Cost-Effective Single-Camera Multi-Car Parking Monitoring and Vacancy Detection towards Real-World Parking Statistics and Real-Time Reporting

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Abstract. Parking is a huge problem in densely populated areas and drivers spend a significant amount of time finding a suitable place to park their cars. A system that could show drivers the nearest available space would result in enormous savings of time, fuel, and street space. In order to achieve that, real-world periodic statistical analysis of car parking areas could help increase efficiency. Ideally, real-time information could also be used to create personalized suggestions to drivers, thus enabling satisficing of a wide range of possible criteria of optimality. We propose a system that uses a single camera for a wide-area external parking, followed by a combination of two kinds of algorithms: static image analysis of parking lot spaces using a combination of histogram classification and edge detection, and dynamic image analysis using blob analysis. Our system thus achieves monitoring of parking spaces and reports statistics as well as empty slots in real-time. Our results indicate that almost 90% of empty spots are reported correctly, resulting in significant savings through a highly cost-effective single-camera system which can monitor more than 100 spaces.

Keywords: Parking Vacancy Static Analysis, Car Movement Dynamic Analysis, Image Processing.

1 Introduction

In crowded cities, the problem of finding an empty parking space can be so dominant that it often enters everyday conversations of citizens. A driver often has to search for several minutes in order to find an empty parking spot close to his intended destination and sometimes after spending enormous amount of time searching in parking lot, the driver realizes that there is actually no space available. In many cases, the projected future does not seem to be more attractive: with rapid increase in population size in many cities, parking spaces are getting filled up fast so that the above situation can only deteriorate further, if no ingenious solutions are found and applied. Furthermore it is estimated that the part of city traffic generated by the vehicles looking for a

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space could represent from 5 to 10% of global traffic – translating to huge losses. Thus, suppression of searching time is an important goal to be pursued [1].

Even more so, this is an important goal, in light of the fact that the current unfortunate state of affairs, has multiple side effects: First of all, driving in circles around the parking lot to find any empty space is time consuming with – and millions of man-hours are spent globally. Second, gasoline and diesel fuel is consumed from the act of examining all the spaces in a parking lot; it is a waste of natural resources and also adds to air pollution and other forms of environmental degradation. And third, this situation causes traffic accidents and frustration for the driver. As a further consequence of these problems, during peak hours, a driver might become tempted to park in authorized areas – which in turn can intensify traffic problems even further.

On the positive side, there do exist many ways this problem can start to be tackled: for example, assigning fixed parking numbers, toll parking, valet parking etc. However, in practice, and even more so when routes are not highly regular, such methods are very inflexible and can be highly inefficient. In reality, when viewed from a higher level, the real overarching goal is optimizing a combination of important parameters: wasted driving time, wasted energy, psychological effects, etc. while providing the right framework for technology adoption, in view of organizational (government institutions and controls, parking space ownership and regulation), as well as financial, cultural, and behavioral considerations. No matter what stance one takes on this highly important matter, towards effective solutions, there is one central point of agreement: towards any solution, long-term *real-world statistics* as well as *real-time information* is vital.

Concentrating on the more technical aspects of the problems involved, several projects in the past have attempted to provide solutions. Focusing on exterior parking spaces, and one-sensor-per-many-car solutions, there is a number of existing vision-based approaches. For example, there exist systems based on a complex algorithmic process using a stereo camera system that aim to create a 3D model of the lot. Also, it is worth noticing that the changing lighting conditions of the exterior spaces make the camera data more difficult to analyze as compared to the interior spaces with much more stable lighting.

Generally, the algorithms used fall into three basic categories [2]. The first category of algorithms centers on car detection, meaning recognizing objects in the image that look like cars, without taking into account temporal dynamics. This approach can be problematic because cars with unusual shapes and sizes may be ignored. The second category utilizes motion and blob detection [3-5]. Usually, methods such as background subtraction, or even simpler ideas such as usage of reference images taken when there are no cars in the parking lot and compared to each frame are used. Another common problem is vehicular occlusion [6-7], making it hard to detect cars because they are partially blocked from the camera. Yet, there is also the possibility of combining aspects of both categories towards achieving better results.

