# 行政院國家科學委員會專題研究計畫 成果報告

## 戶外停車場空位自動偵測系統
## 研究成果報告(精簡版)

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中 華 民 國 101 年 10 月 31 日

中 文 摘 要 ： 在本計畫中，我們提出了一套停車場空位偵測系統。與一般以車輛偵測導向或是空位偵測導向的方法不同，我們是以停車場為導向。在我們系統中，我們將停車場視為多平面組成的架構。在這樣的架構中，為了推論空車位，我們提出了一套基於表面階層的架構，整合三度空間資訊與區塊式的影像觀測。為了增強系統穩定性，我們使用 Histogram of Oriented Gradients (HOG)進行區塊的特徵向量擷取。將這樣的特徵向量整合至系統中，我們可以有效的透過最佳化推論停車場的狀態，特別是針對一些困難的處理情況如遮蔽現象，光影問題，三度空間失真問題以及光照狀況不佳的白天或是夜晚情形。

中文關鍵詞： 停車位偵測、基於表面的偵測、方位梯度統計、貝氏推論

英 文 摘 要 ： We proposed a surface-based vacant parking space detection system. Unlike many car-oriented or space-oriented methods, the proposed system is parking-lot-oriented. In the system, we treat the whole parking lot as a structure consisting of plentiful surfaces. A surface-based hierarchical framework is then proposed to integrate the 3-D scene information with the patch-based image observation for the inference of vacant space. To be robust, the feature vector of each image patch is extracted based on the Histogram of Oriented Gradients (HOG) approach. By incorporating these texture features into the proposed probabilistic models, we could systematically infer the optimal hypothesis of parking statuses while dealing with occlusion effect, shadow effect, perspective distortion, and fluctuation of lighting condition in both day time and night time.

英文關鍵詞： Parking space detection； Surface-based detection； Histogram of Oriented Gradients； Bayesian inference

# 戶外停車場空位自動偵測系統

計畫編號：100-2221-E-009-149-

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## 中文摘要

在本計畫中，我們提出了一套停車場空位偵測系統。與一般以車輛偵測導向或是空位偵測導向的方法不同，我們是以停車場為導向。在我們系統中，我們將停車場視為多平面組成的架構。在這樣的架構中，為了推論空車位，我們提出了一套基於表面階層的架構，整合三度空間資訊與區塊式的影像觀測。為了增強系統穩定性，我們使用 Histogram of Oriented Gradients (HOG)進行區塊的特徵向量擷取。將這樣的特徵向量整合至系統中，我們可以有效的透過最佳化推論停車場的狀態，特別是針對一些困難的處理情況如遮蔽現象，光影問題，三度空間失真問題以及光照狀況不佳的白天或是夜晚情形。

**關鍵詞**：停車位偵測、基於表面的偵測、方位梯度統計、貝氏推論。

## Abstract

We proposed a surface-based vacant parking space detection system. Unlike many car-oriented or space-oriented methods, the proposed system is parking-lot-oriented. In the system, we treat the whole parking lot as a structure consisting of plentiful surfaces. A surface-based hierarchical framework is then proposed to integrate the 3-D scene information with the patch-based image observation for the inference of vacant space. To be robust, the feature vector of each image patch is extracted based on the Histogram of Oriented Gradients (HOG) approach. By incorporating these texture features into the proposed probabilistic models, we could systematically infer the optimal hypothesis of parking statuses while dealing with occlusion effect, shadow effect, perspective distortion, and fluctuation of lighting condition in both day time and night time.

**Keywords:** Parking space detection; Surface-based detection; Histogram of Oriented Gradients; Bayesian inference

## 1. INTRODUCTION

In practice, the major challenges of vision-based parking space detection come from the occlusion effect, the shadow effect, the perspective distortion, the fluctuation of lighting change, and detection in nighttime. Nowadays, to overcome those difficulties, many methods have been proposed. These approaches can be classified into two categories: car-oriented methods and space-oriented methods.

For car-oriented methods, thanks to the progress of object detection [1-2], many algorithms utilized texture features, such as Histogram of Oriented Gradients (HOG), to overcome the lighting change and the geometry distortion during targets detection. Generally, those methods perform well even under environmental variations. However, for the task of vacant space detection in a parking lot, the car-oriented methods may not work as robust as we expected when the impact of the inter-object occlusion is considered [3].

