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# Preference-based smart parking system in a university campus

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**Abstract:** This study introduces the concept of space preferences to enhance the operation of recurrent-users car parking systems. On campus, at KFUPM, several parking buildings are available for students, employees, and faculty. Still, substantial amount of time is wasted just looking for a suitable parking space. The authors propose to enrol all users together with their top ranked preferred parking spots and pedestrian exit of choice. Upon presentation of the user ID card, the system retrieves their preferences, matches them to the updated database of vacant spots, then directs the user to their topmost vacant parking spot. The system directs the user to the nearest parking building if no vacancy. Two options have been evaluated to detect parking vacancies: one is based on ultrasonic sensors and the second uses a set of cameras. The sensor-based system was built around an Arduino platform paired with a wireless channel for communication. For the camera-based system, the authors introduce a new set of features mixing both edge and texture information from the parking spot images. A performance analysis of both systems was carried showing that the sensor-based implementation outperforms the camera-based one for the authors' specific application with an accuracy of 100 and 98%, respectively.

## 1 Introduction

Several intelligent surveillance systems have been developed around the world to assist drivers in finding vacant parking spaces. There are mainly four categories of car parking management systems; see, for example, [1–19] and the references cited therein. These include counter-based, wired-sensor-based, wireless-sensor-based [1–4], and camera-based systems [5–19]. The counter-based systems use sensor detectors that are located at entrances/exits of a car park to count the number of vehicles entering and exiting. This system can only provide the information on how many vacant parking spaces are available in the car park, but does not help in guiding the driver to his/her preferred space.

Wired-sensor-based systems use sensors (e.g. ultrasonic) which are deployed at each parking space. These sensors are connected to a central control unit to manage the parking information. The car park status is then shown on display panels. One disadvantage of wired-sensor systems is the cumbersome wiring network. Also, the cost for deploying such a system is high because of the large amount of sensors and long-distance wiring. With the advancement of the technology, wireless-sensor-based systems have gained more popularity. A wireless sensor node is located at each parking space. When using wireless sensor technology, cost of sensor node, power management, and communication protocols need to be considered. The last category of parking management uses camera-based systems [5–19]. Such systems can be expensive and generate large amount of data. The strengths and weaknesses of different technologies with respect to installation, parameters measured, performance in inclement weather, variable lighting conditions, and suitability for wireless operation are detailed in [1].

On the other hand, several studies focused on driver's parking behaviour and preferences [20–23]. However, most of these studies are mainly concerned with public parking areas. In [20], the authors discussed the users' preferences in relation to location and parking cost. They recommended that cost should be adjusted across different parking areas to optimise utilisation of all available parking spaces. In [21], the authors conducted a survey on parking location choice behaviour in the context of shopping trips. The study showed that the priorities for parking preferences are ranked as: cost of parking, parking availability after 8 min of search, walking distance to the desired destination, and instantaneous availability of parking. As such, it is important to inform incoming drivers of the availability of vacant spaces or the probability of getting a vacant space over the next 8 min. In [22], the authors compared the behaviour of informed drivers to that of unfamiliar drivers in choosing on or off street parking. While informed drivers tend to make their choice based on a number of factors such as safety, walking distance etc., unfamiliar drivers tend usually to prefer less costly parking options.

In [23], the authors discussed the concept of parking guidance and information systems deployed in major cities. Their survey showed that drivers tend not to rely on such guidance as provided information may be inaccurate or out of date. The study showed the importance of having interactive and real-time systems that provide drivers with accurate information either at the macro level (city level) or at the level of the parking areas themselves. An extensive study about technologies and solutions for car parking systems can be found in [24].

While most of the existing systems consider the case of public parking areas, this paper focuses on parking areas with recurrent users, such as university campuses, government organisations, large industrial facilities, among others. Under such scenarios, users tend to have their own preferences as to where to park in relation to their pedestrian exit. Additionally, the paper compares the suitability of sensor-based to that of camera-based techniques for the detection of vacant parking spaces in indoor environments. In relation to the developed camera-based systems, and in contrast with existing techniques, we use here fusion of three relevant features, namely, edge strength, number of closed objects, and texture information. These features are used with a Bayesian framework to identify car spaces as either vacant or occupied.

The paper is organised as follows: Sections 2 and 3 describe the developed sensor-based system and the experimental results obtained. Sections 4 and 5 describe the camera-based system and the experimental results obtained. Finally, Section 6 provides some concluding remarks and an insight into future research directions.

