



A Novel Parking Lot Occupancy Detection System Based on LED Sensing

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Abstract. For the great market value, intelligent parking lot detection system has been studied extensively. Generally, additional sensors such as wide-angle lens cameras, ultrasonic detectors, pressure sensors and so on are required to be deployed in the parking lots, which incur high deployment cost. Considering the lighting infrastructures are widely deployed in the underground garage and the occupancy of a parking lot changes the ambient light intensity, in this paper we novelly reuse the existing lighting infrastructure and exploit the light sensing capacity of the light emitting diode (LED) to monitor the occupancy of the parking lots. The LED illuminators can be switched between light emitting and sensing state so that during sensing state, LED illuminators can work as light sensors. In our scheme, we feed the data collected by LED illuminators in a typical machine learning method, Support Vector Machine (SVM) algorithm to achieve accurate detection accuracy. We conduct simulative experiments and demonstrate the feasibility and effectiveness of the proposed LED sensing based parking lot occupancy detection system. The detection accuracy reaches 98.70%.

Keywords: Visible light technology · Machine learning · Intelligent parking system · Support Vector Machine · Automatic parking space detection

1 Introduction

The worldwide civilian vehicles maintain rapid growth in volume for decades. In China alone, the number of civilian vehicles in the past decade has reached an average of 140.63 million [1]. The rapid growth of civilian vehicles brings increasing demands of intelligent parking management system [2, 3].

The essential issue in an intelligent parking management system is to detect accurately if the parking lots are occupied by vehicles. Existing parking management systems generally deploy cameras [3–5], ultrasonic detectors [6–8], pressure sensors [9], infrared detector [10] and so on for occupancy detection. These systems all require the deployment of extra equipment at the parking space.

What's more, some systems (e.g. using the pressure sensors) even need ground reconstruction. Such as, the method proposed by the author of [3] is to pre-calculate the pixel value difference between the parking space and the registered space groove image. In this way, the occupancy of the parking space is detected. However, there are many difficulties in classifying parking spaces under many conditions in this design. Both natural light and headlamps can cause dramatic changes in image intensity. The wide-angle lens camera used in the design of [2] will cause a large image distortion, and the detection result will also be affected by vehicles, pedestrians or various obstacles.

Fortunately, lighting infrastructure is mandatory in most garages in which economic and energy efficient LED eliminators are mounted on the ceiling of the garages for illumination, particularly in the underground garages [11]. Besides illuminating, LED eliminators can also sense the ambient light intensity by biasing the LED driver and can be used as light sensors. As the occupancy of a parking lot will impact the light diffusion reflection, LED light sensor is an ideal candidate for occupancy estimation. Inputting the gathered data from LED light sensor into Machine learning algorithms yields an inference result for parking lot occupancy. Therefore, in the paper, we aim to design a parking lot occupancy detection system which reuses the existing lighting infrastructure without additional deployment cost for occupancy detection.

In the proposed system, we redesign the driver of the LED eliminators and switch them between the light illuminating state and light sensing state in a high frequency without incurring flicker. During the sensing state, the LED eliminators senses the ambient light diffusion reflection and then feed the sensing measurements to the occupancy inference algorithm to infer the occupancy results. This paper is organized as follows. Section 2 introduces how to design the LED sensing based system and employ Support Vector Machine algorithm to process collected data. In Sect. 3, we conduct simulative experiments to validate the proposed system. Section 4 concludes this paper.

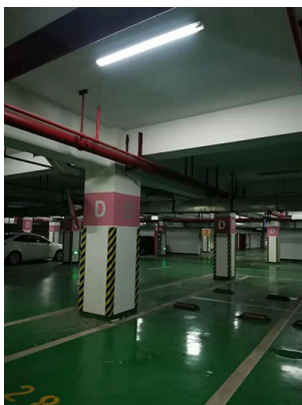


Fig. 1. Underground garage

2 LED Sensing Based Parking Lot Detection System

In this section, we firstly illustrate how to drive the LED eliminators as the light sensors and then describe the parking lot occupancy inference algorithm.

2.1 LED as Parking Lot Occupancy Sensor

The target underground garage is shown in Fig. 1. When designing an underground garage intelligent parking system, we need to consider the standard dimension of vehicles which is shown in Table 1.

