Autonomous Parking Space Detection

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Overview

Introduction

Description

The project aims to automatically predict the availability of a parking spot given the feeds provided by a video camera monitoring the parking area.

Motivation

Hunting for parking brings no joy for students[1]

"...Students at Wits are struggling to find available parking spaces on campuses since..."
"...student X said that finding parking is the biggest issue she faces at Wits."

— Aarti Bhana, Wits Vuvuzela

Problems

Various factors can explain the parking space problems mostly in urban areas:

- Urban planning not following the quick growth of population dynamics
- Drivers not aware of available space due to lack of knowledge of the area or anything obstructing it from the driver
- Bad management of the parking area

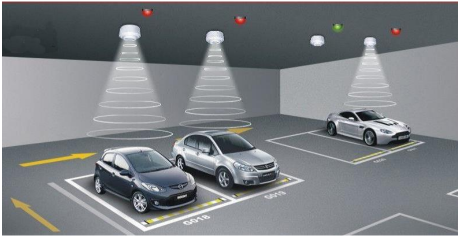
Aims

This project aims to:

- Perform comparative study between existing solutions (SVM based algorithms) and CNN,
- Use video cameras to allocate parking spaces to drivers
- Apply computer vision techniques to infer the status of a space (Background subtraction, Hough transform ...),
- Help the driver to locate a vacant spot using the dedicated web application,
- Run a quantitative analysis of the results produced by the system to predict parking habits of drivers.

Background and related work

Sensors Based Detection



Non-intrusive sensors, [2]

Intrusive sensors, [3]

Sensors Based Detection

Pros:

- Very accurate,
- Since individually installed per spot, the system can return the available number of spots [4],
- Almost no computation required

Cons:

- Expensive in installation in terms of number of devices to place per spot,
- Expensive in maintenance.

Background Subtraction I

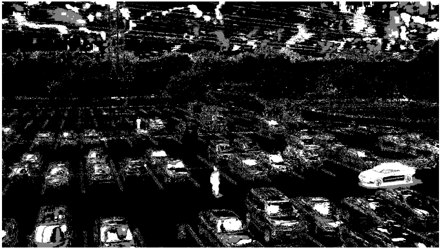
Definition

The background subtraction is a technique used in computer vision and image processing for detecting the foreground from a set a images of the same scenario (video sequence of a non-moving camera) for various types of detection problems.

$$pixel\_value = \begin{cases} 1, & |frame_i - frame_{i-1}| > T_h \\ 0, & \text{otherwise} \end{cases}$$

Background Subtraction II

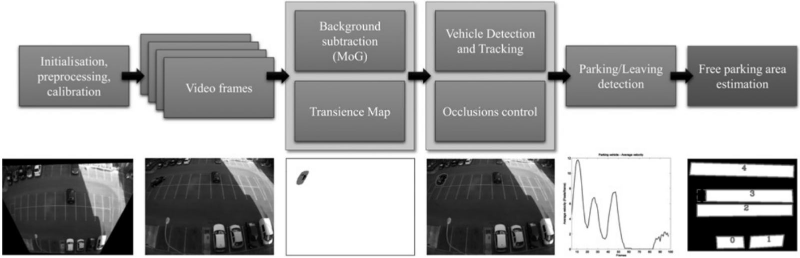
Original image



Background subtracted image

Background subtraction to:

- Create a transience map of the parking area or to model the parking area given the previous positions of vehicles [5]



Background subtraction method proposed by [5]

This method used the background subtraction and the Mixture of Gaussians to detect and track vehicles to infer the availability of remaining spots given a **threshold** on the transient value,

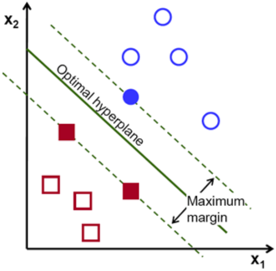
Background Subtraction IV

- Use histograms of spatial features to map the spots of an unmanaged parking area but taking as object the group of pixels generated by vehicles, rejecting the non-vehicle objects by automatically adjusting the **threshold** [6].

Support Vector Machines I

Definition:
Supervised machine learning technique that is based on a decision boundary to separate data into different subsets (classes). Support vectors are the coordinates of data point in the data space that are the closest to the boundary lines, hyperplanes.
Support Vector Machines(SVM) can be used for **classification** and **regression** problems. The classification has been mostly used for the parking space detection.

