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Satellite parking: a new method for measuring parking occupancy

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Abstract.

Parking management plays a critical role in keeping urban spaces accessible and urban managers strive for an optimal balance between not enough and too much parking. Deciding which parking space can be liberated or needs to be extended requires detailed data on parking occupancy trends. In person inspection and in-situ sensors can provide such data but are too costly for city wide deployment. High-resolution satellite imagery is becoming more affordable, has the advantage of instantaneously collecting information from the whole city, is continuously being updated, and available for several years now to allow building a time series. Yet, identifying cars in satellite imagery is not a trivial task. We propose a method for classifying parking spot occupancy based on thresholding the reflectance range. The method requires individual parking spot data to be available and analyses each parking zone individually. We tested the method on a 0.5 metre resolution image (Pleiades satellite) that was specifically ordered for this purpose during a clear spring day in a medium-size city. The method has the advantage of not requiring extensive training data and is non-parametric. To assess accuracy, we collected ground truth data for the exact same moment as the image was ordered. The colour bands (blue, green, and red) performed equally well, while NIR seriously underperformed. We achieved a F1 score of 0.82 for all parking spots in the ground truth. The method is sensitive to tree canopy. When removing the tree obscured spots, the F1 score increased to 0.85. Tree canopy spots were automatically determined and filtered using NDVI.

Keywords. Parking, remote sensing, thresholding, high resolution

1 Introduction

Effective management of parking has many benefits towards sustainable urban mobility, such as liberating public space, improving access to the local economy, reducing traffic and congestion, and improving road safety and air pollution. To better understand parking behaviour and parking needs, we first need to know how many cars are parked in the public space and how this varies in time and space. However, a comprehensive and consistent time series of parking occupancy is lacking in most municipalities. Beyond controlled parking zones such as paid parking areas, only incidental (and often costly) manual parking inventories are available. Even with paid street parking complete time series are often lacking, as registrations are not stored or missing specific users such as permit holders.

In the last decade, several methods have been proposed that attempt to detect parking occupancy. Paidi et al. (2018) reviewed various methods used to measure parking occupancy, mainly focussing on sensor-based systems. Fahim et al. (2021) reviewed smart parking systems, including camera-based systems that use image processing techniques to estimate parking occupancy. Sensor and camera-based systems, however, require individual sensors to detect occupancy at the parking spot or zone level. Such hyper local systems deliver very high accuracy and comprehensive time series, but are costly to maintain and deploy over large areas (Bagula et al., 2015; Fahim et al., 2021).

High-resolution satellite images offer a potentially cost-effective alternative to detect cars and parking occupancy in public spaces. Satellite images usually cover large areas in one image and thus deliver a complete snapshot for a mid-sized town for a single moment in time. This instantaneous, complete coverage is an advantage over alternative monitoring approaches that cover smaller areas (transects or individual spots) and often refer to longer time intervals.

Several studies tried to detect cars from satellite imagery. Starting in the late 2000’s researchers have used classification techniques to detect cars in satellite imagery (Sharma et al., 2006; Eikvil et al., 2009), while in recent years machine learning based approaches have become popular (Golej et al., 2022; Cao et al., 2016). These studies developed methods to detect all cars in a complete image and did not specifically focus on parked or stationary cars. Zambanini et al. (2020) was the first to map parked cars by using stereo satellite images and identifying stationary objects across the images. They applied computationally demanding convolutional neural network method and achieved F1 accuracies of around 0.7. This study attempts a much lighter approach in terms of computing power and data input by restricting classification to parking spots only.

We have set up a methodology that combines high resolution imagery and auxiliary data on parking spots with zonal statistics and thresholding techniques, which has modest computational requirements and thus delivers fast results with a high accuracy. This short paper describes the performance of our thresholding approach to detect the occupancy of parking spots in 0.5m resolution imagery in the city of Alkmaar.

2 Data

2.1 Satellite Data

The satellite data used in this study was captured by the Pleiades 1A satellite on June 1, 2021, at 11:00 UTC. This image was specifically tasked for the purposes of this study. The image has a resolution of 0.5m for the three colour bands as well as for the near infrared (NIR) band. The area that was selected for the purposes of this study encompasses the whole city of Alkmaar, Netherlands.