## 2 Sensor-based vacant parking space detection system

In sensor-based systems, various types of sensors have been used to detect vacant places. Different factors play a role in choosing the

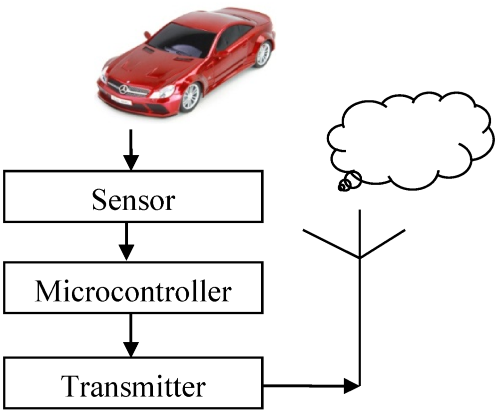


**Fig. 1** *Block diagram of the vacant parking space detection system*

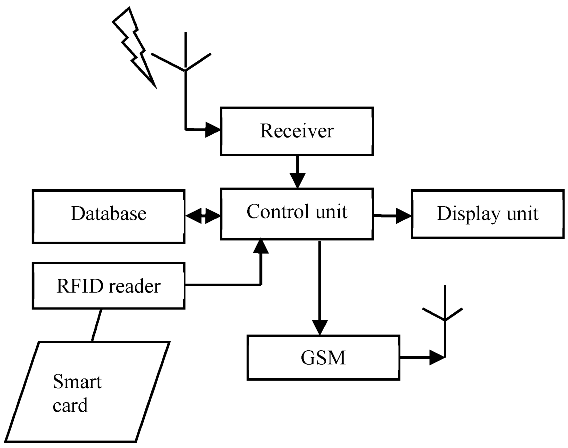


**Fig. 2** *Block diagram of the central control unit*

proper sensors, including size, reliability, environmental changes, cost, and robustness. Sensor technology can either be intrusive or non-intrusive. Intrusive sensors (like magnetometer, inductive loops, and piezoelectric) need to be installed by digging under the surface of the road. Non-intrusive sensors (optical, ultrasonic) are just fixed on the ceiling or on the roadside.

In our implementation, ultrasonic sensors are deployed to detect vacant parking spaces. The sensor readings are obtained and the distance calculated via an Arduino microcontroller. Arduino is an open-source electronics platform based on easy-to-use hardware and software. The developed system comprises two main modules: vacant parking space detection modules and a central control unit. The description of both modules is given below.

### *2.1 Vacant parking space detection module*

The vacant parking space detection module basically detects availability and transmits wirelessly the information. A block diagram displaying the main parts of the detection system is shown in Fig. 1. There will be as many of these detection modules as the number of parking spaces in the building. The circuit at each parking space consists of a sensor, a microcontroller, and a transmitter. The transmitter sends regularly its status with its own ID number to the central control unit. The different components of the circuit used at each parking space are discussed next.

*2.1.1 Ultrasonic sensor (HC-SR04):* The HC-SR04 sensor was used for detecting parking space vacancy. The sensor works by finding the distance to the first obstructing object, which can either be the vehicle or the ground floor. The module automatically sends a pulse and receives the reflected signal. The *Trig* pin is used to send the signal and the *Echo* pin is used to listen for the returning signal. The time delay is then utilised to calculate the distance. The model we used has a detection range of 2–450 cm, with a precision of 3 mm.

*2.1.2 Microcontroller (ATMega328):* For our application, we opted to use the Atmel ATmega328 microcontroller (RISC architecture). It is an 8 bit microcontroller with 32 kB of flash program memory. The main features of the microcontroller are:

- 28-pin microcontroller,
- flash program memory: 32 kB,
- EEPROM data memory: 1 kB,
- SRAM data memory: 2 kB,
- I/O pins: 23,
- timers: two 8 bit/one 16 bit,
- A/D converter: 10 bit six channel,
- PWM: six channels,
- MSSP: SPI and $I^2C$ master and slave support,
- USART: yes,
- external oscillator: up to 20 MHz.

Each parking space is given a unique ID. The microcontroller processes the data received from the ultrasonic sensor and converts it to distance to check the vacancy of the parking space. The status and the space unique ID are then sent wirelessly to the central control unit.

*2.1.3 RF transmitter (WRL-10534) – 434 MHz:* This wireless transmitter pairs with the 434 MHz receiver at the central control unit. They work well with microcontrollers to produce a very simple wireless data link. Both the transmitter and the receiver work at identical frequencies. The RF transmitter operates at a bit rate of 4.8 kbps (kbits/s) and covers a transmission range of ∼160 m.