In this paper, a streamlined and computationally efficient static/dynamic combination method using histogram classification, edge counting, and blob analysis is proposed. The method is robust to varying lighting conditions, and thus suitable for outdoors parking. Furthermore, it only requires a single inexpensive camera, and low processing power, and can provide real-time statistics and data for parking lots of more than one hundred cars, upon suitable placement of the camera.

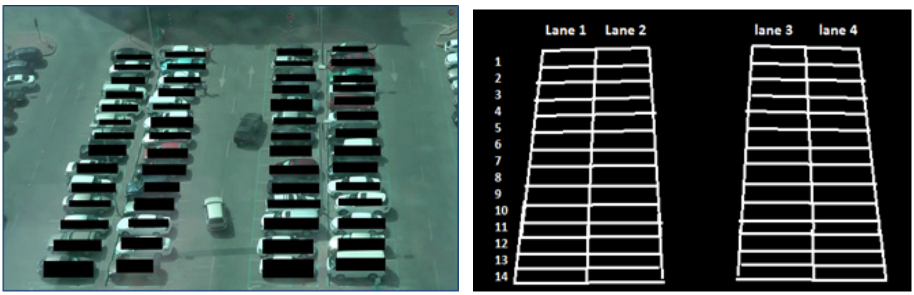
Our system, in comparison to many existing projects, has several advantages. The vehicular occlusion problem, for example, which is important in other approaches, was almost totally alleviated through appropriate camera placement at high floors of surrounding buildings, and as our results indicate, even under the partial occlusions that take place in such a setting, our system still provides good results. Although edge detection and blob tracking have been used before, our overall processing pipeline as well as illumination compensation and combination methods are different as compared to existing approaches. Furthermore, our overall system is highly cost robust, easy to install and calibrate, and last but not least, cost effective.

2 Methods

2.1 Experimental Setup

Our real-world experiment was carried out in a crowded outdoors car park in Down Town Abu Dhabi, namely the parking space behind the multi-floor Sama Tower. In order to obtain a video of the parking lot from a suitable viewpoint, the camera was placed at 12th floor of the Tower. A data set of 45 minutes of video was captured, during 26th April 2012, around 2PM. Then, our algorithms were coded in MATLAB R2011a, and were used to analyze the initial 45 minutes video dataset.

The parking lot consists of 4 lanes with 14 parking spots in each (56 spots total); each spot of each parking lane that was not occluded by other cars was marked by coordinates (Fig.1). In order to enhance the processing speed of code, the video was processed only at the 29 instances when there was any activity or change in the parking lot. The parking states of all 56 spots for each of the 29 frames were initially labeled manually, in order to provide ground truth to be checked against the states observed by the code.



(a) (b)

Fig. 1. Parking space slots

Each frame was then processed, and the final output was a list of spots and their associated vacancy status. For greater accuracy, three different methods of image analysis were combined. These methods can be characterized as two for static and one for dynamic analysis. We utilized edge counting and histogram classification as our static analysis methods, which rely on information available in a single frame for each decision, whereas for our dynamic across-frames method we utilized a specially crafted algorithm for blob tracking, which also served as a corrective mechanism for our static analysis-driven results. These methods are presented in detail in the next section. As a first stage, after the installation of he camera, the parking spots are hand-marked in terms of coordinates of vertices of bounding quadliterals (Fig.1).

2.2 Static Analysis

Edge Counting

The Canny edge detection algorithm was used to count the percentage of edges in each of the 52 parking spots (Fig.2). This algorithm looks for local maxima of the gradient of the grayscale image of the frame from a video. The algorithm is applied to each of the 29 frames of interest. The total area occupied by the edge for each marked parking spot is calculated and the percentage of the edge area with respect to the total area of spot is found. Spots with a higher percentage of edges are more likely to be occupied because cars have more sharp edges than empty pavement.