2.2 Parking Spot Data

The Municipality of Alkmaar publishes a geospatial dataset (see Figure 1 for a sample) featuring individual polygons for each parking spot (Gemeente Alkmaar, 2023).

2.3 Ground truth Data

To avoid operator bias, ground-truth data was not generated from visually detecting cars in the satellite image (which is a challenging task anyhow at 0.5m resolution as demonstrated in Figure 1). Ground-truth data was captured at the same time as the satellite capture using two cars driving around the city while recording videos.

Figure 1. Satellite image sample overlayed with the parking spot polygons demonstrating the difficulty of visually identifying parked cars.

The ground observation cars were equipped with dashboard cameras and GPS trackers which enabled matching the video recorded parking spot occupancy to the location of those parking spots in the satellite image.

Since it is possible for cars to move into or out of a parking spot shortly before or after the satellite image was taken, a short time window of two minutes before and after the moment the satellite image was taken was considered for obtaining the ground truth data. For the interval between 10:58 UTC and 11:02 UTC, the videos and the GPS tracks of both cars were used to identify all the parking spots that were visible, and they were labelled as either occupied or free. Figure 5 shows a still of the video and the corresponding parking occupancy overlayed on the satellite image.

3 Methodology

To determine whether a parking spot is occupied, we focus on the range of reflectance values observed at this spot. As a first step we, therefore, summarise the reflectance values within the parking spots using a "*Range zonal statistics”* operation. Range is the difference between the minimum and maximum pixel values, and it differs most notably when a parking spot is occupied. When a parking spot is free, regardless of its surface (tiles, asphalt, concrete, etc.), it has a uniform colour that delivers a small value range. When a parking spot is occupied, it yields a notably larger range (depending on illumination angle) made up of the low reflectance of the still visible ground and the high reflectance of the occupied part of the parking spot that is influenced by the colour of the car, the reflectance of the windshield, and/or metal.

The second step in our approach, involves determining the threshold for classifying the parking spot as occupied or free. To avoid applying arbitrary or biased thresholds, we decided to use a non-parametric, thresholding algorithm. The triangle thresholding method (Zack et al., 1977) seems most appropriate because the histograms for all bands showed an unimodal skew to the left of the histogram. Figure 2 shows an example of the histogram of the ranges for all parking spots calculated from the green band.

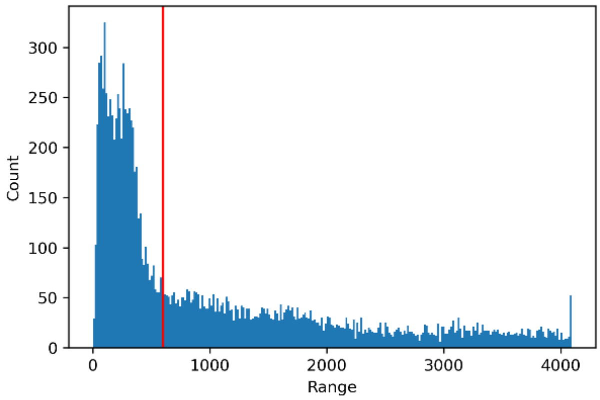

Figure 2. Histogram of the green band with NDVI filtering, including the results from tringle thresholding.

All parking spots were classified into occupied or free using the thresholds determined for all visible bands (red, green, and, blue).

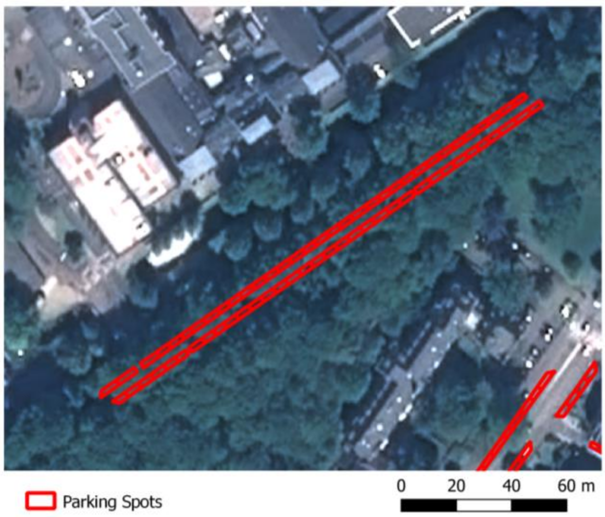

Figure 3. Parking spots expected under tree cover but not visible from the satellite image.

