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RESEARCH PAPER

One-Day Long Statistical Analysis of Parking Demand by Using Single-Camera Vacancy Detection

JERMSURAWONG Jermsak [1], AHSAN Umair [1], HAIDAR Abdulhamid [2], DONG Haiwei [1*], MAVRIDIS Nikolaos [1]

1 New York University, New York, NY 10012, USA
2 Massachusetts Institute of Technology, Cambridge, MA 02139, USA

Abstract: Many researches have focused on parking demand to gain information for traffic management recommendations and decision-making where real-world car park statistics is of great importance. This paper seeks to obtain one-day long statistical analysis of a multi-purpose off-street parking space in downtown Abu Dhabi, using a single-camera vacancy detection system. The proposed methodology to collect one-day long statistics uses pattern recognition to determine occupancy states based on visual features extracted from parking spots. This vacancy detection system has two major advantages. First, it relies on only few pixels compared with other methods, being able to cover more than 150 parking spots within a single camera frame. Second, the system works well in both nighttime and daytime – robust to changing light conditions. The accuracy is 99.9% for occupied spots and 97.9% for empty spots for this period of study. This study also proposes a better indication of parking demand when the park is near its full capacity, as the utilization rate does not capture the parking demand from the motorists who fail to find parking spaces.

Keywords: parking strategy, vacancy statistical analysis, one-day long monitor, parking demand indication

1 Introduction

Parking space management has become a more pressing issue due to growth in private vehicle ownership. On one hand, building too little parking space causes traffic congestion and spillover to other areas[1,2]. On the other hand, having too much parking space, underutilizes scarce land property, encourages people to own more private vehicles, and reverses the trend towards environmentally friendly transportation profile[3]. Real-world statistics is important for informed decision making. This paper seeks to obtain one-day long statistical analysis of a multi-purpose off-street parking space in downtown Abu Dhabi, using a single-camera vacancy detection system.

Many researches have looked into car parking activity to gain information for traffic management recommendations and decision-making. One of the vital information is demand for parking[4]. It is the “accumulation of vehicles parking at a given site at any associated point in time… This value should be the highest observed number of vehicles within the hour of observation[5].” Parking demand therefore indicates level of car park utilization over time. Adjusting size and number of car parks[6], assessing benefits and environmental cost[7], gauging effect of changes in policy, and projection of future need[8] all rely on this parking demand.

In particular, parking demand is first used as considerations for car park size. Currently, many off-street parking areas are based on information compiled by Institute of Transportation Engineers’ Parking Generation. This book specifies the minimum parking demands for different land uses. However, the information collected is from single-use suburban locations[1]. As a result, little is known about profile of parking demand for mixed land use, which would in fact needs less space. Therefore, a low-cost and efficient method to obtain more relevant and accurate parking demand would be valuable in car park design.

Besides car park design, assessing parking demand of existing car parks is also useful for implementing policy changes. The most pertinent one is charging the right price for a parking space. The high parking demand with limited supply of parking spaces results in high price charged. However, while overcharging leads to underutilization, wasting public resources, undercharging leads to shortage of parking space. Getting the right price therefore helps to allocate the resources to those who most need it. A

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*Corresponding author. E-mail: haiwei.dong@nyu.edu
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successful pricing system in San Francisco further optimizes pricing according to parking demands at different time and day-to-day situations [4]. Admittedly, exacting the optimal price for a product, which is previously not on the market, cannot rely on this parking demand alone. While it only presents the number of people who derive some utility from parking, parking demand information is necessarily used in complement with surveys to gauge the right number of customers who are willing to pay at a given price.

There are broadly two ways of evaluating this parking demand. First, it can be modeled based on simulation. The models range from convenient and simplistic ones to highly sophisticated simulations requiring large set of data[9]. In fact, studies have focused on various factors influencing the choice of one parking lot over another in predicting the demand. They include variables like walking distance, parking fees, the availability of parking space, and penalties fees of illegal parking[10,11]. Some models consider when motorists evaluate those factors with perceived cost and utility based on Possibility Theory[12]. Other models use machine-learning approach to determine current demand of parking facilities based on time parameters[13]. Regardless, these models need to be validated by real-world information. Second, the parking demand can be obtained from real-world statistics. Automated system such as smart parking systems[14] efficiently collect vital information on the parking activities[15]. The systems can be further categorized into intrusive and non-intrusive ways[16]. For example, wireless-based[17] or wired-based sensor[18] method require invasive procedures to install the complicated equipment. On the other hand, the non-intrusive ways such as microwave radar, passive acoustic array sensors, and passive infrared sensor are easier to install[14]. Nevertheless, they both are resource-intensive just for short-term data collection. Instead, preferable approaches should be centered on one-to-many detection in image-based detection system, which is inexpensive, flexible and non-intrusive.

In the vision-based field, a lot of research has focused on object detection. Bong et al used pixel detection with threshold to differentiate between cars and empty slots. Although this threshold value is non-adaptive to changing light conditions, he compensated this with edge detection[19]. Still, the method does not work well, when the cars-to-camera distance is high and the car images have few pixels. Fabian based his method on the homogeneity of the car pixel values, counting the number blocks containing pixels of similar homogeneity values[20]. Again, this requires highly detailed images with limited applications in a large-scale single-camera detection system. Our proposed method relies on fewer pixels, being able to cover more than 150 parking spots within a single camera frame.