### *2.2 Central control unit (parking management module)*

The central control unit is the heart of the proposed parking system. The block diagram of the control unit is shown in Fig. 2. The main components of the developed system are:

- parking status receiver,
- LCD display,
- RFID reader,
- database of users with their preferred parking space,
- GSM shield for SMS messaging.

The central control unit communicates with all parking space detection circuits, receives back the status, and updates the database. It also continuously displays the number of vacant spaces on an LCD display. The central control unit database also contains the users' mobile numbers. When the users register in the system, they are asked to provide an ordered list of their five topmost preferred spots over the whole parking area. In addition, the users also provide their preferred pedestrian exit from the parking area.

When a user presents his smartcard close to the RFID reader, the system first authenticates the user ID. Unauthorised users are notified by a message (unauthorised to park). For an authorised user, the system checks first his/her priority list and allocates for him/her the topmost vacant spot in the list. However, if all priority spots are occupied, the system assigns to the user, the closest vacant space to his chosen pedestrian exit. Each exit is paired with a ranked list of all spots in the parking building using certain criteria. For our implementation, we used the shortest distance criterion. However, additional features can be considered, including wider spots, corner spots etc. This user-dependent exit-dependent list is checked, and topmost vacant space is allocated to the user. The number of the allocated spot is sent by an SMS and displayed on a nearby board. The spot status is changed to 'occupied'. Some drivers may choose not to use the allocated spot and park in other vacant spots. The developed system caters for such cases as periodically; it checks all vacant spaces and updates the status according to true occupancies. The overall workflow of the proposed system is shown in Fig. 3.

The different components of the central control unit are described in the following.

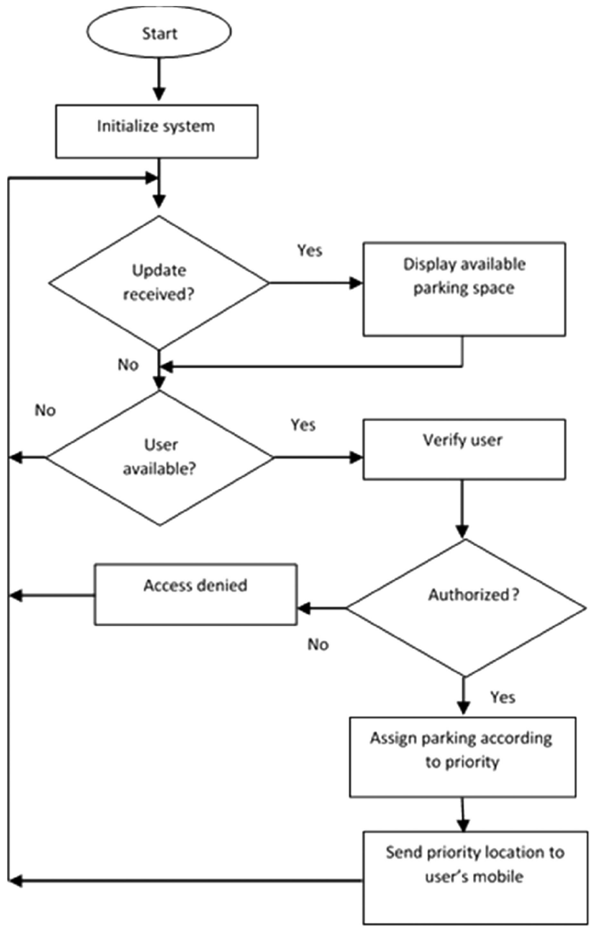


**Fig. 3** *Flowchart of the central control unit*

*2.2.1 RF receiver (WRL-10532) – 434 MHz:* This wireless receiver operates at a frequency of 434 MHz. The selected receiver and transmitter adapt well with Arduino microcontrollers to produce a simple but efficient wireless data link. Note that the WRL-10532 receiver only operates in one way communication mode. It receives the ID information and the status (vacant or occupied) from each of the transmitters. Once the data is received, an interrupt is sent to the microcontroller for updating the database. Similar to the transmitter, the RF receiver operates over a range of 500 ft at a bit rate of 4.8 kbps.

*2.2.2 LCD display (grove serial LCD v1.0):* A generic serial Grove 16 × 2 LCD with a Baud rate of 9.6 kbps was used in our application. It only needs two pins to communicate with the microcontroller.

*2.2.3 RFID reader (parallax):* A serial parallax RFID reader was used for reading the card information. When the user's card is in proximity to the reader, an interrupt is sent to the microcontroller, and data is buffered to the reader. The information is then validated to authenticate users. The reader is enabled/disabled through software and operates at a Baud rate of 2.4 kbps.