Fig. 2. Edge counting of parking spots

Histogram Classification

This method compares the pixels of parking spots with those of an empty parking pavement with road texture. If there is a high degree of similarity in both then it means that the parking spot is probably empty whereas if there is a low degree of similarity then it means that there is a car parked in the spot (Fig.3).

Fig. 3. Pavement pixels subtracted

Each of the 29 frames was converted to the YCbCr color space, and then several regions (five was chosen as adequate) which almost always contain only pavements were marked out. There is a very small probability that the majority of these regions will ever be covered by cars. These five regions act as a reference for the pavement color given the current illumination conditions. Thus, in order to decide whether a pixel most likely belongs to the pavement or to another object (for example, car), we can use the color of these regions as a reference for how the pavement is supposed to be appearing given the current lighting conditions. By having five regions, we can discard one or two of them as outliers – and in our video samples it was only the case that maximally one of these happened not to act as a good reference for pavement color, given passage of a human or other object over it.

Using only these regions, we made histograms of each channel of pavement region by dividing them into 64 bins, and then selected the highest peak from each. This allowed us to find the most prevalent bin value for the pavements. For each pixel of the frame, we calculated the color space distance from the prevalent bin. Pixels below a certain distance threshold were marked as pavement (Fig.3). Total area occupied by pavement for each spot is calculated and percentage of pavement area with respect to the total area of spot is found to determine whether it was empty. This allowed minimizing the error due to different light conditions in different times of the day in determining whether a parking spot looks more like empty pavement.

Weka Combination

The above 'Edge counting' method provides us with the percentage of the parking spot occupied by edges due to a car, whereas the above 'histogram classification' method gives us the percentage of the spot whose color resembles the current pavement color (and is thus conjectured to be empty). The two static image processing methods thus provide us with two feature values for each parking bin (features in the sense that the word is used in pattern recognition literature). These two features were combined to give an estimate of whether a parking spot is empty or not, using machine learning algorithms, using Weka [8] (Fig.4).

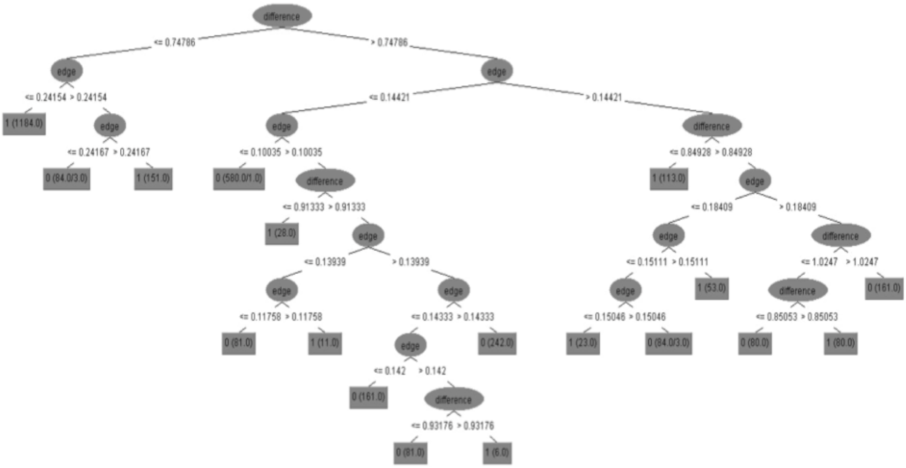


Fig. 4. Empty/Full decision tree based on Weka (1 indicate full and 0 indicates empty)

This decision tree algorithm that we created takes input from both features and decides the parking state of a spot based on the ranges in which both the percentages lie. The tree diagram in Fig.4 illustrates the mechanism of algorithm. For example, if percentage from histogram classification is less than 74%, then left branch is chosen from top box, and if percentage from edge counting is less than 24% for a spot, then next branch is chosen which marks the spot as occupied by giving it the value of 1. Based on this algorithm the parking state of each spot is recorded in a matrix.