There have also been attempts using machine learning to classify the parking states[21,22], but they are not robust to changing light conditions. By contrast, Huang developed a Bayesian framework detection method that is robust to changing in light conditions. This detailed study even modeled shadow from sunlight direction, based on U.S. Naval Observatory to anticipate the false recognition of shadow as black-colored vehicles [23]. However, this method is complicated, because although the shadow could be recognized as the car, it has uniform appearance. Measurement of randomness or spread of pixel values can account for this shadow problem. In addition, although the method achieved up to 99% accuracy[23], the method was only tested during daytime. Our proposed system, also achieved equally satisfactory result, whereas nighttime period was included.

There exist few cases of comprehensive empty slot recognition system that includes nighttime detection [24]. Macdonell and Lobo looked at nighttime but the whole picture frame consisted only five parking spots [25]. Another study in Japan tested a system using Fuzzy C-mean Classifier to identify the vacant parking spots with somewhat satisfactory results. The study collected one-day long data over two months[26], but the parking space was on a rooftop of a multi-story parking lot and contained less than 30 parking spots. As a result, the observed parking space does not accurately represent the parking space system and it has too few cars to obtain meaningful statistics.

While there have been little parking studies for one-day long period, the most comprehensive work is a study commissioned by Transport Department in Hong Kong, to estimate parking demand from 07:30 to 22:30 across almost 4000 parks[27]. The study found similarities in the shape of parking demand profile and there emerged categories of car parks corresponding to different types of land usage nearby. From this known demand pattern, the study then proposed predicting parking demand based on the surrounding land use of an interested car park. Although the method sufficed for its application, subcategories of car parks could emerge when parking demand is observed for the entirety of one-day period. Car parks with similar parking pattern in daytime may have different characteristics at nighttime. As a result, studies should not presuppose the dynamic time period of parking activities, but instead should rely on empirical data of a whole-day period.

Another limitation of current parking studies is relying only on utilization rate even when the park is near its full capacity. Utilization rate does represent parking demand when every motorist who wishes to park can park and consequently be recorded as a part of the total parking demand. However, when the car park is near its maximum capacity, not all motorists who wish to park can successfully secure the parking space. Assessing total parking demand from only the utilization rate inevitably excludes those unsuccessful parkers. One detailed study, in addition to showing the utilization rate over period of time, recorded at the park's entrance the number of vehicles entering and leaving the car park[28]. Indeed, given a nearly full utilization rate, this number of cars entering and leaving can vary and be the indicator of parking demand from motorists who fail to find parking space. However, the study did not analyze such information to show this implicit parking demand. The data gathered from this methodology can account such by considering how quickly parking spots are taken after they are freed up. When most of the parking spots are occupied, high implicit parking demand corresponds to period where new cars promptly take up any freed parking spots. This is a better indication of parking demand when the park is near its full capacity, as it further captures the need of the unsuccessful parkers.

The proposed methodology to collect one-day long statistics uses trained neural networks to determine occupancy states based on visual features extracted from parking spots. This vacancy detection system addresses three technical problems.

a) It responds to changing light intensity and non-uniformity by having adaptive reference pavement pixel value to calculate color distance between the parking spots and the pavement.

b) It approximates images with limited lighting to have similar feature values to images with sufficient illumination, merging the two patterns.

c) The system separately considers nighttime vacancy detection, choosing appropriate regions to get reference color value. Overall, this detection system has two major advantages. First, it relies on only few pixels compared with other methods, being able to cover more than 150 parking spots with in a single camera frame. Second, the approach is robust to changing light conditions and non-uniformity due to shadows from the surrounding buildings. Furthermore, it is quite easy to implement and computationally light. Most importantly, it achieves high performance: The accuracy for this approach was 99.9% for occupied spots and 97.9% for empty spots in this one-day period of study. This methodology is therefore suitable to obtain all day long statistics. In addition, this study proposes an indication of parking demand when the park is near its full capacity, because the conventional indicator, utilization rate, does not capture the need of motorists who failed to find the parking space. Relying on this methodology thus gives a more accurate view on current parking demand of a crowded parking space. In addition, the proposed approach leads to the assessment parking demand on mixed-use land, which is not available from the general resource focusing on single-use land. Furthermore, it can be used as a tool to plan for policy changes such as the introduction of pricing parking space.

2 Technical Problem

(1) Problem 1: Changing Light Intensity and Non-Uniformity in Daytime

In an open space car park, light intensity not only changes with time, but also may be non-uniform (Fig. 1). Partial shadow from the surrounding setting extends across the car park. This problem is especially significant in urban context, because buildings often surround car parks. Therefore, image analysis gives varying features of parking spots at different times, although the parking statuses remain the same. Table 1 shows the decrease in percentage of average statistical measurements of non-shaded parking spots when they are in a shaded region. The proposed solution should dynamically respond the light conditions – both intensity and non-uniformity.

(a) Morning (b) Noon (c) Evening

Fig. 1 Problem 1: different light intensity and non-uniformity in the car park from morning to evening time.

Table 1 Comparison of Average Statistical Measures for the Non-Shaded Spots with the Shaded Spots

Statistical Measures	Occupied	Empty
Standard Deviation	-29.8%	-32.7%
Interquartile Range	-28.9%	-38.4%
Entropy	-6.45%	-20.7%

(2) Problem 2: Limited Light in Early Morning and Evening Time

Even though changing illumination level throughout daytime can be solved, severely limited light intensity compromises the details of images to be analyzed. Such low light intensity happens during the two transitions between daytime and nighttime – before the light posts are turned on in the early morning, and after they turned off in the late evening (Fig. 2 (a,b)). Statistical measurements of pixel values from such images give different range of results compared to ones with sufficient lighting. For example, standard deviation and range of the pixel values at in evening time are significantly lower than ones in the afternoon. As a high level of car activity takes place during this late evening, it is important to accurately detect the vacant parking spaces during this critical period.