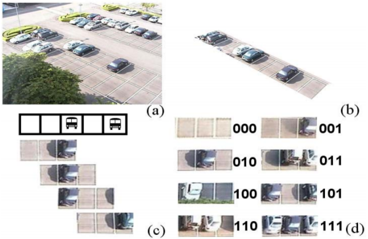
Support Vector Machines II



Support Vector Machines, OpenCVDocs

Support Vector Machines (SVM) have been widely used for the problem.
Usually associated with Histograms of Oriented Gradients (HoG),
Difference of Gaussians (DoG), color histograms, Local Binary Patterns...

- To detect available parking spaces using both multi-class Support Vector Machines (SVMs) and a Markov Random Field (MRF) framework using the color histograms as features [7] with an accuracy of 93.52%,



Multi-class SVM, [7]

- To classify individual spot using DoG- features with an accuracy of 92.33 after a comparative study with the k-NN, LDA and HoG, RGB, HSV YUV (color spaces) as features [8]%

Support Vector Machines IV

- As similar to the previous point,to classify individual spot using Local Binary Patterns and Local Phase Quantization as features with an accuracy of 99% [9].

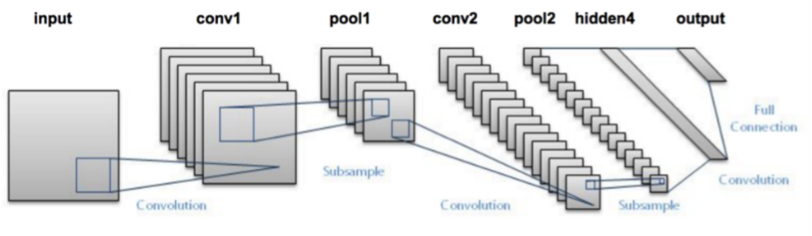
(a) (b) (c)

Segmented image, [9]

Deep Learning - Convolutional Neural Networks I

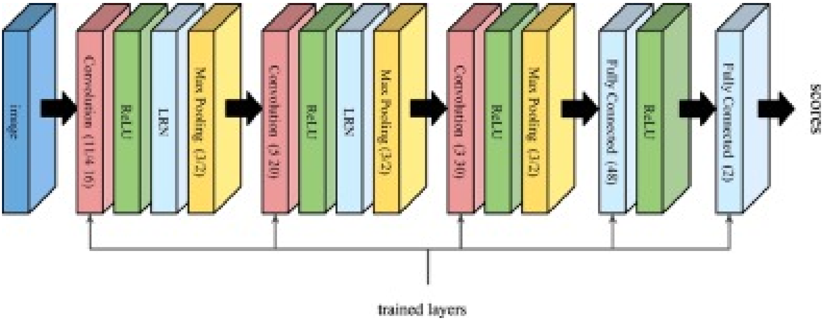
Definition

- Supervised learning branch of machine learning for pattern and object recognition,
- CNN learn extracted features,
- CNN are computationally expensive at the training phase especially when the dataset contains many classes with many objects to classify,
- But high accuracy compared to its direct competitor the SVMs.



Overview of a CNN: Lenet-5, [10]

Deep Learning - Convolutional Neural Networks III

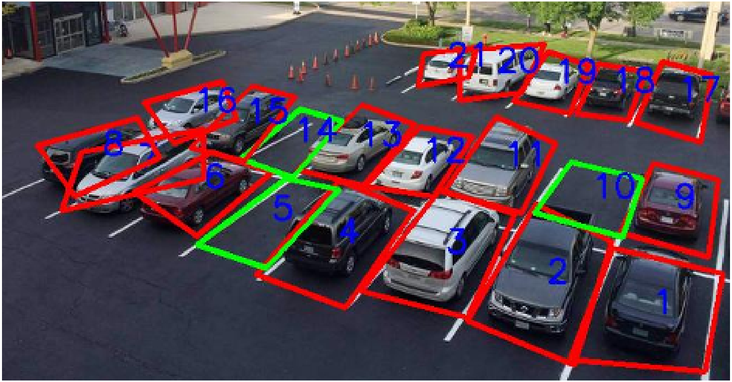


Modern CNN, mini-AlexNet, [11, 12]

Deep Learning - Convolutional Neural Networks IV

CNNs to bring a solution to parking management:

- The classification happens in a remote server that is fed with images coming from cameras facing a parking area.



