Learning-based Visual Perception and Control Applied to Autonomous Vehicles and Manipulators

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CENTRO DE ROBÓTICA - UNIVERSIDADE DE SÃO PAULO



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São Carlos is ...

~ 640 km driving from Rio de Janeiro

~ 250 km driving from São Paulo

Introduction

Motivation

Development of autonomous navigation and control systems for vehicles and robotic manipulators for improving safety and quality of life;

- Perception, motion planning, and control;
- Autonomous cars and trucks;
- Robotic manipulators;

Robotic Plataforms

Autonomous Car



New platform under development within InSAC

Project Carina II (since 2012)

Projects in colaboration with LRM – Mobile Robotics Laboratory (ICMC/USP)

Autonomous Truck



Research Project USP / Scania Latin America (2013-2014)



Projects in colaboration with LRM – Mobile Robotics Laboratory (ICMC/USP)

Autonomous Truck



Projects in colaboration with LRM – Mobile Robotics Laboratory (ICMC/USP)





Robotic Manipulator Kinova Gen3 7-DoF (since 2019)

Perception

Road Marking Segmentation

- Deep Learning for road marking segmentation
- Application on autonomous vehicle localization



HORITA, L. R. T.; GRASSI JR, V. Employing a fully convolutional neural network for road marking detection. In: **2017 Latin American Robotics Symposium (LARS) and 2017 Brazilian Symposium on Robotics (SBR).** 2017.

Road Marking Segmentation



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Road Marking Segmentation



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Monocular Depth Estimation

- Densification of depth measurements using Occupancy Maps;
- Supervised training of a ResNet based network for monocular depth estimation;
- Results show the benefits of densification;



ROSA, N. S.; GUIZILINI, V.; GRASSI JR., V. Sparse-to-Continuous: Enhancing Monocular Depth Estimation using Occupancy Maps. In: **Proc. of the 2019 19th International Conference on Advanced Robotics (ICAR)**. IEEE, 2019.

Monocular Depth Estimation



MENDES, R. d. Q.; RIBEIRO, E. G.; ROSA, N. S.; GRASSI JR., V. On deep learning techniques to boost monocular depth estimation for autonomous navigation. **Robotics and Autonomous Systems**, v. 136, p. 103701, 2021

Monocular Depth Estimation

- Supervised deep learningfor monocular depth estimation;
- Proposed architecture: DenseSIDENet;
- Training parameters: 2M até 12M;
- Prediction rate: 32fps to 88fps;
- Estimates depth and surface normals;



Example of image from camera in a vehicle



Depth estimative results. Warmer colors means objects closer to camera

MENDES, R. d. Q.; RIBEIRO, E. G.; ROSA, N. S.; GRASSI JR., V. On deep learning techniques to boost monocular depth estimation for autonomous navigation. **Robotics and Autonomous Systems**, v. 136, p. 103701, 2021



NAKAMURA, A. T. M.; GRASSI JR., V.; WOLF, D. F. An effective combination of loss gradients for multi-task learning applied on instance segmentation and depth estimation. **Engineering Applications of Artificial Intelligence**, v. 100, p. 104205, 2021.

NAKAMURA, A. T. M.; GRASSI JR., V.; WOLF, D. F. Leveraging convergence behavior to balance conflicting tasks in multi-task learning. **Neurocomputing**, v. 511, 2022.

- Convolutional neural network for grasping points detection;
- Cornell Grasping Dataset was used.





Detected grasping points in blue

• CNN was able to estimate grasping points at 74fps





- A dataset for visual servoing and camera estimation;
- CNN for visual servoing control applied to grasping tasks;



Motion Planning

Path Representation and Planning

• Piecewise linear continuous-curvature paths composed of clothoids, circular arcs, and straight lines



Considered states for planning: localization (p_r) , orientation (θ_r) e curvature (κ_r) .

Example of piecewise linear continuos-curvature path

Curvature (κ_r) and its derivative (σ_r) as function of travelled distance (s).

