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February 2018

ROBUST DRIVE-BY ROAD SIDE PARKING DETECTION ON MULTI-LANE STREETS USING AN OPTICAL DISTANCE SENSOR

Master's Thesis
to confer the academic degree of
Master of Science
in the Master's Program
Computer Science

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Affidavit

I hereby declare that the following dissertation ”Put your thesis title here” has been written only by the undersigned and without any assistance from third parties.

Furthermore, I confirm that no sources have been used in the preparation of this thesis other than those indicated in the thesis itself.

Linz, on November 10, 2017

Markus Hiesmair

Acknowledgment

Summary

Summary ...

asdf

Abstract

Abstract …

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Abbreviations

CNN Convolutional Neural Network

GPS Global Positioning System

LIDAR Light detection and ranging

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Chapter 1

Introduction

Traffic congestion in urban areas became a bigger problem every year in the past decades. Increasing traffic causes several issues, for example high monetary and environmental costs by using gasoline and by emitting CO_2 to the environment. There are several strategies to reduce urban traffic to mitigate these problems like for example new investments in public transport infrastructure. However, the usage of private cars in cities won't stop in the next decades, but increase. According to a study by Hao et al. [5] car sales will continue to grow in the upcoming decades and therefore also traffic will continue to become worse in big cities. Thus, it is important to find ways to reduce traffic in urban areas.

With more vehicles driving in urban areas, there also comes the need for a sufficient number of parking spaces. Finding parking spaces in urban areas can be a really difficult, frustrating and time consuming task for drivers. There often exists some information about the availability of parking spaces in parking garages, but in most cities the situation of road side parking is rather non-transparent. This not only leads to frustrated drivers, who are searching for parking spaces a long time, but again contributes to urban traffic congestion as many cars have to drive around close to their destination while searching for free parking spaces.

There are many studies, which show that the searching for parking spaces adds a lot of traffic. In 2013 a study by Nawaz et al. [11] showed that about 30% of traffic congestion is created by drivers looking for free parking spaces. Another study [6] found that alone in 2007 searching for parking spaces caused costs of about 78 billion US dollars by using 2.9 billion gallons of wasted gasoline and 4.2 billion lost hours only in the United States. Furthermore, this obviously causes a lot of CO_2 emissions which is not only bad for the environment and contributes to climate change, but also lowers the quality of living in big cities through the significant amount of air pollution.

One of the most important contributors to high search times for parking spaces is not only the lack of vacant parking spaces, but also the lack of information, if and where free parking spaces are available. Therefore, one way to mitigate many of the above stated problems is to determine the current parking space situation in the city and make it accessible to the public (e.g. via web application), so that drivers can efficiently navigate to a vacant parking space, or even decide if they want to go by car or use public transportation, depending on the number of parking spaces available close to their destination.

However, detection of road side parking spaces and their states is a challenging task. Of course an obvious approach to the problem would be to put stationary sensors to every parking space in the city, which check, if the corresponding parking space is occupied or vacant. This, however, has the drawback to be very expensive as, for big cities, thousands of sensors would have to be bought, installed and maintained. Furthermore, because the state of parking parking spaces does not often change, the high frequency of sensing with such a system would be rather inefficient.

1.1 Drive-By Park Sensing

A promising novel approach to sense a city's parking situation is the use of mobile sensors instead of static ones. Crowd sensing has the advantage to be usually more cost effective and can provide sufficient accuracy for the purpose of providing parking space availability maps.

There are several approaches to mobile parking availability sensing, which will be discussed in chapter 2. This thesis will focus on "drive-by park sensing". The idea behind the drive-by sensing approach is that there are sensing vehicles which are driving through the city and collecting data of their environment through mounted sensors. Using the collected data parking cars and vacant parking spaces should be detected. There already exists a prototype implementation of such a system. In 2013, Mathur et al. [9] presented their system, called ParkNet, which continuously measured the distance to the nearest obstacle on the right side of the road, as well as the location of the sensing vehicle through a GPS sensor. Using these data, they used thresholding to detect parking cars and vacant parking spaces. A more detailed description of their work is being described in section 2.1.6.1.