(a) In the early morning just after the light posts are turned off (b) In the late evening just before light posts are turned off (c) Nighttime image of the car park

Fig. 2 Problem 2 and 3. (a,b) Limited light intensity. (c) Concentrated light source from the light posts.

(3) Problem3: Different Light Pattern in Nighttime

Although constant lighting from light posts at night does not complicate the feature values over time, a single light source at short distance from the light posts significantly changes pattern of lighting from the daytime (Fig. 2 (c)). Because illumination from streetlights is concentrated only on parking spots, the color of empty parking space is much brighter than that of the nearby road pavement. Directly comparing the two regions gives false indication of car presence, as color difference between the empty spot and the pavement is now significant.

3 Method

The one-day long video recording of an outdoor car park in Down Town Abu Dhabi took place from 09:00 July 3th to 09:00 July 4th, 2012. The camera was placed at 29th floor of the adjacent tall building to avoid occlusions. The recording spanned 9 lanes of car parking spaces – each with 14 parking spots. In a frame, a total of 126 parking spots were considered. This large scope reduced the size of each parking spot to only 30x14 pixels. A neural network was constructed, and trained with a sample of video frames. It was then used to analyze the whole video recording.

3.1 Neural Network

Neural network classification was used to determine the parking states. The two networks, for daytime and nighttime, were two-layered feed-forward, with sigmoid hidden and output neurons. They took in the various features extracted from each parking spot as input to give predicted output as the parking states. During training, each network took a data sample consisting of input features and the ground truth target output, which is the actual status of the corresponding parking space, manually annotated using a special annotation tool that we developed.

This one-day long video recording has 25 frames per second. The training data set for daytime used only 326 frames. However, one problem was that there were significantly less empty parking spots than the occupied ones. Taking samples for ground truth at an equal interval would result in proportionally few vacant spaces. These 326 frames thus span equally throughout the day, except in the evening with a doubled frequency to capture the period of higher parking activity with more empty spots. Nonetheless, the ground truth sample is not biased because the evening period is shorter than the daytime. In fact, doubling the evening sample makes the overall ground truth sample more representative of different lighting conditions. For nighttime, 112 frames were taken, spanning equally for 4 hours after the light posts were turned on. This time interval has significantly more empty parking spots than the one in late night does. However, the sample is still representative of the whole night period because at night the light intensity was constant. As each frame contained 126 observed parking spaces, the daytime training set had in total 41076 parking spots consisting of 39747 occupied ones and 1329 empty ones. The nighttime training set had 14112 parking slots consisting of 13731 occupied spots and 381 vacant ones.

For both training data samples, each of the two networks – daytime and nighttime – further separated its sample into three groups. First, 70% of the data was randomly selected for training using the scaled conjugate gradient back propagation method. The predicted output from the network to ground truth – occupied or vacant– is predicted, and the error term is propagated back through the network to find weight and bias adjustments that take the output closer to the ground truth. Second, after the 70% of the data that was used as training set, another 15% of the data was used as validation set to measure the network performance. The network continued to train until the performance in this validation sample stops improving. Finally, the remaining 15% of the sample data was used as an independent assessment (testing set) of the network.

The selected daytime network contained 11 elements in the hidden layer with 99.9% of occupied spots and 98.5% of empty spots from the testing data being identified correctly. The selected nighttime network contained 10 elements in the hidden layer with 99.9% of occupied spots and 98.4% of empty spots from the testing sample being classified accurately. The accuracy for the vacant spots was lower than the occupied ones in both time intervals, because of the much smaller size of empty spots in the training set. Another observation is that the misclassification in nighttime was equally spread throughout the time, while most of the errors in daytime were concentrated in the early morning and in the evening. This confirmed the problem of limited sunlight in those two periods outlined in Problem 2 and suggested the need to approximate them to the other time period that worked well with the selected daytime network.

3.2 Feature Choice

Features extracted from the parking spots are summarized below. The five broad categories are light-related features, pixel value statistical features, edge features, color-related features, and time-related features.

(1) Light-Related Features

Features in this category tackle the problem of light non-uniformity and varying light intensity. First, the color distance feature extracted has an adaptive reference point. It is noted that because the size of the each parking frame in this study is the same, the color distance is just the sum of the color distance of each pixel in the parking spot. Sum of the color distance per unit area would serve the same purpose. Second, the shadow status feature associated with each parking spot determines if it is in non-shaded region, shaded region, or in the image with no significant shadow. The values assigned are zero, one, and two respectively.