Online classification, [13]

Deep Learning - Convolutional Neural Networks V

- The classification happens in individual customized cameras that contain Raspberry Pi's. Each camera runs a reduced version of AlexNet CNN [12].

Research Methodology

Research Hypothesis

- **Hypothesis1:** Hough Transform for lines detection which implies spot presence (on the first frame) + CNN for classification,
- **Hypothesis2:** Hough Transform for lines detection + Background Subtraction to the incoming frame from the camera to automatically segment the image for parking spaces through their lines + SVM * (Histograms of Oriented Gradients OR Difference of Gaussians OR Local Binary Patterns ...),
- **Hypothesis3:** RCNN for spots detection + (SVM OR Normal-CNN) OR (trained-Normal-CNN AND CNN-learned-features-SVM) for spots classification.

Research Questions

- Do the background subtraction and the Hough transform associated with the Convolutional Neural Networks and the Support Vector Machines efficiently return automatically the status of all the parking spaces?
- Will the RCNN be better at automatically detect the spots without human intervention?
- How could the union of the features generated by a trained CNN and the power of the SVM improve the classification accuracy and credibility of the parking space management?

Background Subtraction

Method 1:

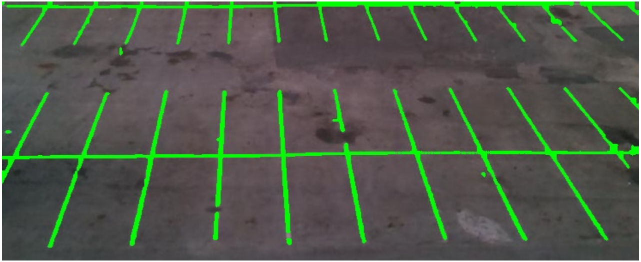
- To automatically create a mapping of all the parking spaces given a parking lot as illustrated in Section 5 when using the transience map [5],
- From the map, feed the cropped spot to either the CNNs or SVMs.

Method 2:

- To use GrabCut on one image of the parking space to crop the background from the foreground, create a map (ground-truth) out of GrabCut
- And classify the results using CNNs or SVMs.

Hough Transform

Parking spots contain lines that can be detected using the Hough Transform. The end-points of those lines will joint altogether by the Convex Hull algorithm to create rectangle of spots to build a map (ground-truth) of the parking area and classify each spot per frame.



Result of Hough Transform

Convolutional Neural Networks: CNN

- **Method 1:** To reduce the depth of the successfull AlexNet, since 2 classes in the project, instead of 1000,
- **Method 2:** A new CNN will be created using state-of-the-art rules for CNN design. CNN design is an art that follows some rules to have both speed and specially accuracy.

Region-based Convolutional Neural Networks: R-CNN

The algorithm will be ran on one frame of the parking area of interest to return the coordinates of the potential parking spots. If all the spots are not mapped, manual labeling will take place to create a full map of the parking area. After all the spots being mapped, the cropped patches will get classified by either the CNNs or SVMs.

Sample Result of RCNN

SVMs

Have been broadly used previously. The hyper-parameters of the SVMs, C, γ, kernel will be computed using grid search.

Selection or Assignment of Parking Space: Conflict management

Automatic assignment:

- Fill the bottom rows first,
- May not be followed as planned, which leads to method 2,

Metered booking:

- Let the user book an available spot,
- Cancel booking after a period X of time,
- If same time booking happens: User1 and User3 book the spotA at the same time *t*, nodern DBMS are able to handle that case, otherwise, cancel both booking processes.

The Data: From A to Z

- Data Collection
- Data Preparation
- Data Labeling
- Datasets

Training & Testing

Research Plan

Research Plan

Path to follow

Guidelines

Our main objectives will be to:

- Compare the performance of the mainly used classifiers based on the literature review: CNN and SVM,
- Collect data for the new experiments to do based on the classifier we will choose,
- Design and implement an algorithm that will automatically withdraw the parking bays to feed them to the classifier (Hough transform for example) given the whole parking lot
- Perform a qualitative analysis of the usage of the parking as a whole to predict the availability of the bays.

End

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