*2.2.4 GSM shield (Arduino):* A GSM shield was used to complement the Arduino with access to the GPRS wireless network. It can also initiate/receive voice calls and send/receive SMS messages. In the developed system, the GSM shield was used for sending an SMS with the selected parking space number. The information is also displayed on the LCD board. The GSM shield is separately controlled by an Arduino Mega module which communicates with the central control unit through the $I^2C$ communication protocol.

*2.2.5 Control unit (ATMega 328):* The central control unit of the system is also based on the Atmel ATmega328 microcontroller. Since the LCD display and the RFID reader both use serial ports, more components can be controlled by the same microcontroller. When the user brings his smartcard in proximity to the RFID reader, the microcontroller is interrupted to receive the data and check the authorisation from the user database. Once a change in the status of any parking spot occurs, the receiver interrupts the microcontroller and updates the parking status database and also updates the number of available parking spaces on LCD.

*2.2.6 Users database:* The database of the users is stored in the central control unit. It includes a list of authorised users with their mobile numbers, together with their parking preferences. Their preference is provided in terms of a ranked list of their five best parking spots in addition to their desired pedestrian exit from the building. We selected five topmost as the second best preferred space could be at a different floor level from the topmost space. The number five is a parameter that can be changed based on the parking building at hands. For our implementation, we developed a local database hosted in the central control unit. For the full implementation, the already available database of all university constituents can be used.

## 3 Sensor-based experimental results

The different components discussed above were merged into a prototype for testing and validation. First, the ultrasonic sensors detect vacancies of parking space, with the status indicated by red LED for 'occupied' and green LED for 'vacant'. In our experimental set-up, the detection circuits report their status to the central control unit in a continuous fashion.

The communication between each of the parking detection circuits and the control unit is via simplex transmission. This arrangement saves on the number of components and the consumed power. The parking detection circuits need to continuously transmit the status so that the control unit keeps a check on them. If a parking status is not received for a period of 30 min (a parameter that can be changed), the system reports a fault to technical support.

To assess the performance of the developed sensor-based system, we considered a number of realistic scenarios in our experiments. These include: changing the number of vacant spots, different preference list for each user, faulty detection circuits at several spots, and changing the number of vacant spaces from no vacant to fully occupied parking area. The performance of the system was tested in each case. The system was able to assign the user successfully according to his pre-defined preference list. We then changed the order in the preference list of some users and checked the system response. The system responded correctly by assigning the user to the best available parking space according to his preference list. Finally, we used different numbers and placements of faulty detection units and observed that the system detected and reported these faulty detection units under all scenarios. In performing the above-mentioned tests, we used different types, sizes, and colours of cars and the system performed correctly in all cases. Also, we tested cases where cars are parked in the centre, left side, and right side of the parking space and in all cases, the status was detected correctly. With all of the software-related problems debugged, and defective electronic components replaced, over a database of 30 users, and out of 100 trials, the system performed as planned achieving 100% detection accuracy.

It is worth mentioning here that in our initial experiments, we noticed that the simultaneous transmission of all parking detection circuits led to data corruption and hence the wrong number of vacant spots is displayed. To solve this problem, we reconfigured the system to transmit in a round-robin fashion. When a given detection circuit completes its transmission, it interrupts the next detection circuit to transmit its data and so on. The disadvantage is the delay in the update of parking status due to the serial configuration. The worst case can occur when a change of status of a given spot happens immediately after its transmission turn in the cycle. Owing to the limited number of car spots in our implementation, the worst-case delay in displaying the real status was only few seconds. This delay can be significant in the case of

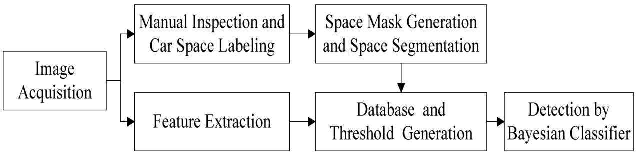


**Fig. 4** *Block diagram of the camera-based system*

large parking areas. However, in real-time deployment, this can be solved by using duplex transmission in the parking detection circuit as well as in the central control unit.