Table 1. Standard dimension of vehicles and parking space

	Minicar	Small car	Parking lot
Height (m)	1.8	2.0	≥ 2.2
Length (m)	3.8	4.8	2.5~2.7
Width (m)	1.6	1.8	5~6

The LED driver is redesigned in order to allow the LED to switch between light emitting state and light sensing state.

Due to the low SNR of a single LED bulb and also the illumination requirement, the LED illuminator mounted on the ceiling in the parking lot detection system is actually an LED array consisting of multiple LED bulbs. We refer to the LED illuminator as LED array hereafter. In order to enable the LED array to switch between the light emitting and sensing states, the LED array needs to connect to a Microcontroller Unit (MCU) by a bidirectional interface as shown in Fig. 2 and the specific connection method is shown in Table 2. Moreover, Fig. 3 re-designs the LED driving circuit as in [12, 13]. When both switches SW1 and SW2 are turned on at the same time, the LED array works in the light emitting state. When only switch SW3 is turned on, the circuit is in the ready-to-light-sensing state and the remaining charge on the LED array is cleared. When both switches SW4 and SW5 are turned on, the LED array switches to the light sensing state. When the LED array senses the reflected light from a vehicle, it can generate a small photocurrent. To measure the generated photocurrent, we use resistor R2 greater than 10 M Ω to convert the weak photocurrent into a voltage signal that drives the amplifier to produce the sensing result.

2.2 LED Sensing Based Vehicle Detection

As shown in Fig. 4, when a vehicle enters the parking lot covered by an LED array, the LED array can capture the change of light diffusion caused by the vehicle movement. Figure 5 presents the LED reading caused by the occupancy of a vehicle. During the first 60 s, there is no car in the parking lot and the LED

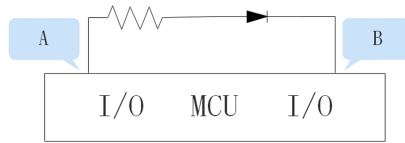


Fig. 2. Bidirectional interface between LED and MCU.

Table 2. The way the LED array connects to the I/O pins of the MCU

Working state	A-I/O	B-I/O	Description
Light emitting	VCC	GND	In the LED lighting status, the anode and cathode of the LED array are connected to VCC and GND through a simple I/O configuration
Ready-to-sense	GND	VCC	When the LED array is to be used for light sensing, the I/O configuration needs to be restored to the reverse bias mode, and the internal stray capacitance of the LED array needs to be charged
Light sensing	GND	IN	During the light sensing status, MCU reads the voltage change across the LED cathode and calculates the time it takes for the photocurrent to discharge the capacitor to the digital input threshold of the I/O pin and further the amount of incident light

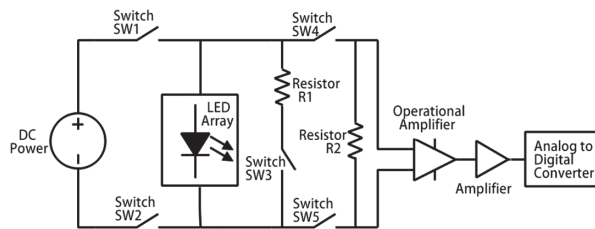


Fig. 3. LED array sensing circuit.

reading stays in a low level. Until 60s, a vehicle enters the parking lot and the LED reading increases largely and stays in a high level afterwards. This implies that the occupancy detection can be realized by comparing the LED reading.

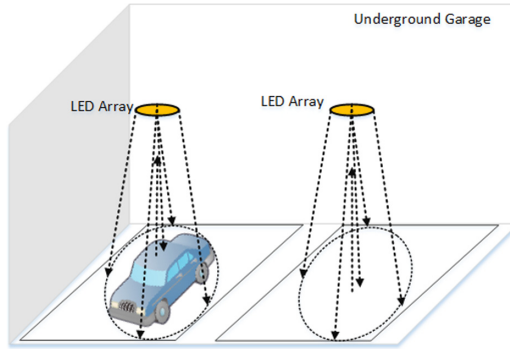
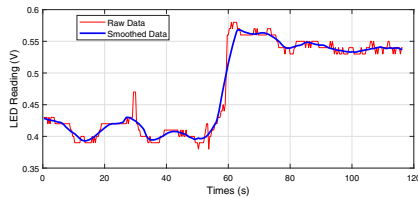
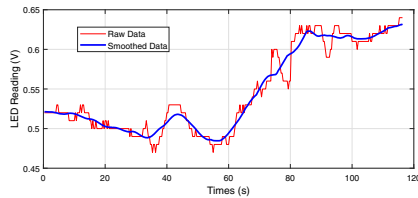


Fig. 4. Vehicles within the sensing range of the LED array.