Figure 1.1 shows a standard drive-by scenario of a sensing vehicle which passes two parallel parked cars and a vacant parking space in between them. The distance measurements while passing the parked cars will be much shorter than the measurements

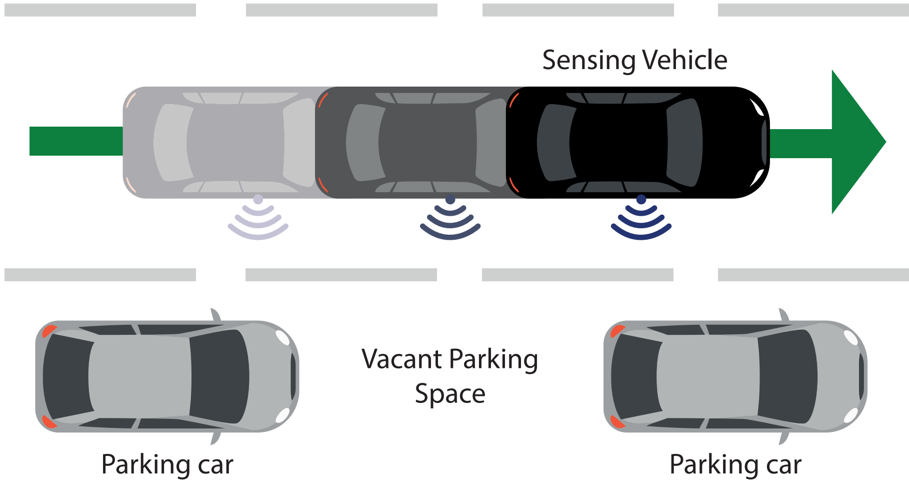

Figure 1.1: The sensing vehicle passes two parked cars and should identify a vacant spot in between using distance and location measurements. **To-Do:** Hier Referenz zu Parknet-Paper??? Ähnliche Grafik...

taken while passing the vacant parking space. This should allow a basic algorithm to recognize parking cars and vacant parking spaces.

However, the situation which is shown in figure 1.1 is an idealistic one. In real life traffic, there will be much more complex situations to face, which are not as easily detectable and which might influence the success of the detection. For instance, the sensing vehicle might not drive in the right-most lane, therefore the measured distances will be much longer. Another possible issue are other driving cars, motorcycles or bicycles which the sensing car overtakes. There are many of such distractions which have to be filtered out to ensure that there are as few false detections as possible. The existing ParkNet prototype does not take any of such situations into account, because it was only evaluated on parallel parking cars on single lane roads.

The high complexity of urban traffic and the many distractions during sensing make it nearly impossible to create a rule set based on the sensor measurements which would be able to detect parking situations at a sufficient accuracy. Therefore, simple thresholding as applied in the ParkNet prototype will not work in real life traffic scenarios. Furthermore, such rule sets would have to be created for each city individually because of the different nature of the roads and the parking spaces. For instance, the distance between roads and parking spaces can vary highly in two different cities. Thus, to be able to detect parking situations, new methods have to be found, which should be more flexible to distractions and changes in the environment.

1.2 Research Goals and Methodology

The overall goal of this thesis is to determine which accuracy can be achieved for detecting the parking space situation in urban real world traffic scenarios using drive-by park sensing. Furthermore, distracting situations should be identified and strategies to cope with them should be found to be able to keep the detection accuracy high. In contrast to existing approaches in this thesis machine learning will be applied to classify different road traffic and parking scenarios to be able to better cope with the high variety of situations possible. As a first step, sensor data has to be collected in real world traffic scenarios including distance sensor measurements and GPS locations of the sensing vehicle. To be able to apply supervised learning all sensor measurements have to get assigned their ground truth manually. As next step different machine learning algorithms will be applied, evaluated and compared to each other in terms of accuracy for the different classes. The detailed methodology which will be followed includes the following steps:

