 5.2	59
5.4	The selection space for the parameters under reinforcement learning controlled vehicle.	66
5.5	Decoding reinforcement learning actions into effect on the controlled parameters. (A) The effect of each action on parameters under control. (B)The mapping of each action into delta changes on the parameters under control.	68
5.6	The reward function definition for approaching a slower car test.	69

List of Figures

1.1	The statistics reported by AV's companies in the U.S. during 2018 [1]. . .	1
1.2	The types of sites used for AVs testing in the U.S. [2].	2
1.3	The aggregated star rating of EuroNCAP tests from 1997 to 2007 [9]. . .	4
2.1	An illustration of the three learning algorithms, unsupervised learning (on the left), supervised learning (in the middle), and reinforcement learning (on the right) [11].	7
2.2	Reinforcement Learning Problem Components: Agent, Environment, Reward, and State [12].	8
2.3	Example of training a reinforcement learning agent in an environment [13].	9
2.4	DQN used for Atari2600 agent [16].	12
2.5	The DQN training algorithm[16].	14
2.6	The DQN training average score while training two models for Atari games. [16].	14
2.7	The DQN's performance surpassed human performance in 29 out of 49 games supported by Atari2600 [16].	16
3.1	Reinforcement learning action space encoding [25]	19
3.2	Reinforcement learning action space encoding [25]	20
3.3	Reinforcement learning action space encoding [25]	20
3.4	The framework for performance testing with reinforcement learning [18] .	22
3.5	The framework for performance testing with reinforcement learning [26].	22
3.6	The allowable actions to be taken by the agent [26].	23
3.7	The performance results of the model generated in [26].	25
3.8	The results of RL agent trained to penetrate network port hacking problem in [21].	28
3.9	The results of RL agent trained to penetrate server hacking problem in [21].	29
3.10	The results of RL agent trained to penetrate website problem in [21]. . .	29
3.11	The structure of the network used to train the model of unit test generation in [23].	32

3.12	The structure of guiding random test generation with a guiding block Directing Engine to achieve direct test generation [24].	34
3.13	The coverage results of the models built using reinforcement learning versus benchmarking model MTG [24].	36
4.1	The actor-critic RL block diagram used [1].	41
4.2	The LG simulator scene for full density fog causing AV to stop [1].	42
4.3	The LG simulator scene for full density fog causing AV to stop [1].	43
4.4	The custom Q function used in [29]	45
4.5	The loss function vs. training episodes of the trained RL model to avoid accidents during lane switching in [29].	46
4.6	The reward function vs. training episodes of the trained RL model in [29].	46
5.1	The components of traffic driver used to make a decision by motion planner in Carla simulator.	50
5.2	Examples of identifying the coordinate system in Carla's environments . .	52
5.3	(a) The test scenario starting a scene with the autonomous vehicle under test and stationary reinforcement learning vehicle, (b) The objective of the reinforcement learning model is to cause a failure in the autonomous vehicle.	54
5.4	A screenshot for the Carla simulator with the possible locations that the reinforcement learning model can select from starting -6 till -13.5.	56
5.5	An example of how the reinforcement learning components interact to- gether to find the optimum location for crash occurrence.	58
5.6	Approaching a slower car test scenario.	60
5.7	Autonomous vehicle passes the test in case the safe distance is maintained and no crashes occur	61
5.8	Autonomous vehicle fails to maintain a safe distance and crashes with the slower car.	61
5.9	Autonomous vehicle fails to maintain a safe distance and crashes with the slower car.	62
5.10	Four parameters are specified by the reinforcement learning model for the test of approaching a slower car.	63