(2) Pixel Value Statistical Features

This feature group considers dispersion and spatial arrangement of the image pixels of the parking spots. Cars are more likely to have greater spread and more non-uniform spatial arrangement of pixel values than the empty spots do. Nevertheless, certain cars in limited light had similar range of these statistical measures to the empty pavement. These measures therefore have two levels of strictness so that through training of the neural network the ideal weightage can be found for each level of strictness to find the optimal contribution from these statistical measures. Less strict features are standard deviation and entropy of the whole observed frame, and range of pixels. When cars are present, these standard deviation and entropy measures inevitably include the pavement pixels in the calculations, because cars often do not occupy the total frame of the parking slots. Although including the whole frame further increases the dispersion and randomness of an occupied spot, strengthening the indication of car presence, it may include shadow and overlapping of the adjacent cars falsely increasing the spread and randomness. The other feature, range, measures the maximum difference of the pixel values in the parking spot. It is also less strict because it may include outliers of the pixel values. Stricter features are standard deviation of an inner frame of the parking spot and interquartile range. This standard deviation reduces the noise from adjacent cars by taking in pixel values only from the inner fame, which is 20% the size of the actual observed frame. Interquartile range is robust to outliers, because it measured the difference between the 25th and 75th percentile of the pixel values, excluding the extreme values.

(3) Edge Features

Again, edge features have two levels of strictness. The less strict one uses Canny edge detection method. Canny method is sensitive to weak edges, because it identifies edges from local maxima gradient of the gray scale image. In addition, two different thresholds for weak and strong edges are used. It outputs not only strong edges and also weak edges that connected to the strong ones. Although, this less strict edge detection can identify cars with similar colors to the empty pavement, it includes unnecessary weak edges such as stains on the empty parking spot. The stricter edge feature uses Sobel method, identifying edges only at the maximum gradient of the gray scale image. Details of car have to be much stronger for Sobel method to recognize.

(4) Color-Related Features

The color-related features are good indicators of colored cars. Maximum and mean values of red, green, and blue filter of colored cars were likely to be higher than that of the empty parking space. The other feature, maximum difference in RGB filters does similar job in identifying colored cars from empty pavement. Grey tone colors had very close values in red green and blue filter. Vacant spot is therefore likely to have smaller maximum difference between any two of the color filters.

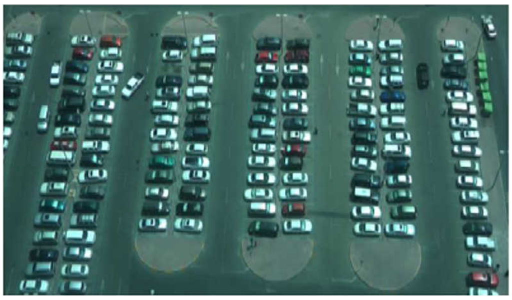
(5) Time-Related Features

This feature group considers the information from the previous frame. When parking status changes from one frame to another, the features extracted show significant change. If the spread, edge, and randomness values decrease from the previous frame, this suggests that the parking spot of interest in the current frame has now become empty. On the contrary, when the values increases, the parking spot is more likely to be occupied. This relative change at each new frame negates the effect of changing light conditions throughout the day, as it is robust to constant or slowly changing noise. Although these features are not useful when there parking states remain constant, they can be key features in determining the parking states during high traffic flow when parking states are quickly changing.

3.3 Solution for Problem 1: Adaptive Pixel Value Reference

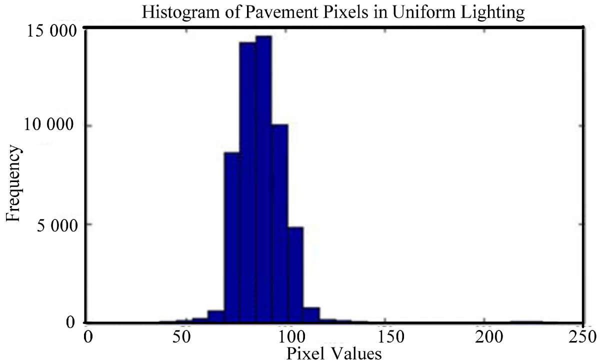
The light-related features address the changing light intensity and non-uniformity. Color distance measures the sum of each distance between pixel in the parking spot and the most prevalent pixel of the road pavement. This most prevalent pixel serves as an adaptive reference point, changing with different light intensity throughout the day. When light is not uniform, two most prevalent pixel values are returned – each corresponding to a shaded and non-shaded region. The shadow status then determines if the parking spot of interest is in a shaded region. After that, the distance color is calculated, comparing each pixel in the parking spot to the corresponding reference pixel in shaded or non-shaded region. High color distance extracted from a parking spot suggests presence of cars, while low distance suggests high degree of similarity to the empty pavement of empty space.

To find the most prevalent pixel value as the reference point, the images were first converted to YCbCr color space. The regions of empty pavement were marked out by hands along the region indicated in yellow color in Fig. 3(a). Histogram of pixel values from all those regions was made. When the light is uniform, the distribution has one peak Fig. 3(c). However, when shadow moves in the image, the histogram shows bimodal distribution Fig. 3(d). These two situations would be now considered separately.

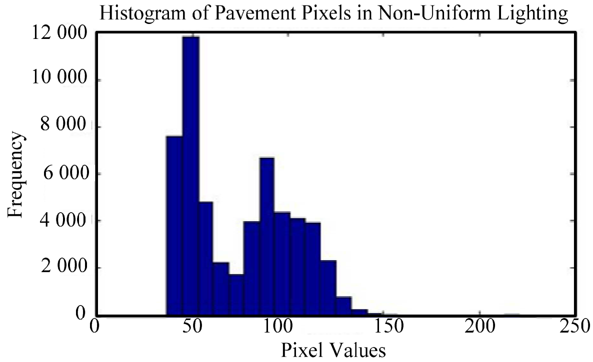


(a) Yellow strips indicate the region of pavement used

(b) Non-uniform lighting due to the shadow



(c) Histogram of pavement pixels in uniform lighting corresponding to (a)



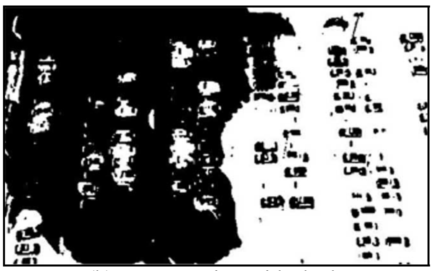
(d) Histogram of pavement pixels in non-uniform lighting corresponding to (b)

Fig. 3 Uniform and non-uniform lighting.