Parking spots under tree canopy are much more difficult to be analysed for occupancy (see an example of parking spots blocked by in Figure 3), so we generate a normalized vegetation difference index (NDVI) to identify these areas. Parking spots that included a maximum NDVI value higher than 0.5 were labelled as being (partially) covered by trees. In our accuracy assessment we analyse the difference in performance for all spots and for a set with spots without tree coverage.

We provide some basic accuracy statistics to indicate the performance of our approach to classify parking spot occupancy. The statistics are based on a comparison with our ground truth data and reported for each band separately, distinguishing between the data sets with and without tree-covered spots.

3.1 Data and Software Availability

The thresholding algorithm was implemented using the Python programming language and the SciKit-Image library (the code is available at: https://github.com/stopicr/satellite_parking).

The range and max NDVI values for each parking spot were determined using zonal statistics method with QGIS version 3.28.2. The table with the ranges for all the bands as well as maximum NDVI values is provided along with the polygon dataset of the parking spots with indication of the ground truth data derived from the videos (Stopic et al., 2023).

The Pleiades satellite image has a commercial closed license and is not provided.

4 Results and Discussion

The accuracy results of the three bands for the complete dataset are presented in Table 1, while Table 2 shows the same metrics but for tree canopy filtered dataset. It is clear that the performance is better for parking spots that were filtered out by NDVI. Removing parking spots that were assumed to be under tree cover boosted the overall accuracy from 76% to 80%. The main difference between the two can be seen in the share of false negatives, which dropped by 5%.

The three bands gave similar performances. The green and the blue colour bands slightly outperform the red colour band but only marginally.

Table 1. Accuracy results for all parking spots.

Band	Red	Green	Blue
TP	0.530	0.532	0.554
TN	0.216	0.223	0.205
FP	0.049	0.042	0.060
FN	0.205	0.203	0.181
OA	0.746	0.755	0.759
F1 Score	0.807	0.813	0.822

It is noteworthy that the same thresholding exercise was also performed on the near infrared band, but that demonstrated very poor results leading to excluding it from further analysis already in an early stage.

Table 2. Accuracy results for spots not under the tree canopy (NDVI max > 0.5).

Band	Red	Green	Blue
TP	0.569	0.569	0.569
TN	0.225	0.233	0.233
FP	0.054	0.047	0.047
FN	0.152	0.152	0.152
OA	0.794	0.801	0.801
F1 Score	0.847	0.851	0.851

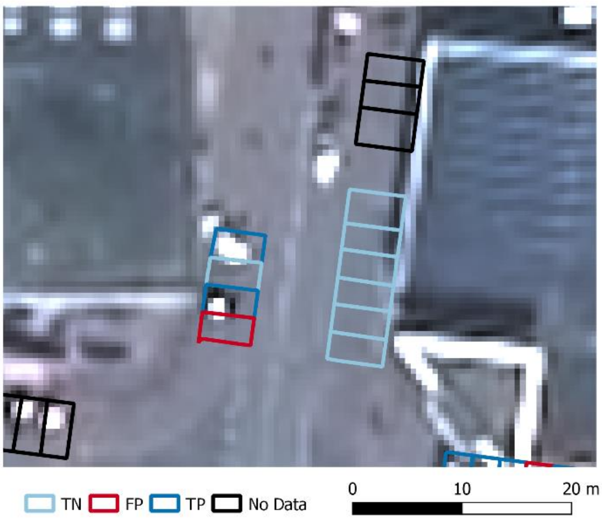

Figure 4. False positive parking spot caused by the car being parked across the parking spot line.

Errors are mainly due to false negatives (around 15% of total observations), while false positives have a share of less than 5%. A visual exploration of the false positives reveals that a high proportion of them are due to the way cars were parked. Improperly parked cars that cross the lines of a parking spot (effectively partly occupying two spots) mean that both spots are labelled as occupied in our model. In some cases, the disobediently parked car does indeed occupy the two spots, but in others the second spot remains mostly free (as illustrated in Figure 4).