Building a test bed As a first step a test bed has to be built, which is able to access the required sensors to record all the necessary data. A Raspberry Pi will be used as processing device because of its popularity and the many compatible sensors which work with this platform. It is connected to a LIDAR-Lite v3 sensor which continuously measures the distance to the nearest obstacle on the right side of the road. A GPS receiver will track the location of the sensing vehicle and a camera will be used to record images of the ground truth for evaluation purposes only. In section 3.1 the complete setup of the test bed is described as well as all the specific hard ware parts and their abilities.

Acquiring a dataset As soon as the test bed is ready, the sensors should be mounted on the prototype car to be able to start recording the dataset. Test drives should be done in some selected streets in Linz, Austria with the focus of variety of the recorded situations. The test scenes should include single lane as well as multi lane streets and measurements in all streets should be done several times. Furthermore, the car should be driving as it would in regular traffic (not only in the right most lane, etc...) and the scenes should also include high and low traffic scenarios to have a high amount of diverse data. All measured distances, GPS locations and ground truth images have to be saved to files with the according timestamps to be able to evaluate the results of different approaches later on. Furthermore, using the images taken by the camera, ground truth values will be manually labelled in different classes (Parked car, free space, overtaken car, ...). A detailed description about the dataset and the ground truth tagging can be found in section **To-Do:** ref **??**.

Data processing and segmentation As next step the measured sensor values have to be preprocessed and filtered in order for the following algorithms to work. Sensing and overflow errors as well as outliers in the measurements should be identified and removed before further processing. After the raw data has been filtered, the sensor data has to be segmented. As parking cars and other cases which should be classified consist of several sensor measurements, the corresponding sensor measurements should be grouped together and merged to segments which will be later classified. All preprocessing steps and the segmentation process are described in more detail in section **To-Do:** ref 3.3.

Classification using basic machine learning techniques Features on the created segments are calculated (for instance length, average distance and variation of the distances) and are being used to train and evaluate several machine learning algorithms which will be compared on their performance. Furthermore, some deep learning models will also be evaluated on the raw sensor data of the segments and will be compared to common machine learning results. The results of all experiments can be found in section **To-Do:** ref **??**.

Further improvements **To-Do:** todo

Chapter 2

Related Work

This chapter will cover work related to park sensing and machine learning. Section 2.1 will discuss different approaches to sensing current parking situations in cities. Furthermore, a comparison of them will be given as well as advantages and disadvantages of the specific approaches. **To-Do:** Machine Learning...

2.1 Approaches to Park Sensing

There already exist numerous approaches to detecting the states of parking spaces as well as the parking situation in a city. In this section parking detection approaches will be categorized in five different categories and in the following subsections several reference papers for all categories will be discussed. The first section about stationary park sensing (section 2.1.1) will reference approaches where sensors are stationary deployed per parking space. Section 2.1.2 will cover camera-based systems which detect parking spaces in a dedicated area. Counting in- and outgoing vehicles to coarsely estimate parking space counts is discussed in section 2.1.3. Another approach is to detect certain events (for instance parking and unparking) to estimate parking space counts. Section 2.1.4 will discuss several related papers in this area. Drive-by sensing will be discussed in sections 2.1.5 and 2.1.6. Using cameras to detect parking spaces while driving by will be referenced in section 2.1.5, while section 2.1.6 will cover using distance sensors. **To-Do:** evtl. comparison, advantages, disadvantages section

2.1.1 Stationary Park Sensing

The most obvious and technically simple solution to park sensing is to use stationary sensors to determine the state of parking spaces. Usually one sensor per parking space is used which determines its state (occupied or vacant) and sends it to a central server.

Several reference projects already exist [13, 12] implementing this technique. In this section as an example of all similar systems, the SFpark project will be examined.

