Parking Space Detection Based on Information from Images and Magnetic Sensors

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Abstract

Parking space detection is a key technology in the parking lot management system. When performing parking space detection using magnetic sensors, there may be interference from the adjacent parking space, which will result in false detection. However there still will be false detection when only cameras are used to detect the parking spaces because the performance of the cameras is inclined to be affected by the environment. Considering that the magnetic sensors are only sensitive to ferromagnetic objects and insensitive to the environment effect and images often contain a wealth of information, we propose a parking space detection algorithm combining the information from magnetic sensors and images. The algorithm performs primitive detection using magnetic sensors. If the sensor reports that there is a vehicle nearby, the algorithm analyzes the image information of the parking space gathered by the camera, extracts the image features of the parking space and classifies the features to confirm whether the parking space is occupied. The experimental results show that our algorithm can make more precise decisions for parking space detection with much lower complexity and less computational efforts. Furthermore our algorithm can effectively reduce the burden of image or video processing of the system.

Keywords: Parking Space Detection, Magnetic Sensor, Contour Features, Texture Features, Minimum Risk Bayesian Classifier

1. Introduction

In order to assist people in parking efficiently, the parking lot management system need to perform parking space detection to determine whether the parking space has been occupied. Up to now, parking space detection techniques can be divided into two types [1]: the first is deploying sensors such as magnetic or ultrasonic sensors on each individual parking space and processing signal acquired by these sensors to identify the states of parking spaces [2, 3]. This method is easy to implement due to low cost of devices and low complexity of signal processing algorithms. However, less information will be gathered from signal of the sensors, which will result in false detection. For example, there may be interference from the adjacent parking space when using magnetic sensors because the magnetic sensor can detect any ferromagnetic objects nearby, but it cannot make correct decisions because less information is acquired. While the second is using cameras mounted at high positions of the parking lot to acquire image information of the parking space for further analysis. In recent years, many algorithms based on image or video processing technology have been proposed. For example, Ching-Chun Huang et al [4] suggested each parking space can be deemed as a 3D cube and performed parking space detection by a 3-layer Bayesian hierarchical detection framework; Qi Wu and Yi Zhang [5] defined two states for each individual parking space, i.e. 0 and 1. They rotated the raw input frames of parking space into uniform axis and segmented them into small patches which include 3 parking spaces each. Then they classified the patches into 8 states by multi-class SVM and finally they built Markov Random Field (MRF) to improve the accuracy; Jae Kyu Suhr et al. [6] performed parking space detection using optical flow based method. Because of their higher complexity and more computational efforts, some of these algorithms have a high requirement for storage and computing capacity of the system. On the other hand, if only cameras are used to identify available parking spaces, they have to work all the time to monitor parking spaces. However, cameras in the parking lot are also used for other purposes such as security surveillance and abandoned object detection, which will impose a heavy burden on image or video processing of the system. Meanwhile, the performance of cameras is
inclined to be affected by the environment. As a result, only using cameras for parking space detection may lead to false results.

Considering the problems mentioned above, we propose an algorithm for parking space detection based on magnetic information and image information. In the parking lot where magnetic sensors have been placed on each individual parking space and a camera has been mounted at the high position, the proposed algorithm firstly performs a primitive detection based on magnetic information to determine there is a vehicle nearby. Then the camera captures the image of the corresponding parking space and sends it to the algorithm. The algorithm extracts the image features of the parking space and classifies the features to confirm whether the vehicle is on the corresponding parking space. The proposed algorithm can effectively reduce the interference from the adjacent parking space with lower complexity and less computational efforts. Furthermore, the algorithm does not require the camera to monitor parking spaces all the time, which will reduce the burden on image and video processing. Finally the algorithm is insensitive to the environment effect so as to get more precise detection results.

This paper is organized as follows. In section 2 we will discuss the magnetic information for primitive detection. In section 3 we introduce the image features used for detection. In section 4 we discuss feature classification for final detection. Experiments and results are presented in section 5 and conclusions are given in section 6.

