Master Research Internship Offer

Département **Control Identification et Diagnostic** (CID),
Centre de Recherche en Automatique de Nancy (CRAN)
UMR 7039, CNRS,
Université de Lorraine.

Topic: Learning for safe control design: Application on Autonomous Vehicles (Quanser Qcar)

Research Lab: *Centre de Recherche en Automatique de Nancy*, CRAN **(**Research Centre of Automatic Control in Nancy), UMR 7039, Université de Lorraine (University of Lorraine), France.
Department: Control Identification and Diagnosis (CID), CRAN**.**

Websites: CRAN: http://www.cran.univ-lorraine.fr/

Scholarship Duration: 5 months
Period: April 2024 - August 2024

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Didier Theilliol, Full Professor, CRAN, University of Lorraine, France.

Description: The subject seeks development as well as implementation of the existing state of the art methods for design optimal (sub-optimal) control laws for autonomous vehicles. In particular, optimal control design using state feedback approaches [1,2] will be envisaged for various purposes such as trajectory following (point to point, line following etc.), lane following, obstacle detection and avoidance, without as well as with vision (camera) based knowledge.

The internship will focus on objectives in a progressive manner starting from model-based feedback control design for control of dynamical systems that require safe control design, followed by learning strategies within the framework of reinforcement learning.

Recent advancements in the domain of adaptive dynamic programming and Reinforcement learning (ADP-RL) have led to remarkable results in optimal control design for non-linear systems in the absence of system knowledge (complete or partial)(Kiumarsi et al. 2017). RL is a mature field with well-established mathematical grounds for optimal (sub-optimal) control of non-linear dynamical systems in continuous as well as discrete time (Bertsekas et al. 1995). RL has become one of the most important and useful approach in control engineering. RL uses a trial-and-error learning process to maximize a decision-making agent's total reward observed from the environment. Here, the optimal control synthesis is largely based upon iterative solution for non-linear Hamilton-Jacobi-bellman equation (HJB) using neural network-based structures. Such a strategy is well applicable to discrete time as well as continuous time systems (Wang, Liu, and Wei 2012; C Mu, Wang, and He 2018; Chaoxu Mu et al. 2016)(Lewis 2008). Deep RL based approaches typically employ deep neural networks as efficient function approximators that approximate the system states, value/policy equations using various Deep neural network structures (deep learning structures) that lead to optimal control solution in an approximate manner (Bertsekas and Tsitsiklis 1996), (Lillicrap et al. 2015; Dulac-Arnold et al. 2015)(Buşoniu et al. 2018). It should be noted that such solutions are intelligent and typically address the needs of unknown systems

The algorithms will be implemented in real time over the 1/10th scaled autonomous car Quanser CAR (QCAR) studio (see information here), available at CRAN (Polytech Nancy). See Annex for more details.

Objectives:
In this research subject, learning of control laws using policy gradient methods including DDPG will be targeted. The objectives at high level include:

- Study of existing work (bibliographic survey) on state feedback control design and reinforcement learning for safe control learning of a dynamical system.
- Control design for point to point, line and trajectory following and lane following.
    - Hands on tests on QCAR.
    - Implementation of Code/program in MATLAB/Python.
- Design of health aware control by incorporating battery degradation data within the control design.

The internship will provide possibilities for scientific publication in international conferences and reputed scientific journals.

References

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Annex

QUANSER
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QCAR

Sensor-rich autonomous vehicle for self-driving applications

QCar, the feature vehicle of the Self-Driving Car Research Studio, is an open-architecture, scaled vehicle designed for academic research. It is equipped with a wide range of sensors including LIDAR, 360-degree vision, depth sensor, IMU, encoders, as well as user-expandable IO. The vehicle is powered with an NVIDIA® Jetson™ TX2 supercomputer that gives you exceptional speed and power efficiency.

Working individually or in a fleet, QCar is the ideal vehicle for validating your research concepts such as dataset generation, mapping, navigation, machine learning, artificial intelligence, and many more.

Features

High Performance
NVIDIA® Jetson™ TX2 supercomputer

Dependable
Robust mechanical design

Open Software Architecture
Design and deploy applications using Simulink®, Python™, C/C++, TensorFlow & ROS

Extensive & Expandable
Wide range of sensors with user-expandable IO for custom applications

Research Studio

The Self-Driving Car Research Studio comes with everything you need to jumpstart your research.