In San Francisco a first prototype of the SFpark project [13] has been implemented from 2008 to 2011. In specific down town areas in San Francisco with high amounts of traffic, wireless stationary sensors have been placed at about 8.200 road side parking spaces. These sensors are able to detect the state of one parking space in real time and send this information to a central server. Furthermore, parking garages also count the in- and outgoing vehicles and shared this information, so that the parking situation in the areas with park sensing can be derived. The gained information is being shared as open data, so third party developers and researchers can also use the dataset for all kind of projects. Furthermore, there exists an App from SFpark itself to help drivers find available nearby parking spaces, navigate to it and pay as they go with their phones.

A top priority goal of the SFpark project is to increase the availability of parking spaces in every block throughout the city. To achieve this goal, they are using demand responsive pricing. If (almost) all parking spaces in a neighbourhood are occupied for a long time, they raise the price in this specific area and vice versa if no parking spaces are occupied they lower prices. This leads to high overall parking space availabilities (20 - 40%) and also to lower traffic congestion and lower greenhouse gas emissions. However, besides the advantages of high accuracy and being a real time system, there also are disadvantages. First of all, only metered parking spaces can be tracked, as sensors have to be installed per parking space, so areas where parking is allowed but there are no clearly marked parking spaces cannot be sensed with a reasonable accuracy. Furthermore, another big drawback are the high overall costs. The about 8.200 stationary sensors have to be bought, installed and maintained, which obviously causes high costs while only covering a tiny fraction of the overall San Francisco down town. So if the system should be available in the whole down town, costs would increase dramatically.

2.1.2 Stationary Park Sensing using Cameras

Another approach while using stationary sensors is to use fixed deployed cameras which continuously record images of parking areas and analyze it for vacant parking spaces. Cameras can monitor up to one hundred parking spaces simultaneously with an accuracy up to 96 %. Challenges of image detection are of course different lightning and weather conditions as well as occlusions depending on the angle which the camera records the parking scene. Detection algorithms using standard digital image processing will be discussed in this section as well as approaches using deep learning and Convolutional Neural Networks (CNNs).

Parking Detection using Digital Image Processing

There exist a few common approaches using digital image processing to detect the state of parking spaces using a captured image of a parking area. First of all, edge detection is often used for parking space classification. Common edge detectors such as Canny Edge Detector or Sobel can be used to derive the edge pixels of an image. As next step the edges or edge pixels are counted and if they are above a certain threshold, the space will be detected as occupied. The assumption behind this approach is, that usually a vacant parking space has a plain surface and therefore a low amount of edges whereas a image of a parking car should have a lot of edges. Blumer et al. [2] and Liu et al. [7] both used this technique as part of their algorithms.

Often a slightly different yet related approach is also used, namely object counting [7]. The edges of the image segment of a parking space are analyzed and closed contours (treated as objects) are detected and counted. Then again depending on a threshold which has to be set first, a parking space will be classified as either vacant or occupied depending on the object count.

Another common image processing technique is to use foreground/background information of the images. Using this approach the main background color is being identified and compared to the whole image. The background of a parking space can either be defined via extracting a certain part of an image which should always represent the main background color of a parking space's pavement (done by Blumer et al. [2]) or via an histogram of the image assuming that the background uses the most pixels in a recorded image (done by Liu et al. [7]). After the background color is available it is being subtracted from the original image and using thresholding foreground and background pixels are identified and counted. Depending on the count of the respective pixels, the parking space is then classified as vacant or occupied.

Liu et al. [7] used all of the above mentioned techniques to build a more stable prototype. They only tested their prototype indoors which is why weather and lightning conditions were no problems. With sensing only a maximum of seven cars, it provided an ensemble technique which should be more reliable. However, they did not include a statistic of how well their algorithm performed on a bigger dataset. Another ensemble method was developed by Blumer [2]. They used edge counts and background/foreground information as input for different machine learning techniques, which should then classify a parking space as vacant or occupied. Their plain algorithm achieved an accuracy of about 77.8%. However, they improved it using frames of preceding and following images to identify parking/unparking events and then achieved an accuracy of about 88.8%.