False negatives seem to be mainly related to the environmental conditions on the parking spot and not related to the parked cars. The false negatives appear to be mainly caused by shadows that lower the reflectance range below the classification threshold as illustrated in Figure 5 where seven false negative spots are marked in a single parking lot. After consulting the ground truth video (see a video still in Figure 5b), it is clear that the seven false negative spots were completely in a shaded area. Note, furthermore that five additional parking spots directly underneath the tree are not considered due to the NDVI filtering. Similar to the NDVI filtering, such false negatives could be filtered in future work using view coverage or shadow analysis by using the location of the sun at satellite image capture and a high-resolution DSM.

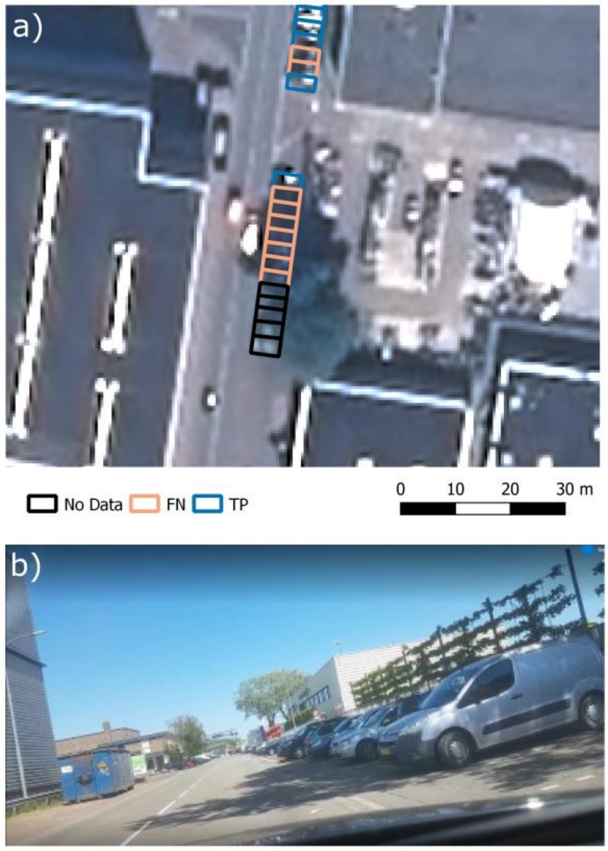

Figure 5. a) False positives due to shadows, b) still of the same location in the ground truth video.

5 Conclusion

The method to classify parking spot occupancy described here is based on thresholding the reflectance range. This approach has multiple benefits compared to alternative methods that use machine learning to identify cars in satellite images. The most notable one is the time it takes to run the model. Compared to creating a training and testing dataset, and running the machine learning model, thresholding takes much less time, both when it comes to getting the necessary data (since there is no need for extensive and comprehensive training and testing labelling) and executing the thresholding calculations.

Besides speed, the non-parametric nature of thresholding means that this approach is not limited to one city or satellite. The approach outlined in this paper should yield similar result even when applied to other 0.5m resolution satellite images and other cities. Nevertheless, this approach relies on having data available that delineates individual parking spots. This data may not be available in all cases, implying that it should be created first from, for example, detailed topographic maps.

The relatively detailed 0.5m resolution satellite images applied in this study are becoming more common and are available from several commercial companies. Beyond Pleiades, other sources of imagery with 0.5 m resolution and enough spectral resolution include SkySat, SuperView, KompSat (0.55 m), GeoEye and WorldView This availability means that it is possible to create parking occupancy data with a high temporal resolution, assuming that there are favourable weather conditions. Nevertheless, even with daily images, the analyses of short-term (within the day) dynamics are unfeasible, but it does enable the identification of long-term patterns and impacts of large-scale parking policy changes associated with, for example, the introduction of paid parking or the removal of parking spots.

The relatively high accuracy and F1 score of triangle thresholding, combined with the fast nature of data preparation and threshold calculation, ensure this approach is easily implementable and applicable to many cities. Increased data availability is likely to give the approach a further boost. Parking spot is data is becoming more easily available with the ongoing digitalisation of public services and the advent of crowd-sourced initiatives such as OpenStreetMap. High-resolution satellite imagery as applied in this study is more affordable now and expected to become available for multiple times a day from different providers. Parking occupancy is thus likely to be more easily monitored in the near future.

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