2. Magnetic Information Extraction

In our parking lot, there is a magnetic sensor placed on each individual parking space. The sensor is sensitive to ferromagnetic objects but insensitive to the environment effect. Therefore we use this characteristic of the sensor to reduce the environment effect and the burden on image or video processing.

The sensor has three axes for monitoring changes in geomagnetic field in three directions and outputs acquired signal in digital mode. The x-axis of the sensor is parallel both to the plane of the parking space and the vehicle moving direction; the y-axis of the sensor is parallel to the plane of the parking space but perpendicular to the vehicle moving direction; the z-axis is perpendicular to the plane of the parking space. When a ferromagnetic object such as a vehicle is moving on the parking space, there will be fluctuations in the signal indicating that geomagnetic field has changed because of geomagnetic induction. For the reason that the signal of the magnetic sensor changes slowly, the frequency of signal acquisition is low and 1.25Hz is chosen in our work. The acquired signal of the magnetic sensor is shown in Figure 1.

![Figure 1. The output signal of 3 axes of the magnetic sensor](image-url)
not so stable and there exists disturbance. In our algorithm, we firstly decide whether there is a vehicle nearby based on the magnetic information. The procedure to do this is presented as the following:

**Step 1** Acquire the signal of the sensor as the background signal when there is no vehicle nearby; compute the mean value and variance of the signal from each axis of the sensor respectively, i.e., \( m_{hx}, m_{hy}, m_{hz}, v_{hx}, v_{hy}, v_{hz} \), where the subscripts \( x, y, z \) correspond to x-axis, y-axis and z-axis of the sensor.

**Step 2** Set a sliding window on the signal of each axis, where the length of the window is 5 and the sliding distance is 1; compute the mean value and variance of the signal in the window, \( w_{hx}, w_{hy}, w_{hz}, v_{hx}, v_{hy}, v_{hz} \).

**Step 3** Compute \( v_{dx} = |v_{wx} - v_{hx}|, v_{dy} = |v_{wy} - v_{hy}|, v_{dz} = |v_{wz} - v_{hz}| \); if more than two of the inequalities \( v_{dx} > th_{hx}, v_{dy} > th_{hy}, v_{dz} > th_{hz} \) are satisfied, which indicates that there are fluctuations in the signal, then the counter \( cnt \) is increased by 1; otherwise repeat step 3; here \( th_{hx}, th_{hy}, th_{hz} \) are the predefined thresholds and selected based on practical experience.

**Step 4** Continue computing \( v_{dx}, v_{dy}, v_{dz} \) until \( v_{dx} < th_{hx}, v_{dy} < th_{hy}, v_{dz} < th_{hz} \); because the duration of geomagnetic field disturbance is short, if \( cnt < nth \), which indicates that there is disturbance in geomagnetic field, jump to step 1 to re-acquire background signal; otherwise the sensor reports that there may be a vehicle on the corresponding or adjacent parking space. Here \( nth \) is the threshold for \( cnt \) and has been predefined.

From the above analysis we find that the magnetic sensor is only sensitive to ferromagnetic objects but outputs little information about the parking space. As a result it cannot effectively handle the interference from the adjacent parking space. Therefore we use the camera to acquire image information of the parking space for precise detection results. Without monitoring the parking spaces all the time, the camera starts to work only when the sensor reports that there is a vehicle nearby. At this time the camera captures the image of the corresponding parking space and sends it to the algorithm for further analysis.

### 3. Image Information Extraction

Because of a wealth of information in images, we reduce the interference from the adjacent parking spaces by image processing. The algorithm processes images of the parking spaces captured by the camera based on the differences between the vacant and occupied parking spaces. Then it extracts contour information and texture information of the parking spaces as image features.