Parking Detection using Deep Learning and CNNs

In recent years deep learning, which is a specific variant of neural networks, gained a lot of significance in the field of machine learning. For example in image recognition, convolutional neural networks (CNNs) preform nowadays as well as humans in classifying everyday objects in digital images. A CNN is a neural network with a possibly large amount of hidden layers of which some of them are convolutional layers, which take into account the spatial relationship between neighbouring pixels (in the case of image recognition). This rise in learning power also leads to projects which try to train CNNs in classifying the states of parking spaces while using camera images of a parking area.

In 2016 Amato et al. [1] trained two different CNNs on classifying parking space states and compared their performances afterwards. They used the publicly available PKLot dataset as well as a dataset collected by themselves to train and evaluate their neural networks. In total they had over 700.000 images in different weather conditions and with different levels of quality (in some situations parking lots were almost fully occluded by trees or lamp posts, etc.). Results of the CNN's classifications were promising. Despite the fact that some of the images did not exactly match the parking space and there were a lot of occlusions, the best performing deep neural network gained an accuracy of above 91% on all subsets of the datasets.

Another work in the field of deep learning has been done by Di Mauro also in 2016 [3]. They also used CNNs and the PKLot dataset as well as a self acquired dataset. However, they had a slightly different CNN as they also used a technique called pseudo-labelling of the data which can be seen as semi-supervised approach. When using pseudo-labelling both labelled and unlabelled data are used at the same time to train the network. For unlabelled data the label which was computed by the CNN in the forward pass is used, that is also why it is called pseudo-labelling. Furthermore, a different loss function has to be used as the pseudo labelled data has much less significance than the ground truth labelled data. Di Mauro et al. trained the CNN with about 5% of the data and achieved an accuracy of above 96% with a the fully supervised approach. The pseudo-labelling approach reached about the same levels of accuracy, but the dataset had to be balanced for it to work.

Advantages and Disadvantages of using stationary Cameras

As described in this section, there is already a lot of research how cameras can be used to classify the states of parking spaces. Advantages of cameras are the high level of accuracy they reach while covering a lot of cars at once. However, most of the research focused on the use of cameras for detection the parking space situation of a single parking area, for instance in front of a super market. For this approach to work at a city wide scope, cameras would have to be mounted at least at every block. Similar to the dedicated sensors per parking space (section 2.1.1) this would cause high costs not only in the form of hardware costs but also in installation and maintenance. Furthermore, mounting cameras throughout the city obviously brings up privacy issues.

2.1.3 Counting Vehicles

smart urban parking detection [14]

2.1.4 Event Detection based Park Sensing using Smartphones

updetection[8]

parsense [11]

pocketparker [10]

2.1.5 Drive-by Park Sensing using Cameras

ParkMaster

parkmaster [4]

2.1.6 Drive-by Park Sensing using Distance Sensors

2.1.6.1 ParkNet

parknet... [9]

2.2 Machine Learning

Chapter 3

Prototype Implementation

blabblabla

3.1 System Design

- System description (type of sensors, requirements); overall envisioned system of cars detecting free spaces and communicating the information - Testbed description (concrete HW and technical capabilities)

3.1.1 Test Bed Description

3.2 Experiment description and data collection

- Description of experiments (scenarios we are interested in: parking car, etc.) - Data set derived (raw data, size, etc.) - Map data and camera ground truth data

3.3 Data processing

- Preprocessing, feature definition ... - Traditional ML Algorithms (incl. a short description of each algorithm and configuration options) - Deep Learning

3.4 Experimental results

- Results of the different ML approaches, important features, difficult cases, etc. - Comparison of traditional ML and Deep Learning (cf. our demo)

Chapter 4

Results and Discussion

Chapter 5

Conclusions and Future Work

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