We also explore the impact of the vehicle height on the LED reading. Figure 5(a) and Fig. 5(b) shows the LED reading when the distance between the vehicle roof and the LED array is 40 cm and 100 cm, respectively. In Fig. 5(a), due to the close proximity, the LED reading change resulted by the occupancy is high up to 0.15 V. In Fig. 5(b), the LED reading caused by the vehicle occupancy only increases by about 0.1 V, which is nevertheless can be detected easily. By comparison, we can conclude that the farther vehicle roof from the LED array, the more difficult it is to accurately infer the occupancy of the parking lot. The height of a vehicle is typically 1.6–1.8 m and the height of the garage is typically 2.2–2.8 m. Thus the distance of the vehicle roof and the LED array is roughly 0.4–1.2 m, which means the proposed LED sensing based occupancy detection is feasible in most cases.



(a)



(b)

Fig. 5. Raw and smoothed LED readings.

Due to the raw voltage signals collected by LED array are subject to random noise and so on, we use an exponential moving average method to remove the noise from the raw LED reading.

$$v_t = k * v_{t-1} + (1 - k) * \alpha_t \tag{1}$$

where α_t is the raw voltage value at time t , v_t is the weight voltage value at time t , and k is the weight. The smoothed LED readings can be seen in Fig. 5. As the parking lot occupancy detection can be formulated as a binary classification, we feed the smoothed LED readings in Support Vector Machine (SVM) [14], as it is proven efficient in [12], and obtain the inference result.

3 Evaluation

In order to verify the proposed LED sensing based parking lot occupancy system, we conduct extensive simulative experiments. We use five paperboards in the most common colors, including black, white, red, frosting red, frosting black, to mimic the vehicles. Figure 6 shows the detailed experiment setup. The LED eliminator consists of the LED driver as shown in Fig. 6(a) and the LED array including 8×12 LED chips [15]. We use ultra-low-power microcontrollers MSP430F2418 as the MCU of the driver circuit [16]. The LED array take one sample every 1 ms the Fig. 6(c) shows the five paperboards in different colors. As measured, the field of view (FoV) of the LED eliminator is about 30 degree as shown in Fig. 6(d). According to the construction standard of the underground garage, the height of the garage is generally 2.2m–3m. It can be calculated that

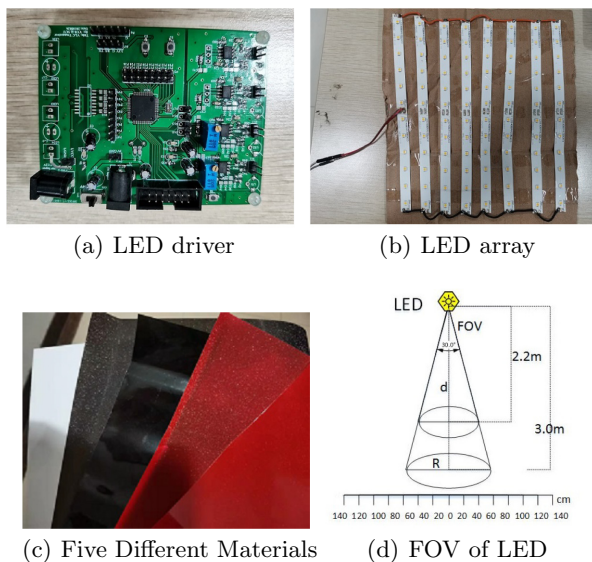


Fig. 6. Experimental setup.

the coverage area of one LED eliminator is much less than the area of one parking lot. Therefore, we can ignore the interference of the surrounding environment on the occupancy detection.