#### 3.1. Image Preprocessing

The camera has been mounted at the high position of the parking lot. As the position and angle of the camera will remain unchanged from the time of installation, there is no necessity to label each individual parking space automatically every time the system performs parking space detection. As a result, the system can utilize human labeled parking spaces which are obtained once the system is installed for further operation. Each labeled parking space is corresponding to the magnetic sensor placed on it. When the magnetic sensor reports that there is a vehicle nearby, the camera acquires the RGB image of the corresponding parking space and sends it to the algorithm. The algorithm reads the image, and captures the sub-image containing only the region of the parking space which is so called region of interest (ROI) based on the labeled parking space. Then the sub-image is converted from RGB image to grayscale image. For the existence of noise during image acquisition, the grayscale image is passed to median filter to filter out noise. The whole process of image preprocessing is shown in Figure 2.
3.2. Contour Feature of the Parking Space

The basic principle of contour detection is based on detection of intensity discontinuity [7]. Compared with the vacant parking space, the occupied parking space has more contour information because there are significant differences between the vacant pixels and occupied pixels, which result in much more discontinuity. Figure 3 and Figure 4 show the comparison.

Figure 3. The left image is RGB image of the vacant parking space and the right image is binary image after contour extraction of the left image

Figure 4. The left image is RGB image of the occupied parking space and the right image is binary image after contour extraction of the left image

Obviously, there are much more contour points in the occupied parking space than in the vacant parking space. Even though there is shadow in the vacant parking space, the shadow does not have much contour information. Therefore we choose contour information as one of the image features. The algorithm firstly extracts contours in the parking space, then it counts the number of the contour points which is represented as \( N_c \), at last it divides \( N_c \) by the total number of pixels in the parking space \( N_r \), that is

\[
 f_d = \frac{N_c}{N_r},
\]

where \( f_d \) is the density of contour points in the parking space which is the contour feature of the parking space.

3.3. Texture Features of the Parking Space

There are generally 3 methods of describing region texture in image processing which are statistical
method, structured method and spectral method [8], [9]. The statistical method describes smoothness, roughness and granularity of the region surface. As we can see, the surface of the vacant parking space is smooth while the surface becomes “rough” when there is a vehicle on the parking space. Therefore we use statistical method to describe texture features of the parking space.

The definition of the mean value of intensity of the grayscale image is [8]:

\[
m = \sum_{i=0}^{L-1} z_i p(z_i),
\]

where \(z_i\) is a random variable of intensity, \(p(z)\) is the normalized grayscale histogram and \(L\) is the number of grayscale levels. Then we get the \(n\)th moment of the mean value of intensity of the grayscale image

\[
\mu_n = \sum_{i=0}^{L-1} (z_i - m)^n p(z_i).
\]

Thus the standard deviation of intensity of the grayscale image

\[
\sigma = \sqrt{\mu_2}.
\]

Then we define smoothness of the region surface as [8]

\[
f_R = 1 - \frac{1}{1 + \sigma^2}.
\]

When there is no vehicle on the parking space, the intensity distribution of the parking space region is uniform with a low randomness. On the contrary, when there is a vehicle on the parking space the intensity distribution becomes more stochastic. Referring to the concept of entropy in information theory, we use entropy to measure randomness of the intensity distribution [8].

\[
f_e = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i).
\]

As a result, based on the above analysis we compute the density of contour points, smoothness and entropy to describe image features of the parking space.

4. Feature Classification

As we know, the parking space can be vacant or occupied. We use \(\omega_1\) to represent the former and \(\omega_2\) to represent the latter. After image feature extraction, we classify the features into \(\omega_1\) or \(\omega_2\) to determine whether the parking space has been occupied. There are two kinds of classification mistakes. The first is that the occupied parking space is mistaken as the vacant one and the second is the opposite. It is obvious that the risk of the former mistake is higher than that of the latter. Because when a user is told that some parking space is vacant while actually it has been occupied, both of the user and the parking lot will face losses. Therefore, we use minimum risk Bayesian classifier [10] to classify image features of the parking space to get the final detection result after image feature extraction.