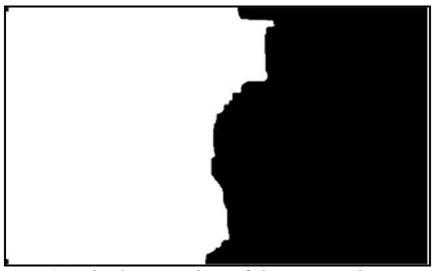
If the histogram of all the regions has only one peak, the regions are now considered individually to find the most frequent pixel values. These most prevalent pixel values were averaged to give the final reference pixel value for a uniform lighting condition. In the event that there are cars along the road pavement that could potentially distort the prevalent pixel value in a region, the value from that region could be discarded as an outlier.

When the histogram shows two distinct peaks, one peak corresponds to the most frequent pixel value in the non-shaded region and the other corresponds to the shaded region. The mean of these two value is used as a threshold to distinguish between shaded and non-shaded region. Depending if each pixel exceeds the threshold value, each pixel are assigned one or zero. The biggest connected region in now binary image is then identified, as seen in Fig. 4(b). The image is filtered to remove noises before being morphologically eroded to fill in the wholes to get the final separation of shaded and non-shaded region, as seen in Fig. 4(c). Each parking spot can then be identified if it is in the shade and the reference pixel value is one of the two peaks corresponding to the parking spot's current shade status.

(a) Image with non-uniform lighting



(b) Detect region with shade



(c) Final separation of the two region

Fig. 4 Shade detection.

3.4 Solution to Problem 2: Approximating Sufficient Lighting

As outlined in problem 2.2, the dispersion features and pixel values in color-related features are significantly lower in limited light intensity. In daytime, image has high contrast due to the sufficient sunlight. Such images have well spread-out histogram in gray scale or intensity layer. Therefore, with the right amount of histogram stretching, the poorly-contrasted image with limited light can be approximated to the time of sufficient lighting that the selected neural network works well.

A measure of contrast can be extracted from a gray-level co-occurrence matrix constructed from an image of interest. Each element, with index values i and j, in this co-occurrence matrix indicates how often the pixel values i and j from the image of interest occurred in a specified spatial relationship. In other words, each entry in the matrix indicates the number of co-occurrences between two pixel values, and that pixel values are the two index values of the entry. In this study, spatial relationship was specified to be adjacent to the left. From this constructed matrix, the contrast sums the product of the squared difference between the two index values and the entry value at the two index values. When the image is constant, the contrast from corresponding co-occurrence matrix is zero.

It was found that the contrast value in the late evening declines rapidly (Fig.5 (a)). Histogram stretching of poorly-contrasted image compensates for the contrast. This was done by mapping pixel values that exceed a certain threshold to higher values. Threshold value decreases until the new contrast value reached that of a well-contrasted image. In other words, more and more pixels are pushed to the right in the brighter region. The target contrast value was selected from the graph shown in Fig. 5 (a) to be 0.28, just before the contrast started to fall. Fig. 5 (b, c) shows the stretching of histogram to this desired contrast value.