3.1 Impact of Vehicle Color

In this subsection, we explore the impact of vehicle colors on the LED readings. Figure 7 shows the LED reading change caused by the vehicle presence with different colors. When the vehicle is white, the change of LED reading is the most significant and black incurs the most trivial change. This conforms to our intuition since the white object reflects the light of all colors and on the contrary the black object absorbs all light. Also, we observed that frosted paperboards incurs less change too.

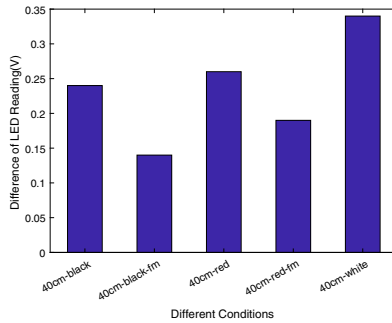


Fig. 7. The impact of different vehicle colors on the LED readings.

3.2 Impact of Distance

Figure 8 illustrates the change of LED reading caused by vehicle presence with varying distance between the white paperboard (vehicle roof) and the LED array. With the distance varies from 40 cm to 120 cm, the change of LED reading becomes more insignificant. As the typical distance is about 100 cm, the proposed system can work well in reality.

3.3 Occupancy Detection Accuracy

We use the SVM classification algorithm to infer the occupancy of the parking space. As we only need to infer whether the parking lot is occupancy or not, it is a binary classification problem. Assume that “1” indicates that the parking space is free, and “2” indicates that the parking space is in the parking space. We carried out extensive experiments with different heights between the vehicle roof and the ceiling of the garage.

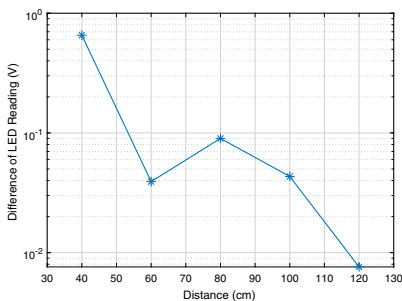


Fig. 8. The change of LED reading v.s. varying distances.

Table 3. Accuracy and precision of parking space detection

Distance	Accuracy	Precision
0.4 m	98.70%	98.07%
1.0 m	86.04%	78.27%

We move the paperboards of different colors into the coverage of LED array and move it out at vertical distance 1 m and 0.4 cm repeatedly, 20 times for each paperboard. Thus for each vertical distance about 3550×20 samples in total are collected and 70% samples are used as the training data. Accuracy and precision are used to evaluate the performance. The two metrics are defined as

$$accuracy = \frac{(TP + TN)}{(TP + FN + FP + TN)}, \tag{2}$$

$$precision = \frac{TP}{(TP + FP)}, \tag{3}$$

respectively, where TP denotes true positive, FN denotes false negative, FP denotes false positive, TN denotes true negative. The obtained occupancy detection accuracy and precision are shown in Table 3. The accuracy rate of the detection results of the SVM algorithm reaches 98.70% when the vertical distance is 0.4 m. The accuracy would stay above 86.04% as the vertical distance is generally below 1.0 m. The accuracy can be further improved by increasing the LED array size.

4 Conclusion

In this paper, we novelly reuse the existing lighting infrastructure and exploit the light sensing capacity of LED to detect the occupancy of the parking lots. The LED illuminators can be switched between light emitting and sensing states

so that during sensing state, LED illuminators can work as light sensors. We conduct simulations and demonstrate the feasibility and effectiveness of the proposed LED sensing based parking lot occupancy detection system.

Currently, we only conduct simulative experiments and we plan to deploy a testbed in an underground garage and collect daily data to evaluate the practicality of the proposed system. Our system only considers the LED deployment that one LED eliminator is mounted on the top of one parking lot. In reality, in order to save costs, a single LED eliminator may cover multiple parking lots. Therefore, we plan to verify the feasibility of one LED eliminator monitoring multiple parking lots.

In this paper, we only use SVM to infer the occupancy. As the collected LED readings are of high temporal correlation, LSTM, Markov model and the other algorithms considering temporal correlation might improve the detection accuracy highly. Thus in the future work we aim to exploit more inference algorithms.

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