UNIVERSIDADE DE AVEIRO
DEPARTAMENTO DE ELECTRÓNICA TELECOMUNICAÇÕES E INFORMÀTICA

Machine Learning - 2019/2020

PROJECT 2

Each group of two students is supposed to work on one project topic.
If you prefer to work on a different topic not listed below, discuss your idea with the instructor.

I. PROJECT PROPOSALS

Project proposal 1. Autonomous Driving – object classification based on 3D point cloud data. See more details in the Appendix.

Project proposal 2. Skin Lesion Analysis Towards Melanoma Detection. Lesion Classification.
https://challenge.kitware.com/#phase/5840f53ccad3a51cc66c8dab

Project proposal 3. Face Detection from images. Data provided by the course instructor.

Project proposal 4. Face Recognition from images. Data provided by the course instructor.

Project proposal 5. Reuse the Project 1 problem, apply new ML methods and compare with the previous results (discuss this option with the course instructor).

II. WORK LOAD AND STRUCTURE OF THE PAPER

1. State of the art review

Search and review of at least 5-6 references (papers, reports, thesis, etc.) handling the same or similar problem. Make a review of different techniques used to solve the problem you want to explore.

2. Data description, visualization and statistical analysis

Describe the problem you want to solve, the features and visualize the data (if it is difficult due to high dimension, show only some samples). Provide some statistical analysis such as metadata (e.g. features range of variation), histograms, try to identify if there are some data quality problems, detect interesting subsets.

3. Data preprocessing (if relevant)

Describe possible preprocessing steps to construct the final input to the machine learning algorithm from the initial data, such as data normalization, feature selection or dimensionality reduction in case of redundant features.

4. Description of the applied machine learning algorithm(s)

Apply a suitable ML algorithm (learned in class or self-learned) to solve the problem with the chosen dataset. Introduce the method shortly, define its parameters. Make a selection of the most important model hyper parameters after their variation in a selected range. Show graphically the results of this search.

5. Presentation and discussion of results

Presentation of the results preferably in a graphical format. Analysis, discussion, interpretation. Compare your results with the results in the reviewed references or apply and compare at least two ML methods on the same problem. For new data sets apply at least one new ML method not applied in Project 1. For projects that reuse dataset from Project 1 apply new ML methods and make a comparison with the previous results.

6. Conclusions

Critical discussion of the gained knowledge regarding the advantages/disadvantages of the applied methods on the problem in hand. Suggestions for potential future directions of study.

III. PROJECT ASSESMENT (25 % of the final grade)

The project is evaluated based on a submitted paper according to the IEEE format. The paper should follow the structure of the Work Load. The work done by each student has to be explicitly specified. All project's files (pdf and Latex files of the paper, and the code implementing the algorithms) are sent to the course instructor (petia@ua.pt) in a compressed format having the following name: P2_ML2019_XXXXX_YYYYY (where XXXXX and YYYYY are substituted by the academic (mechanographic) number of each student. If the file is too big to email as an attached document, feel free to use any big file transfer option you may know (we transfer, dropbox, link in a cloud. etc.)

IV. **Evaluation criteria** (total score 20)

1. *Report content (13)*
   – State of the art review.
   – Data Description.
   – Data Preprocessing. Train/validation/test data devision. K-fold cross validation.
   – Description of the Applied Machine Learning methods.
   – Results.
   – Conclusions.

2. *Report formatting (4) :*

– IEEE Latex format, affiliation (Department, University, subject, course instructor), abstract, keywords, work load per student.
– Sufficiently detailed report.
– References, reference citation in the report.
– Clear figures (title, legends, axis labels) and tables referred in the text.

3. *Novelty and contributions (3)*

– Based on the references and what has been done previously by other authors, propose a better solution, e.g. improve the performance of the ML model in solving the problem you work with.

Appendix: Project Proposal 1.1

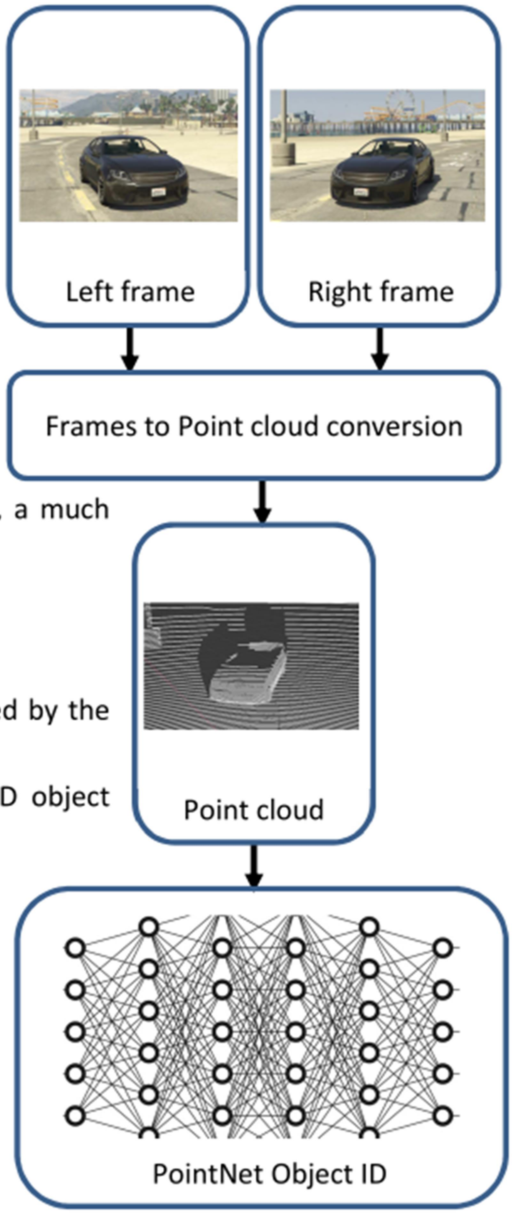
3D object detection based on a point cloud obtained from a stereo camera

Supervisor: Pétia Georgieva (petia@ua.pt)
Co-supervisors: Miguel Drummond (mvd@av.it.pt),
Diogo Guedes (diogoguedes@ua.pt)
Keywords: LIDAR, object ID, neural nets, stereo cameras

Scope

Self-driving cars will require that a rich suite of sensors for observing its surroundings in detail:

- Location sensors (such as GPS): needed to know where the car is within the high-definition maps;
- Vision sensors (RADAR, LIDAR, SONAR, camera): required to detect obstacles such as cars, pedestrians and cyclists.