2.3 Dynamic Analysis

Blob Analysis

In order to detect motion in parking spot where cars were parking or unparking, background/foreground estimation was used. This method starts looking from a few

(a) (b)

Fig. 5. Tracking of moving blobs

hundred frames before our frame of interest and uses the frames to find a mean frame value and its standard deviation. When a new frame is analyzed, its difference from mean frame is calculated as

$$
\begin{aligned}
Mean_t &= \gamma \times Frame_t + (1-\gamma) \times Mean_{t-1} \\
Diff_t &= \gamma \times |Frame_t - Mean_t| + (1-\gamma) \times Diff_{t-1} \\
Change_t &= Diff_t - (Mean_t - Frame_t)
\end{aligned}
$$

where

$Frame_t$	pixel matrix of current frame
$Mean_{t-1}$	mean calculated using all the previous frames
$Diff_{t-1}$	Standard deviation calculated using all the previous frames
$Mean_t$	New mean calculated using previous mean and current frame
$Diff_t$	New standard deviation calculated using previous mean and current frame
γ	Weightage of current frame
$Change_t$	Change in the value of current frame from mean value of previous frames

Pixels whose values differ beyond a threshold from the mean frame value calculated using previous frames, indicate that some motion took place in those pixels. These pixels are extracted and converted into white blobs whereas the rest of the pixels are discarded (being assumed to be not moving, i.e. background). Then by applying twice dilution and once erosion to the blobs with a circular structuring element, we effectively unify small blobs that happened to be disconnected and remove noise. We took this measure as it was found that often a moving car would appear as two disconnected blobs moving with similar velocity – but with a very small gap between them, and thus the dilation/erosion morphological operation was helpful in unifying them. Blobs below a certain minimum size were neglected as pedestrians and only large blobs were considered to be cars. Blobs whose centers were moving into or out of a parking were determined to be cars moving into or out of a parking space (Fig.5). Hence if a blob's center was moving into a parking spot, the spot was marked full, and if the center was moving out of a parking spot, the spot was marked empty.

2.4 Composite Analysis

Static analysis is not very useful in telling whether a parking spot is empty if there is a car moving in or out of the parking spot since it uses static analysis. Therefore dynamic analysis is needed that can estimate from the motion of the car, whether it is parking in the spot or unparking, hence whether the spot is empty or full (Fig.6). At the beginning of the dynamic analysis, each parking space has already been determined by the static analysis; some of which could be wrong. Output from dynamic analysis updates the state of those parking spots where some motion was occurring during the time of estimation.