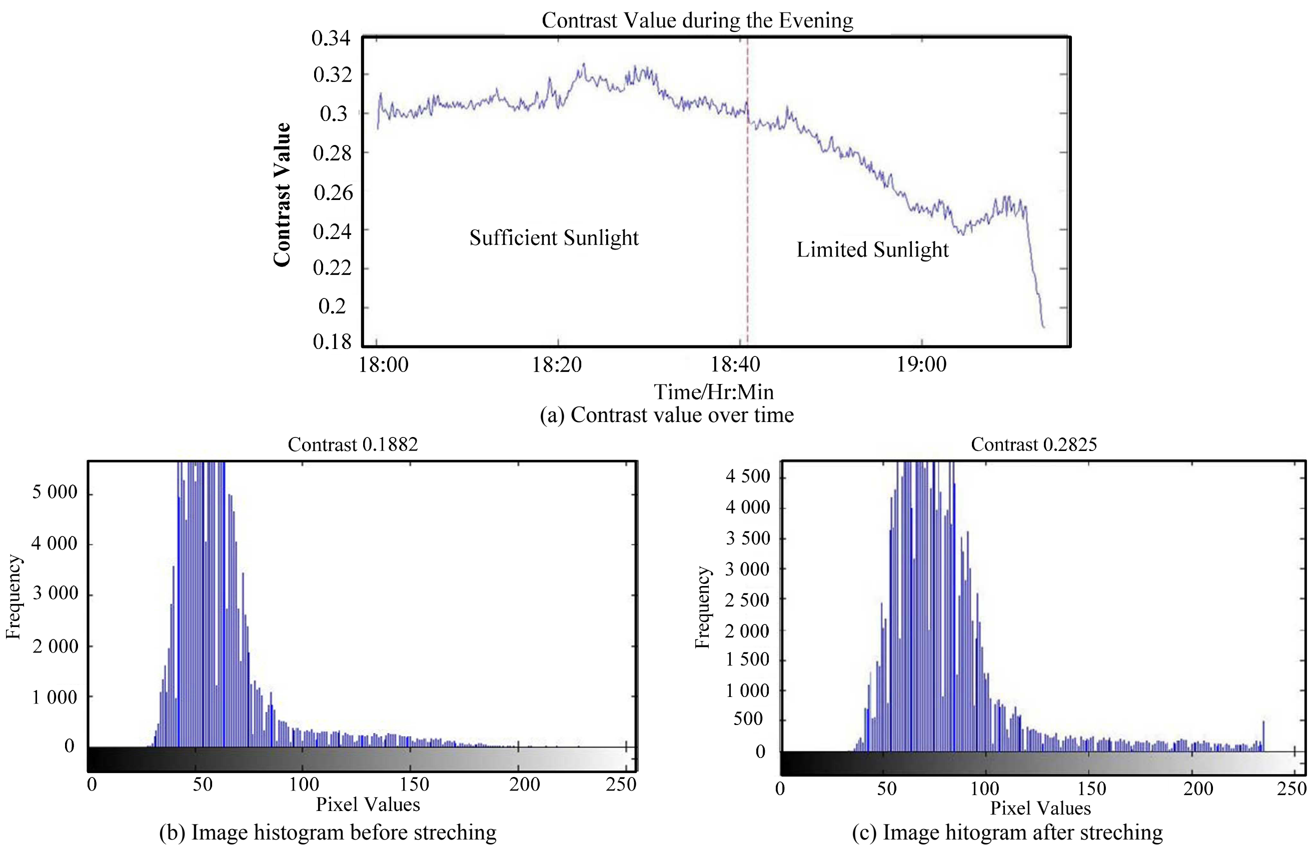
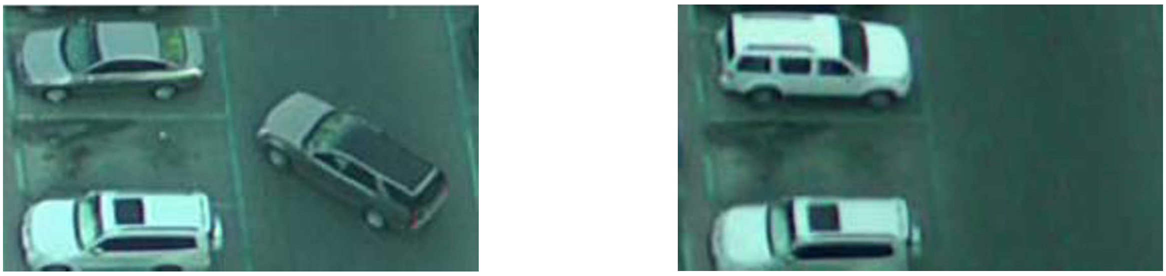


Fig.5 Light adaptation. The contrast value declines rapidly in (a) due to insufficient sunlight. The contrast value increases from 0.1882 in (b) to 0.2825 after the adjustment in (c).

Table 2 shows that after adjusting to the target contrast value, color-related values were very close to the frame with sufficient sunlight where the neural network works well for both empty and occupied spots. Spread values were also well approximated for occupied spots. However, contrary to the expectation, spread values for empty spaces increased after the histogram stretching. In fact, the spread values in limited light, even without adjusting, were higher than that in sufficient sunlight. This was because the black stains on the empty spot became more visible in limited light (Fig. 6), increasing the spread values. Nonetheless, the spread in empty spots was still significantly less than that of filled spots.

Table 2 Average Values of Features after Adjusted to the Target Contrast Value

Features	Occupied Spots			Empty Spots		
	Sufficient Sunlight	Limited Sunlight	Histogram Stretched	Sufficient Sunlight	Limited Sunlight	Histogram Stretched
Standard Deviation (Less Strict)	28.4	26.3	29.3	4.84	5.96	7.51
Interquartile Range	42.3	37.8	42.2	6.81	9.69	12.3
Max Red	129	113	126	71.4	55.1	69.4
Max Green	179	153	170	105	82.6	104
Max Blue	180	154	171	99.3	79.7	101



(a) Weak stain in early evening (b) Stronger stain in late evening

Fig. 6 Dark stains of the same spot intensified in the limited sunlight.

3.5 Solution to Problem 3: Selecting Appropriate Regions for Reference

Fortunately, because the lighting condition in nighttime remained constant, it did not need pre-processing. Still, the minor problem was finding appropriate regions to find the reference point for calculating color distance. At night, the light source was concentrated only along the parking spots, and not on the pavement. The color of the empty space was therefore significantly different from that of the pavement. The semi-circle regions at the top of each parking lanes were chosen, because these pavement sections also received constant and similar lighting from the light posts.