## 4 Camera-based vacant space parking detection

Camera-based vacant parking detection systems have been extensively used in car park management, especially in open areas with high-density parking spaces. Such systems gained much popularity in recent years with a lot of research efforts put on systems that focus on certain practical set-ups or scenarios. In [6], for example, a camera-based system was developed focusing on outdoor parking. The system predefines the road area as the background. A binary foreground image is generated after fitting the road colour to the whole parking region and defining the colour difference between the input image and the background image. The occupied spaces are detected from the foreground area using a basic thresholding approach. In [7–9], the authors used the concept of edge strength over segmented parking areas with excellent experimental results. In [10], an approach using fuzzy *C*-means clustering and particle swarm optimisation was used to classify the segmented areas into vacant or occupied spaces, while in [11], a three-layer Bayesian hierarchical neural network was used for classification. In [12], the authors considered a texture-based approach using local binary patterns and local phase quantisation to classify parking areas as either vacant or occupied. Instead of processing whole images, patch-based approaches have also been proposed for detecting vacant parking spaces, especially for images covering large numbers of car spots [13]. Along the same directions, the authors in [14] focused on large outdoor parking areas. Their major contribution was the use of a simple binary classifier based on convolutional neural networks to classify pre-segmented parking spaces into occupied or vacant. The authors also suggested an approach based on contour nets with limited success. One advantage of the proposed technique was its simplicity. However, it is only applicable to pre-segmented areas covered by well-calibrated stationary cameras. The authors tested their algorithms on the standard public database called the PKlot [15], achieving an accuracy of 99%.

From our survey of the literature, we noted that most existing camera-based methods follow one of two main research directions: one based on edge strength while the second focuses mainly on texture attributes. Edge-based techniques are useful when amplitude discontinuities across the image are prominent; these, however, will not perform well with smooth image areas. For such cases, texture information is more robust to detect changes between vacant and occupied parking regions in a given image. To avoid the disadvantages of edge-based and texture-based approaches when used separately, we introduce in this paper a new robust hybrid approach which uses both texture and edge information. Moreover, we propose to use a general Bayesian framework to classify the fused features as either representing vacant or occupied parking spaces. The block diagram of the developed system is shown in Fig. 4.

The proposed system starts by acquiring the stream of images. We use here a single off-the-shelf camera of medium resolution that covers 5–7 car spots. The first stage of the system involves the extraction of a set of characterising features covering both edge and texture information from each of the parking spots. The features considered here include edge density, number of closed objects, and background/foreground ratio. Note that this feature extraction stage is preceded by a calibration step in which the different car spots covered by each of the cameras are identified in the image by a set of quadrilateral shapes.

The first extracted feature simply represents the number of objects detected in the individual parking space. This number is usually very small for vacant spaces, while occupied spaces result in a large number of closed objects. The number of edges in the parking area of interest may be related to the number of objects but is more general as it represents the density of discontinuities in the image region. This number is also expected to be large for occupied parking spaces. Several algorithms exist for extracting edge information from images; these include the Canny algorithm as well as the Roberts, Prewitt, and Sobel operators [25]. All these techniques are based on estimating first derivatives in the horizontal ($G_x$) and vertical ($G_y$) directions using masks. From these operators, the edge gradient and direction ($\Theta$) are obtained as

$$G = \sqrt{G_x^2 + G_y^2} \tag{1}$$

$$\Theta = \arctan\left(\frac{G_y}{G_x}\right) \tag{2}$$

The result of these operations is a greyscale image with a black background and varying shades of white around the edges of the different objects in the image. The edge pixels are then obtained by thresholding using the Otsu technique [25]. To obtain the number of closed objects in the image, we start with the edge image then use four- or eight-connectivity concepts traditionally used in image processing. The final number of objects is simply the number of four-connected or eight-connected objects [25]. For our images, the eight-connectivity property was found to provide better match to the parking spaces considered in our experiments.

Finally, to take into account texture information, we use the foreground mean pixel value (FMPV) as a feature and compare it with a given threshold (relative to the background). To find the background pixel value, the histogram of the greyscale image is obtained and the bin with the highest probability is declared as the background value. This parameter is estimated from all vacant parking spaces. After obtaining the background value, image subtraction is performed between the grey level original image and the artificial uniform background image and vice versa (grey level image minus the background, and background uniform image minus the grey level image). The two foreground images are averaged to obtain the final foreground image. We applied the above procedure to handle the case of both lighter and darker colour (than the background) vehicles. With the final foreground image, the mean of the pixels within every parking space is calculated, and this feature is defined as the FMPV.

To combine the information obtained from the three features discussed above, we have used two main strategies: the first strategy was based on simple majority voting among the three individual decisions. A major challenge was the estimation of the three thresholds, namely $\mathrm{Th}_1$, $\mathrm{Th}_2$, and $\mathrm{Th}_3$. To find these thresholds, we carried extensive experiments based on the popular Otsu method [25]. The technique was shown to provide robust segmentation results for bimodal histograms as is the case here. The overall camera-based vacant space detection system using the voting strategy is displayed in Fig. 5.