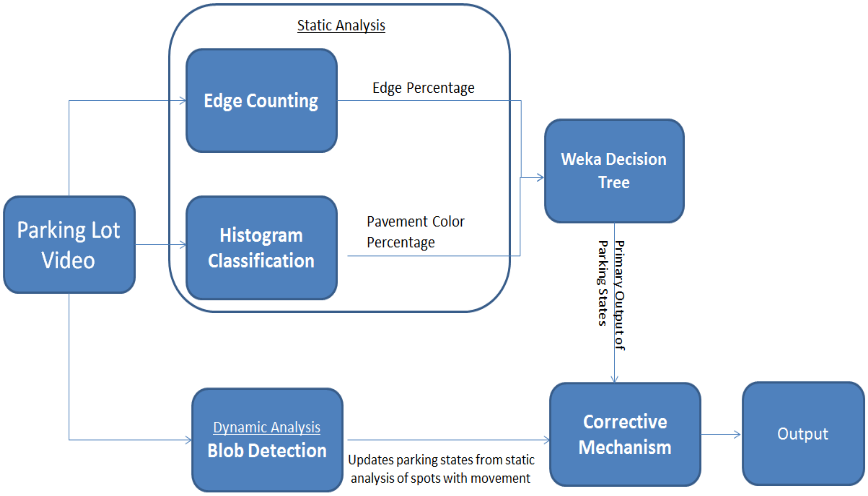


Fig. 6. Block diagram of algorithm mechanism

3 Results

3.1 Car Parking Status Measurements

During the 45min video of car parking, 29 instances were investigated when there was a change in the parking spots. For each of these 29 frames, the empty or full state of each of the 52 spots was recorded manually in matrix in the form of 1(full) or 0 (empty). This matrix was imported in MATLAB program to be compared against the output matrix of observed states estimated by the algorithms. The matrix of actual results resembles the format of output as Table 1.

Table 1. Format for storing parking states

Frame	Lane	Spot 1	Spot 2	Spot 3	Spot 4	……	Spot 13	Spot 14
	1	1	1	1	1	……	1	1
	2	1	1	1	1	……	1	1
6600	3	1	1	1	1	……	1	1
	4	1	1	1	1	……	1	1
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
	1	0	1	1	1	……	1	1
	2	1	1	1	1	……	1	1
	3	1	1	1	1	……	1	1
156720	4	1	1	1	1	……	1	1

3.2 Vacancy Detection Result

After analyzing the 29 frames, the algorithm gives an output matrix in the form of Table 1 which stores the estimated full/empty states of all parking spots in terms of 1s and 0s. Each value of the parking spot from estimated matrix is compared with the corresponding value from actual matrix to check whether correct estimate has been made or not.

3.3 Comparison

Using static analysis alone shows that 14 out of 18 or 77.8% of the empty spots were estimated correctly whereas 1597 out 1605 full spots were estimated correctly. However combining dynamic analysis with static improves the accuracy of the results. With both methods combined, 16/18 or 88.8% of the empty spots were calculated correctly, whereas 1596/1605 of the full spots were calculated correctly.

3.4 Discussion

We are thus achieving almost 90% detection of empty spots. Inaccuracies in the estimation can be attributed to many reasons. First, the video sample had few empty slots test because the parking slot was heavily occupied at all times. Second, the video was recorded from the side view of cars, which meant that blocked view of the car parked behind it. This led to many errors because if there was any empty slot behind a car, it was covered by small part of image of a car that was not parked inside it and hence led to presence of false edges and color in the empty slot. The results can be tremendously improved if the video is recorded from an angle perpendicular to the parking lanes. Most importantly, at the moment we are experimenting with much larger data sets that we have collected and which we are labeling, spanning over several days, and fine-tuning our algorithms, as well as combining them with larger-scale trajectory tracking for cars, enabling us to get quantitative estimates of searching times, waiting times, search strategies and other such interesting features. Furthermore, we are developing a real-time sms notification system for drivers entering the park that are subscribing to the service, which instantly assigns the nearest unassigned free slot to them, if one is available, and informs them of its position.

4 Conclusion

After having discussed about the multi-faceted importance of parking statistics and real-time management techniques in densely populated areas, in this paper we presented a cost-effective camera-based system that can supervise open air parking lots, can provide statistics, and that can show drivers the nearest available space. In our system, a single camera is placed on a tall building adjacent to the lots, and its output is fed to a combination of two kinds of algorithms: static image analysis of parking lot spaces using two types of features (derived from histogram classification and edge detection), and dynamic image analysis using blob analysis (based on background subtraction). Our system achieves monitoring of parking spaces, and reports statistics as well as empty slots in real-time. Our results indicate that almost 90% of empty spots are reported correctly, and acts as a highly cost-effective single-camera unit which can monitor more than 100 spaces. The widespread application of the currently evolving versions of our system could well potentially result in enormous savings of time, fuel, and street space, and thus help citizens save time and fuel, preserve our environment, and enjoy a much more pleasant everyday driving experience.

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