From these sensors, LIDAR is able to provide a detailed 3D view of the surroundings, as it provides a dense point cloud. However, LIDAR is a very expensive sensor, and alternative methods are being studied for providing a dense point cloud for a lower cost.

One of such methods is Pseudo-LIDAR. Instead of using a LIDAR, a much cheaper stereo camera is used.

Objective

The objective of this work is to:

1. Produce a dense point cloud from the pair of frames captured by the stereo camera;
2. Assess the accuracy of the produced point cloud using a 3D object classifier (PointNet).

The stereo images will be extracted from GTA V using Script Hook V-based mods done by Diogo, available here.

Work plan

1. Implement a GTA V mod to produce a pair of frames as:
   a. Frame 1: Camera to the left of the character's position.
   b. Frame 2: Camera to the right of the character's position.
2. Use an algorithm for depth estimation in order to produce a point cloud of the environment using the pair of frames. Algorithms for this are available in the Pseudo-LiDAR and Pseudo-LIDAR++ papers.
3. Correctly classify the object as a car using PointNet.
4. Run various scenarios to assess the accuracy of PointNet.

Appendix: Project Proposal 1.2

Combining HD maps with LIDAR for simplified 3D object detection

Supervisor: Pétia Georgieva (petia@ua.pt)
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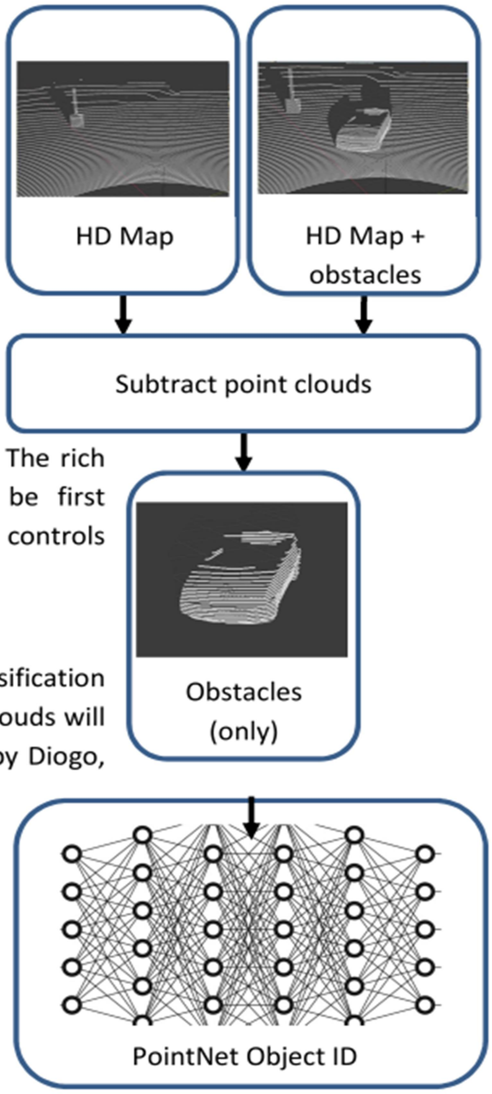
Diogo Guedes (diogoguedes@ua.pt)
Keywords: LIDAR, object ID, neural nets

Scope



Safe self-driving cars will likely resort to high-definition (HD) maps to know everything about the surroundings, except for existing obstacles.

Storing such a huge amount of prior knowledge (the entire world map can easily take Petabytes) does *not* mean that a rich suite of sensors is not required; quite on the contrary:

- Location sensors (such as GPS) are required to pinpoint the car in the high-definition maps;
- Vision sensors (RADAR, LIDAR, SONAR, camera) are required to detect obstacles such as cars, pedestrians and cyclists.

Autonomous cars will therefore resort to a rich suite of sensors. The rich but highly redundant data produced by such sensors must be first "distilled", before being fed to a decision-making algorithm that controls the vehicle.

Objective

The objective of this work is to implement a simple object classification flow based on HD maps and LIDAR alone. Maps and LIDAR point clouds will be extracted from GTA V using Script Hook V-based mods done by Diogo, available here.

Work plan

1. Implement a GTA V mod to produce a pair of frames as:
   a. Frame 1: Point cloud of the surroundings *without* any cars in sight. This frame will work as the HD map.
   b. Frame 2: Point cloud of the surroundings *with* one car at the front. This frame will work as HD map + obstacles.
2. Subtract frame 1 to frame 2, and discard all resulting points that go to origin (0,0,0). This will result in a much lighter point cloud only containing the points of the car. Such a light point cloud is much simpler to process.
3. Correctly classify the object as a car using PointNet.
4. Run various scenarios to assess the accuracy of PointNet.

Note: in real life, producing a point cloud from an HD map is not trivial, nor is aligning a point cloud captured by the LIDAR with the point cloud produced from the HD map. For a matter of simplicity, in this work both these processes are made trivial.