The second strategy combines the estimated features into a three-dimensional feature vector followed by a Bayesian framework to decide whether a given spot is vacant or occupied. One advantage here is that we do not need to estimate the different thresholds separately, and the decision is based on the fused information from the three features rather than the individual features separately.

## 5 Experimental results

For our experiments, we tested the proposed algorithm on a database of ∼80 images taken from different student parking areas at KFUPM. The images were taken with an off-the-shelf camera covering four to seven parking spaces. We display in Fig. 6 a sample image covering four parking spaces. In Fig. 7*a*, a specific parking space from Fig. 6 is selected for processing. Figs. 7*b–d* show the processed images for extracting the three features,

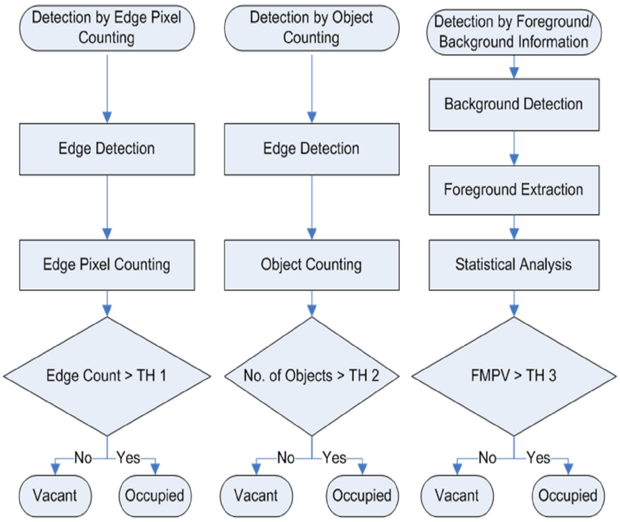


**Fig. 5** *Flowchart of the majority voting vacant parking detection system*

**Fig. 6** *Sample image covering four parking spaces*

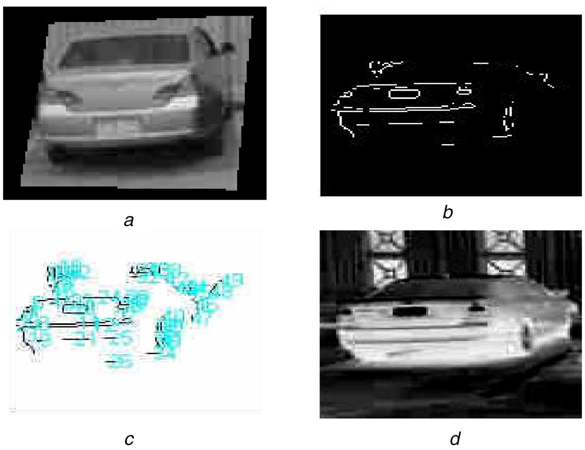


**Fig. 7** *Processing stages for a sample car space*
***(a)*** A selected parking space, ***(b)*** Detected edges, ***(c)*** Detected objects, ***(d)*** Foreground/ background map

namely, number of objects, edges, and foreground/background ratio.

For the example of four parking spaces shown in Fig. 6, we display in Table 1, the results for edge and object counts. For the foreground/background segmentation, we used the histogram to identify the background pixels.

As discussed above, the grey level bin corresponding to the peak of the histogram is averaged to obtain the estimated background value. Using this background value, we obtain the two foreground images which are then averaged and the resulting FMPV is obtained. The results for the FMPV values corresponding to the four parking regions from Fig. 6 are shown in Table 2.

We also considered the case of images covering seven parking spaces. The results for a typical image are displayed in Table 3, where O and V stand for occupied and vacant, respectively. It is important to note that the threshold values used in the algorithm can change with image resolution. This is not a problem as the calibration and training stages can accommodate such a change. The foreground/background technique alone did not provide accurate detection. However, the majority voting process provided accurate detection of parking vacancies.

**Table 1** Edge and object counts with individual classifier decisions for Fig. 6

| # | Space 1 | Space 2 | Space 3 | Space 4 |
|---|---|---|---|---|
| # edge pixels | 379 | 551 | 480 | 803 |
| decision 1 | occupied | occupied | occupied | occupied |
| # objects | 41 | 32 | 44 | 61 |
| decision 2 | occupied | occupied | occupied | occupied |

**Table 2** Detection results using the foreground/background method for Fig. 6

| Spaces | Space 1 | Space 2 | Space 3 | Space 4 |
|---|---|---|---|---|
| FMPV | 131 | 101 | 115 | 104 |
| decision 3 | occupied | occupied | occupied | occupied |