4.1. Minimum Risk Bayesian Classifier

Suppose that there are \(M\) pattern classes in pattern space \(W\) that is \(W = \{\omega_1, \omega_2, \cdots, \omega_M\}\). With regard to some pattern \(X\), the conditional probability density function (PDF) of its belonging to \(\omega_j\) is \(p(\omega_j | X)\). An error occurs when we determine that \(X\) belongs to \(\omega_j\) but actually it belongs to \(\omega_i\). Because \(X\) may belong to any pattern class of \(W\), the average risk of determining \(X\) belongs to \(\omega_j\) is [10]
where $\lambda_{kj}$ is a loss function to evaluate the loss of determining $X$ belongs to $\omega_j$ while actually it belongs to $\omega_k$. Simply we define that the loss of correct classification is 0 while the loss of misclassification is 1. That is

$$
\lambda_{kj} = \begin{cases}
1 & k \neq j \\
0 & k = j
\end{cases},
$$

(8)

Then considering total probability formula and condition probability formula, Eq. (7) can be rewritten as

$$
R_j(X) = p(X) - p(X | \omega_j)P(\omega_j),
$$

(9)

where $p(X)$ is the PDF of $X$, $p(X | \omega_j)$ is the PDF of $X$ under the condition of $\omega_j$ and $P(\omega_j)$ is the probability of $\omega_j$. Therefore the decision rule of minimum risk Bayesian classifier is that if

$$
\omega_j = \arg \min_{j=1,2,\ldots,M} R_j(X),
$$

(10.a)

then

$$
X \in \omega_j.
$$

(10.b)

From Eq. (9) and Eq. (10), we can see that the decision rule can be represented as the following:

if

$$
p(X | \omega_j)P(\omega_j) > p(X | \omega_i)P(\omega_i) \quad \forall i = 1, 2, \ldots, M; i \neq j,
$$

(11)

then $X \in \omega_j$.

Let

$$
d_i(X) = p(X | \omega_i)P(\omega_i) 
$$

(12)

then $d_i(X)$ is called Bayesian decision function.

### 4.2. Parking Space Detection

Focusing on the problem of parking space detection, the pattern space is $W = \{\omega_1, \omega_2\}$, where $\omega_1$ indicates that the parking space is vacant and $\omega_2$ indicates that the parking is occupied. The pattern $X$ is defined as the image features of the parking space, i.e. $X = [f_d, f_R, f_s]^T$. According to the above discussion, in order to determine the state of the parking space, we should compute decision functions $d_1(X), d_2(X)$ respectively to determine whether $X$ belongs to $\omega_1$ or $\omega_2$. It is obvious that the probabilities of $\omega_1$ and $\omega_2$ are both 0.5, i.e. $P(\omega_1) = P(\omega_2) = 0.5$. In addition to $P(\omega_1)$ and $P(\omega_2)$, the PDF $p(X | \omega_i)$ need to be computed to get the final results. Here we use Gaussian probability density function to estimate $p(X | \omega_i)$ for simplicity. That is

$$
p(X | \omega_i) = \frac{1}{(2\pi)^{n/2} |C_i|^{1/2}} e^{-rac{1}{2}(X-m_i)^T C_i^{-1}(X-m_i)}.
$$

(13)

where $n$ is the number of feature dimensions, $n = 3$, $m_i$ and $C_i$ are the mean value and covariance.
matrix of the features respectively. We estimate the mean value and covariance matrix using training samples. The estimating equations are presented as the following [8]:

\[
m_i = \frac{1}{N_i} \sum_{X \in \omega_i} X, \quad i = 1, 2, \tag{14}
\]

\[
C_i = \frac{1}{N_i} \sum_{X \in \omega_i} XX^T - m_i m_i^T, \quad i = 1, 2, \tag{15}
\]

where \(X\) is the training sample and \(N_i\) is the number of samples belonging to \(\omega_i\). Thus according to Eq. (11), for pattern \(Y\) if

\[
\frac{d_1(Y)}{d_2(Y)} = \frac{p(Y | \omega_1)}{p(Y | \omega_2)} = \sqrt{\frac{|C_1|}{|C_2|}} \frac{|Y - m_1| - (Y - m_2)^T C_2^{-1} |Y - m_2|}{|Y - m_1|} > 1 \tag{16},
\]

then \(Y\) belongs to \(\omega_1\), i.e. the corresponding parking space is vacant and vice versa.