4 Results

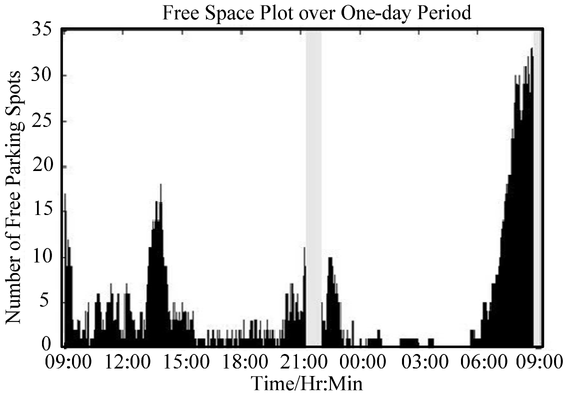
4.1 Accuracy

The one-day long video was analyzed using the selected networks for nighttime and daytime and with pre-adjustment to the images in limited sunlight. Throughout the video recording, frames were extracted for every 10 seconds, a duration that safely captured changes in parking states even in the high traffic period. From these frames, features of the parking slots were extracted and given to the neural network to determine the parking states. After that, every one frame for 60 analyzed frames was taken as a sample set to evaluate accuracy. This means that the predicted parking states for every ten minutes of the recording were verified. In total, 17640 parking spots were checked. Only 9 out of 17083 occupied spots and 11 out of 537 empty spots were misclassified. The accuracy was 99.9% for occupied spots and 97.9% for empty spots for this one-day long video.

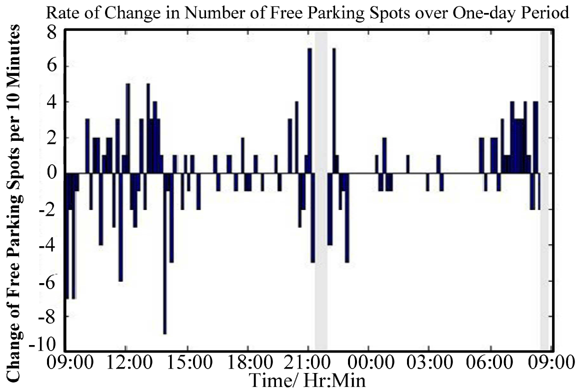
4.2 One-day Long Statistical Analysis

It is worth noting that, due to technical limitations in video recording, the one-day long statistics had missing data for 40 minutes from 21:20 to 22:00 and 15 minutes from 08:45 to 09:00. These two time intervals are indicated by grey regions in the graphs to be discussed in this section. However, we had complete coverage of all of the remaining 23 hours and 5 minutes; i.e. more than 95% time coverage.

The Free Space Plot (FSP) over one-day period (Fig. 7 (a)) shows the number of empty parking spots over time. The highest number is 33 out of 126 available spots or 26% of the total parking slots. The parking spaces start to free up from 6:00 to 9:00. People who park the cars overnight go for their daily work. After 9:00, the peak declines as people from other areas arrive in this area for work and park their cars. The second highest number of vacant spots is 18 or 14%, almost half of the highest number. It is between 13:00 to 14:00 suggesting that many people leaving in lunchtime. This peak in the afternoon has lower spread than that in the morning. This is probably because while people have different starting time for their morning work activities, people who leave for eating places generally go for lunch at the same time. Generally, the number of empty parking spots is below 10. This means that for most of the day, 92% of the parking slots remained occupied, indicating high utilization rate. Rate of change in number of free parking spots (Fig. 7 (b)) illustrates many positive and negative values alternating throughout the time, suggesting high rates of activity. When cars leave, there are new cars taking up the spots. The periods of consecutive positive values correspond to the two major peaks discussed. The highest increase in empty spots occurred at around 21:00 to 22:00, when people who finish their activities at nighttime are likely to leave.



(a) Free space plot over one-day period. The number of free parking spots over time, out of 126 total spots



(b) Rate of change in number of free parking spots over one-day period. Each net change is over 10 minutes

Fig. 7 Statistical result.

4.3 Indication of Parking Demand

A better indication of parking demand when the park is near its full capacity is how actively the cars are searching for parking spots. This can be understood from how quickly a parking spot gets occupied after a car leaves that spot. This indication thus gives a better understanding of the parking demand, as the utilization rate can only reflect parking demand at most equal to the number of parking spots occupied. Occupancy Plots show black lines, each corresponding to a vacant parking spot over a period of time. Y-axis labels the index of the parking spot, and X-axis represents time. The four patterns are observed from the plots.

First, high number and short length of black lines indicate high rates of cars leaving the car park and high rates of cars actively searching for the empty spots. When any car leaves the parking spot, that parking space is quickly filled up. As a result, the parking space fluctuates nearly at a full utilization rate. This was illustrated well in time 19:00 to 19:30 (Fig. 8).

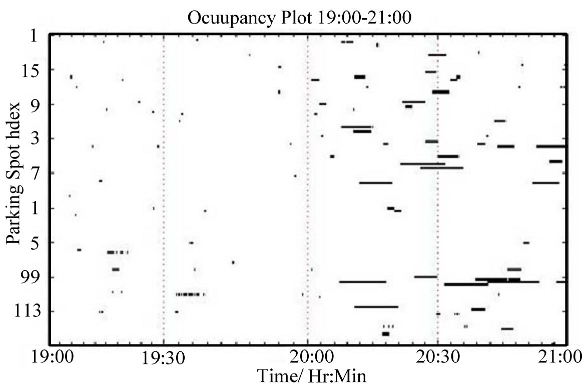
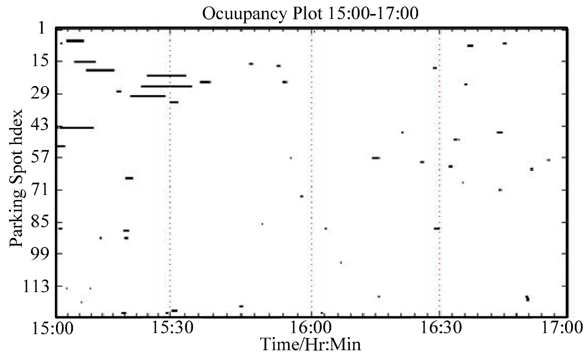
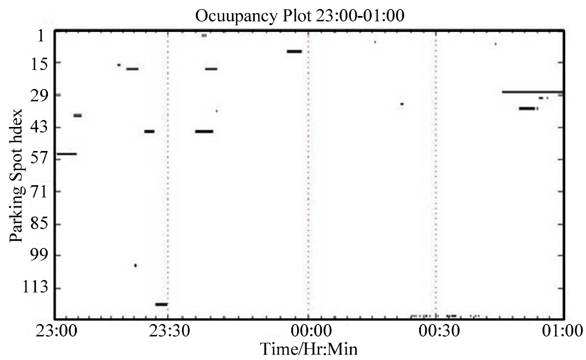