Path Representation and Planning

• Piecewise linear continuous-curvature paths





Path Representation and Planning

• Piecewise linear continuous-curvature paths



Path Representation, Planning and Control



Decision Making

- Inverse Reinforcement Learning for longitudinal velocity control;
- Observation of state and distance of traffic light ahead;
- Observation of current distance and velocity of other vehicles ahead;
- Mixed discrete-continuous POMPD model to deal with uncertainties on state transitions;
- Intention of other vehicles are partially observed;



SILVA, J. A. R. da; GRASSI JR., V.; WOLF, D. F. Continuous Deep Maximum Entropy Inverse Reinforcement Learning using online POMDP. In: Proc. of the **2019 19th International Conference on Advanced Robotics (ICAR).** IEEE, 2019.

Control

Gaussian Process/ Bayesian Optimization

- Black-box dynamic model of a truck using Gaussian Process;
- MPC using the learned model;



ROCHA, F. H. M.; GRASSI JR, V.; WOLF, D. F. Identificação do Modelo Longitudinal de um Veículo de Grande Porte Utilizando Processos Gaussianos. In: XII Simpósio Brasileiro de Automação Inteligente (SBAI). Natal, RN, 2015.

ROCHA, F. H. M. D.; GRASSI JR., V.; GUIZILINI, V. C.; RAMOS, F. Model Predictive Control of a Heavy-Duty Truck Based on Gaussian Process. In: Proceedings - 13th Latin American Robotics Symposium and 4th Brazilian Symposium on Robotics, LARS/SBR 2016. IEEE, 2016.

Processos Gaussianos / Otimização Bayesiana

- Black-box dynamic model of a truck using Gaussian Process;
- MPC using the learned model;
- Learning using Bayesian Optimation to find an optimal policy for longitudinal velocity control;



ROCHA, F. H. M.; GRASSI JR, V.; WOLF, D. F. Identificação do Modelo Longitudinal de um Veículo de Grande Porte Utilizando Processos Gaussianos. In: XII Simpósio Brasileiro de Automação Inteligente (SBAI). Natal, RN, 2015.

ROCHA, F. H. M. D.; GRASSI JR., V.; GUIZILINI, V. C.; RAMOS, F. Model Predictive Control of a Heavy-Duty Truck Based on Gaussian Process. In: Proceedings - 13th Latin American Robotics Symposium and 4th Brazilian Symposium on Robotics, LARS/SBR 2016. IEEE, 2016.

OLIVEIRA, R.; ROCHA, F. H. M.; OTT, L.; GUIZILINI, V.; RAMOS, F.; GRASSI JR., V. Learning to Race through Coordinate Descent Bayesian Optimisation. In: 2018 IEEE International Conference on Robotics and Automation (ICRA). Brisbane, Australia, 2018.

Robust Lateral Control

- Cargo trucks;
- Vehicle model uncertainties;
- Articulated and non-articulated trucks;





BARBOSA, F. M.; MARCOS, L. B.; SILVA, M. M. Kain EBBRA, M. H.; GRASSI JR., V. Robust path-following control for articulated heavy-dury vehicles. Control Engineering Practice, V. 85, p. 246–256, 2019.

Eco-cruise Model Predictive Control (MPC)

- Longitudinal velocity control for fuel economy;
- Considers a known elevation profile road model and dynamic vehicle model;
- Model includes lateral accelaration for passengers comfort;
- NMPC is computed using C/GMRES algorithm;



CALDAS, K. A. Q.; GRASSI JR., V. Eco-cruise NMPC Control for Autonomous Vehicles. In: Proc. of the **2019 19th** International Conference on Advanced Robotics (ICAR). IEEE, 2019



• Application for autonomous vehicle lateral control;



MORAIS, G. A. de; MARCOS, L. B.; BUENO, J. N. A.; RESENDE, N. F. de; TERRA, M. H.; GRASSI JR., V. Vision-based robust control framework based on deep reinforcement learning applied to autonomous ground vehicles. **Control Engineering Practice**, v. 104, p. 104630, 2020.

Ongoing research and future works

- Movement intention estimation of pedestrians and other vehicles;
- Deep learning for uncertainty estimation;
- Deep learning for visual odometry and SLAM considering uncertainties;
- Perception on challenging weather and environmental conditions;
- Local path planning and control using MPC;
- Decision making using deep reinforcement learning;

Acknowledgements













Thank you!

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