5. Experimental Results

We test the proposed algorithm in the parking space where the magnetic sensor is fixed on each individual parking space and the camera is mounted at the high position. At the time of system installation, we label the region of each individual parking space and make it correspond to the magnetic sensor on it. We extract image features of parking spaces as the training samples for the minimum risk Bayesian classifier under different conditions. The number of the training samples is 100 and some of the parking space images used for feature extraction are shown in Figure 5.

![Figure 5.a. Some of the images of the vacant parking spaces](image)

![Figure 5.b. Some of the images of the occupied parking spaces](image)

The training samples are shown in Figure 6.

![Figure 6. The comparison between features of vacant and occupied parking spaces](image)

It is obvious that the image features, which are density of contour points, smoothness and entropy, can effectively discriminate between the vacant and occupied parking spaces with lower complexity and less computational effort.

The performance of the proposed algorithm can be evaluated by computing false alarm rate (FAR) and miss alarm rate (MAR) measures which are defined as the following:
where $N_f$ refers to the number of mistakes that the vacant parking spaces are mistaken as the occupied ones, $N_m$ refers to the number of mistakes that the occupied parking space are mistaken as the vacant ones, and $N_d$ refers to times of detection.

When the magnetic sensor reports that there is a vehicle nearby, no matter whether the vehicle is on the corresponding parking space actually, the camera captures the image of the parking space and sends it to the algorithm for parking space detection. For comparison, we use the magnetic signal processing algorithm proposed in practical applications before and our algorithm to detect the parking space. The results are shown in Table 1.

| Table 1. The comparison between our algorithm and the magnetic signal processing algorithm |
|--------------------------|--------------------------|--------------------------|
|                          | Magnetic signal processing algorithm | Our algorithm |
| FAR                      | 8.1%                     | 1.6%                     |
| MAR                      | 0                        | 0                        |

From table 1, we can see that MAR of both algorithms are 0. The reason is that the magnetic sensor is so sensitive that it can detect any ferromagnetic object in the neighborhood. However FAR of the magnetic signal processing algorithm is much higher than that of our algorithm because our algorithm can more effectively handle the interference from the adjacent parking space by image processing.

In order to evaluate the performance of reducing interference of the weather and illumination conditions, we test the algorithms when there are no vehicles near some of the specified parking spaces. The results are shown in Table 2. Because no ferromagnetic objects appear in the neighborhood of the magnetic sensors, there are no fluctuations in the signal of magnetic sensors. As a result, the sensors keep silent, and FAR of our algorithm is 0. Simultaneously, we capture the images of the corresponding parking spaces to perform parking space detection using the proposed image features without any magnetic information. The results show that FAR is higher because of light reflection of the surface and illumination conditions. Therefore our algorithm can effectively reduce the environment effect.

| Table 2. The comparison between our algorithm and the algorithm using image features only |
|--------------------------|--------------------------|
|                          | The algorithm using image features only | Our algorithm |
| FAR                      | 3.3%                     | 0                        |

6. Conclusions

Considering that images contain much more information and the magnetic sensors are insensitive to the changes of the environment, we propose an algorithm combining the information of magnetic sensors and images to detect whether the parking space is vacant. The algorithm uses magnetic sensors to monitor the parking spaces all the time instead of the camera. If the sensor reports that there is a vehicle nearby, the algorithm extracts image features of the corresponding parking space and classifies the features using minimum risk Bayesian classifier to confirm whether the parking space has been occupied. The results of the experiments show that our algorithm can effectively reduce the interference of the adjacent parking space and environment with lower complexity and less computational effort. Moreover it reduces the burden of image or video processing of the system. Therefore the research results of this paper are valuable to practical applications.
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8. References