Fig.8 High number and short length during time 19:00 to 19:30.

Second, low number and short length show low rates of cars leaving but the empty space are immediately filled up (Fig. 9). This pattern is seen from time 15:45 to 16:30. Few people leave their mid-afternoon activity, but almost exactly as soon as they leave, the spot is filled up. The pattern is prominent from 23:30 to 00:30. People rarely leave at such nighttime, but when they do, there are always cars quickly taking these new empty spot. It showed that even at late night, there was significant number of cars searching for an overnight parking spot. Although this pattern also shows full utilization similar to the first pattern, the traffic is less heavy.



(a)



(b)

Fig.9 Low number and short length during time 15:45 to 16:30 and 23:30 to 00:30.

Third, low number and long length show that few cars are searching for the parking spot at this time, and very few cars are leaving (Fig. 10). This pattern is observed from time 02:00 to 03:00. In this case, one car left and the space remained unoccupied for an hour. This is when the utilization tends to remain constant at full utilization rate.

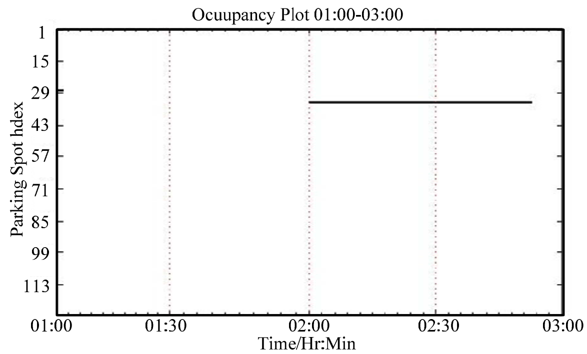


Fig.10 Low number and long length during time 02:00 to 03:00.

Fourth, high number and long length of the black lines indicate a lot of cars leaving the parking spot and those spots remain empty (Fig. 11). This corresponds well to morning time from 7:00 to 9:00. In this time, people leave for work. Another time interval with a similar pattern is from 13:00 to 14:00. Probably, people leave for restaurants, freeing up parking spaces.

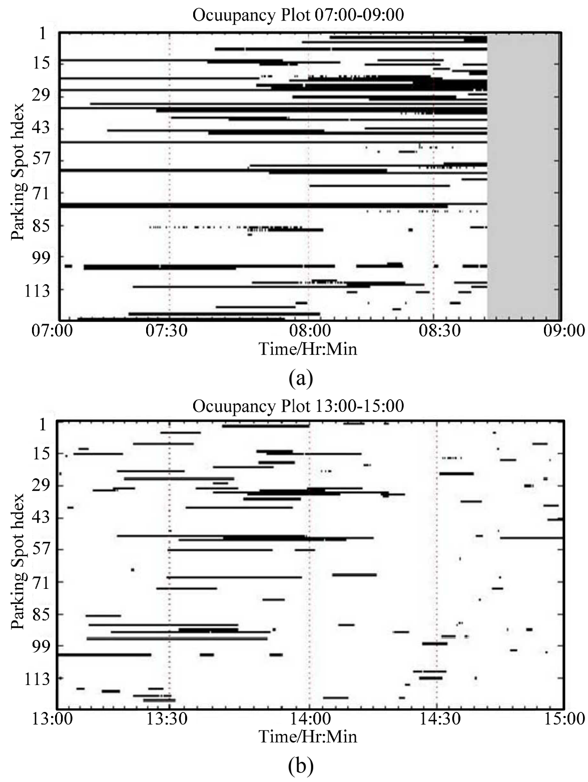


Fig.11 High number and long length during time 7:00 to 9:00 and 13:00 to 14:00.

5 Conclusion

Given the need for parking space management, real-world statistics of parking demand has become very important for informed decision-making. In this paper, we have presented a compact and highly cost-effective single-camera vacancy detection system, which can deliver round-the-clock statistical analysis of outdoors parking spaces. Our system was tested in a real-world general-purpose outdoor parking space in downtown Abu Dhabi, and we presented full one-day cycle results. Our proposed method that was used in our system to collect the statistics uses specially trained customized neural networks to determine occupancy states and parking demand based on visual features extracted from parking spots. In our study, we found that for our case, for most of the day, 92% of the parking slots remained occupied. Except in the morning and in the early afternoon, people leave for morning work activities and lunch respectively. In addition, the methodology that was utilized in our system, gives refined understanding of parking demand from unsuccessful parkers, when the car park is near its maximum capacity. With the proposed methodology, accurate parking demand throughout the day is obtained to propose policy such as varying price of parking space according to parking demand or sharing parking space with car park of different parking demand to average out the parking needs.

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