Vehicles
- QCar
(single vehicle or vehicle fleet)

Ground Control Station
- High-performance computer with RTX graphics card with Tensor AI cores
- Three monitors
- High-performance router
- Wireless gamepad
- QUARC Autonomous license

Studio Space
- Set of reconfigurable floor panels with road patterns
- Set of traffic signs

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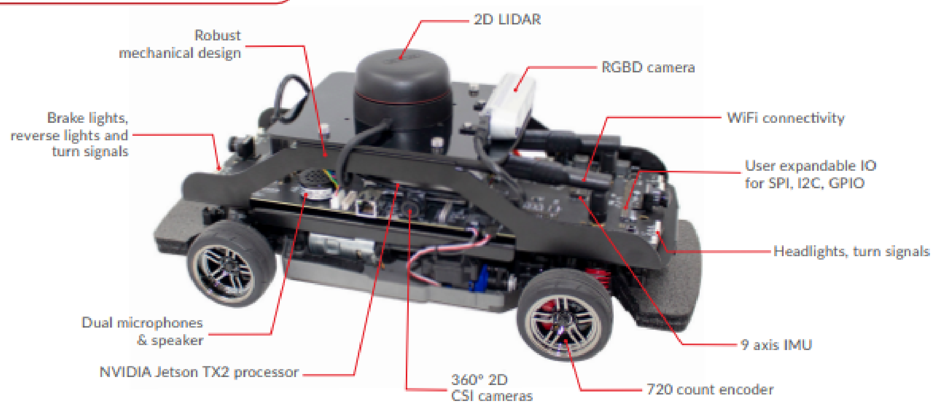
Product Details



Device Specifications

Dimensions	39 x 19 x 20 cm	
Weight (with batteries)	2.7 kg	
Power	3S 11.1 V LiPo (3300 mAh) with XT60 connector	
Operation time (approximate)	2 hr 11 m (stationary, with sensor feedback)	35 m (driving, with sensor feedback)
Onboard computer	NVIDIA® Jetson™ TX2 GPU: 2 GHz quad-core ARM Cortex-A57 64-bit + 2 GHz Dual-Core NVIDIA Denver2 64-bit	GPU: 256 CUDA Core NVIDIA Pascal™ GPU architecture, 1.3 TFLOPS (FP16) Memory: 8GB 128-bit LPDDR4 @ 1866 MHz, 59.7 GB/s
Lidar	LIDAR with 2k-8k resolution, 10-15Hz scan rate, 12m range	
Cameras	Intel D435 RGBD Camera	360° 2D CSI Cameras using 4x 160° FOV wide angle lenses, 21fps to 120fps
Encoders	720 count motor encoder pre-gearing with hardware digital tachometer	
IMU	9 axis IMU sensor (gyro, accelerometer, magnetomter)	
Safety features	Hardware "safe" shutdown button	Auto-power off to protect batteries
Expandable IO	2x SPI 4x I2C 40x GPIO (digital) 4x USB 3.0 ports 1x USB 2.0 OTG port	3x Serial 4x Additional encoders with hardware digital tachometer 4x Unipolar analog input, 12 bit, 3.3V 2x CAN Bus 8x PWM (shared with GPIO)
Connectivity	WiFi 802.11a/b/g/n/ac 867Mbps with dual antennas	2x HDMI ports for dual monitor support 1x 10/100/1000 BASE-T Ethernet
Additional QCar features	Headlights, brake lights, turn signals, and reverse lights (with intensity control) Dual microphones Speaker	LCD diagnostic monitoring, battery voltage, and custom text support
Supported Software and APIs	QUARC for Simulink® Quanser APIs TensorFlow TensorRT Python™ 2.7 & 3 ROS 1 & 2 CUDA® cuDNN OpenCV Deep Stream SDK VisionWorks® VPI™ GStreamer Jetson Multimedia APIs	Docker containers with GPU support Simulink® with Simulink Coder Simulation and virtual training environments (Gazebo, QuanserSim) Multi-language development supported with Quanser Stream APIs for inter-process communication Unreal Engine

About Quanser:
For 30 years, Quanser has been the world leader in innovative technology for engineering education and research. With roots in control, mechatronics, and robotics, Quanser has advanced to the forefront of the global movement in engineering education transformation in the face of unprecedented opportunities and challenges triggered by autonomous robotics, IoT, Industry 4.0, and cyber-physical systems.