To avoid the problem of determining a priori the different thresholds for the different features, we propose here to use a Bayesian framework with the input being a three-dimensional feature vector (no. of objects, edge density, foreground/ background). Such a model has the advantage of taking into account any correlation that may exist between the features, and does not require any threshold to be set in advance. The framework uses a multidimensional normal distribution to represent the statistical characteristics of the extracted features under two possible scenarios: vacant or occupied. The model starts by assigning a joint normal distribution to the random feature vector $\boldsymbol{x} = (x_1, \ldots x_N)$ (here $N = 3$). Such a joint PDF is conditioned upon the different parking space status, $C_j$, [26]

$$P(\boldsymbol{x}/C_j) = \frac{1}{2\pi^{N/2}\sqrt{\det(\boldsymbol{R}_j)}} e^{-(1/2)\left[(\boldsymbol{x}-\boldsymbol{m}_j)^{\mathrm{T}} R_j^{-1}(\boldsymbol{x}-\boldsymbol{m}_j)\right]} \quad (3)$$

where $\boldsymbol{m}_j$ and $\boldsymbol{R}_j$ $\{j = 1, 2\}$ are the mean vector and covariance matrix corresponding to class $C_j$ ($j = 1$ for vacant or 2 for occupied), and $N$ is the number of features (here $N = 3$).

For each class, $C_j$, we estimate the mean vector and the covariance matrix from the training data using [26]

$$\boldsymbol{m}_j = \frac{1}{M_j} \sum_{x \in C_j} \boldsymbol{x} \quad (4)$$

$$\boldsymbol{R}_j = \frac{1}{M_j} \sum_{x \in C_j} \boldsymbol{x}\boldsymbol{x}^{\mathrm{T}} - \boldsymbol{m}_j\boldsymbol{m}_j^{\mathrm{T}} \quad (5)$$

where $M_j$ is the number of training vectors from class $C_j$ and the summation is taken over these vectors. To take into consideration the correlation between the three features, we use a non-diagonal autocorrelation matrix, hence a general Bayesian model.

The Bayes classifier combines the model above with a decision rule. One common rule is to select the class that results in the maximum a posterior probability (MAP) [26]:

$$P(C_k/\boldsymbol{x}) > P(C_j/\boldsymbol{x}) \quad j \neq k \quad (6)$$

The above decision rule can be re-written in terms of $P(x/C_j)$. For our experimental set-up, we collected 100 images from different parking areas. We then used a ten-fold cross-validation set-up in which 9/10 of the images are used for training, while the remaining 1/10 are used for testing. The above set-up is randomly repeated 100 times and the classification results are averaged over these 100 runs.

We display in Fig. 8, the typical receiver operating characteristic (ROC) curves obtained for two individual classifiers, namely, the edge-based and the FMVP-based classifiers.

While the results of the individual classifiers are satisfactory, they are not excellent as shown in Table 4. The table shows that the individual accuracies vary between 85 and 96%. However, when

**Table 3** Parking status using majority voting strategy for a typical image covering seven parking spaces

| Space no | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| edge pixels | 2817 | 193 | 3961 | 4328 | 9603 | 8130 | 6634 |
| decision 1 | O | V | O | O | O | O | O |
| objects | 178 | 9 | 263 | 315 | 516 | 545 | 553 |
| decision 2 | O | V | O | O | O | O | O |
| FMPV | 52 | 42 | 49 | 47 | 55 | 70 | 53 |
| decision 3 | O | O | O | O | O | O | O |
| final decision | **O** | **V** | **O** | **O** | **O** | **O** | **O** |

Bold values indicate the final results.

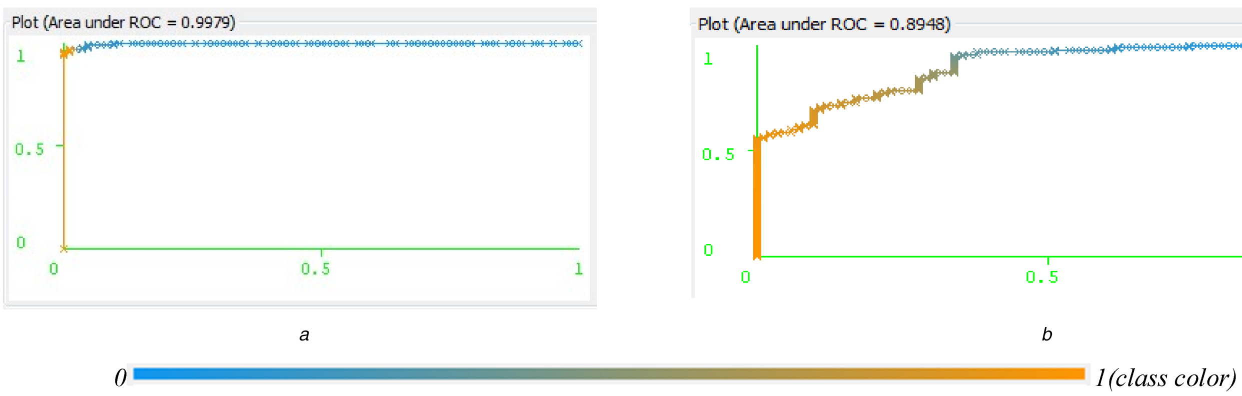


**Fig. 8** *ROC curves for the edge-based and the FMPV-based classifiers when applied independently*
***(a)*** ROC of the number of edge pixels, ***(b)*** ROC of FMVP

**Table 4** Confusion matrix and recognition results using a Bayesian classifier

| | Detect as occupied | Detect as vacant | Recognition accuracy, % | Probability of misclassification, % |
|---|---|---|---|---|
| detection using edge pixel counts | | | | |
| occupied | 225 | 8 | **96.83** | 3.17 |
| vacant | 2 | 80 | | |
| detection using object counts | | | | |
| occupied | 223 | 10 | **95.87** | 4.13 |
| vacant | 3 | 79 | | |
| detection using FMVP | | | | |
| occupied | 215 | 18 | **85.39** | 14.60 |
| vacant | 28 | 54 | | |
| detection using the three features | | | | |
| occupied | 231 | 2 | **98.73** | 1.27 |
| vacant | 2 | 80 | | |

Bold values indicate the final results.

all three features are combined together under a Bayesian framework, the overall accuracy increases to 98.73%.

## 6 Analysis and discussions

Two approaches have been followed to detect the status of every parking space: a sensor-based and a camera-based. The sensor-based system uses an ultrasonic sensor at each parking space to check its status and transmit it wirelessly to the central control unit. Extensive experiments have shown that the system can provide 100% accuracy in detecting vacant spaces.

For the image-based system, we used off-the-shelf cameras. While for outdoor applications, cameras can be used to monitor large numbers of parking spaces, indoor cameras can only be sued to monitor four to seven parking spaces. We have shown that using a combination of edge and texture features together with a Bayesian classifier can result in a robust vacant space detection system. An accuracy of >98% was achieved on vacancy detection.

Our implementation showed that sensor-based systems exhibit a number of advantages. These include: excellent detection accuracy, resilience to vehicle size, colour, environmental conditions, low computational and communication loads, simple architecture, and operation. However, these systems exhibit some limitations including dedicated circuit for each car spot and higher chance of malfunctioning components. On the other hand, the advantages of camera-based systems include: multiple spots monitoring by a single camera, images can be used for security and surveillance applications, and suitability for outdoor applications. However, the data traffic exchanged over the system can be substantial, the computational load is high, and regular cleaning of the camera lenses is required. It is worth noting that the sensor-based system is more suitable for indoor parking, while the image-based system is more efficient for outdoor parking areas. Based on the above, our recommendation was heavily oriented towards the adoption of a sensor-based system for this particular application.

It is worth noting that in recent times, a lot of research efforts have been put in developing systems for autonomous navigation [27, 28]. The work discussed in this paper fits well with the current trends as the issue of preferred pedestrian exit in parking buildings continues to be of major relevance to passengers of autonomous vehicles. The detection of the closest vacant parking space (to the preferred pedestrian exit) is still desirable for efficiency. Furthermore, we have also witnessed recently some hybrid systems which are based on the fusion of image-based and sensor-based approaches for improved performance. For example, in [29], the authors proposed to fuse image-based and sensor-based data to improve object classification accuracy to assist in autonomous navigation. For future work, we plan to extend the work using fusion approaches for ready integration with intelligent vehicles.

## 7 Conclusion

In this paper, we have developed a preference-based indoor parking system with recurrent users such as university campuses, government organisations, companies etc. The system directs registered users to one of their five topmost preferred parking spaces or the closest vacant space to their chosen pedestrian exit. The preference list for each user is stored in a central database and retrieved upon presentation of his/her smartcard to the reader. The main server searches for vacancies according to the ordered list of this particular user, assigns the topmost vacant space if available. In case all five topmost spaces are occupied, the system assigns to the user, the closest vacant space to his chosen pedestrian exit.

The detection of vacant parking spaces was achieved using two approaches, a sensor-based and a camera-based. Both systems were implemented and tested over a range of scenarios. A thorough performance analysis was carried showing that the sensor-based implementation outperforms the camera-based one for indoor applications with an accuracy of 100 and 98%, respectively.

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