For space-oriented methods, the space modeling is the key step. Eigen-space representation [4] and many background modeling algorithms [5-6] were proposed to adapt to the lighting variations. However, those pixel-based space modeling methods are sensitive to shadow effects. To lower the interference of the shadow effects, the texture-based methods, based on homogeneity measurement, are then proposed, such as [7]. Even so, space-oriented methods still suffer from inter-object occlusion.

Recently, unlike car-oriented or space-oriented methods, which simply focus on limited aspects of a parking lot, Huang et al. [8] proposed a Bayesian hierarchical framework (BHF) for vacant space detection, which is specifically constructed from the parking-lot-oriented viewpoint. In this method, by integrating the 3-D scene knowledge and the pixel-based classification into the framework, both the pixel-based appearance and the structural scene property of a parking lot are well-utilized to improve the performance of vacant space detection. However, though BHF offers a flexible framework, this method, which mainly adopts a pixel-based classification process, does not benefit from the great success of texture-based classification.

Generally, pixel-based classification is sensitive to lighting change. To overcome the problem, the authors in [8] assumed the scene is uniformly lighted by sunlight. Based on the assumption, the authors put much effort to dynamically compute the environmental illumination and the direction of sunlight to model the lighting change. Although their method produced robust detection result during day time, the method may not be directly applied in night time due to the difficulty to model the complex nighttime lighting condition especially the unpredictable lighting change caused by car headlights. In fact, to the most of our understanding, few systems discuss the vacant space detection in night time.

In this project, we aim to find the suitable modeling so that the power of texture-based object classification could be incorporated into BHF to overcome the lighting change and inter-object occlusion. Comparing with the pixel-based method, the use of texture information lets us have more discriminative features for object classification, have more robust features against lighting change without an accurate lighting model, and have a unified manner to develop a day-and-night system. To use texture information, we proposed a surface-based vacant parking space detection system. In the system, we integrate the 3-D scene information into our framework by treating the whole parking lot as a structure consisting of plentiful surfaces. With the proposed framework, HOG features combined with the 3-D scene information are well-used to detect vacant parking space. Our experiments showed that the proposed surface-based framework could deal with occlusion effect, shadow effect, perspective distortion, and lighting changes in day time and night time.

## 2. SURFACE-BASED PARKING LOT STRUCTURE

As the aforementioned, car-oriented approaches, which tend to capture the texture characteristics of vehicles, seem to provide suitable solutions to handling the occlusion and shadow effects. In contrast, the space-oriented approaches, which were designed to analyze the texture of the image area corresponding to a vacant parking space, can better handle the perspective distortion by adding 3-D scene information. Hence, if we can find a way to benefit from both kinds of approaches, we may achieve robust performance.

In terms of car-oriented approaches, systems usually check the image area, as shown in Figure 1(a), to check the existence of a car. As for the space-oriented approaches, the pixel-based or texture-based feature inside the region of a parking space is used for analysis, as shown in Figure 1(b). In comparison, our approach treats the parking spaces as a set of cubes, as illustrated in Figure 1(c). Each cube is composed of six patches like Figure 1(d). If looking into the details, we may find that the ground plane of a parking space is the ground patch, while a car is made up of patches. Thus, we suggest using surfaces to represent the parking lot structure so that we can benefit from both the car-oriented and space-oriented methods.

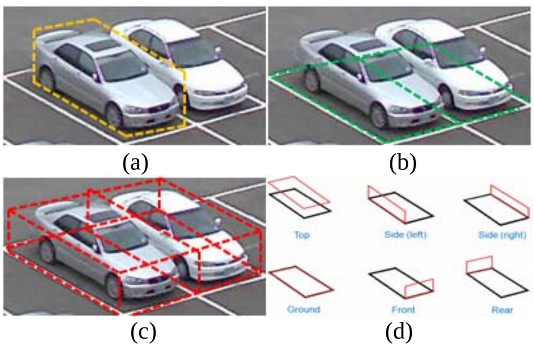



Figure 1. (a) Image area for car-level regions. (b) Image area for ground patches. (c) Model the room of a parking space as a cube. (d) The elementary planes for a parking space.

## 3. SURFACE-BASED INFERENCE FRAMEWORK

### 3.1 Image Observation

For a structural parking lot, we may detect the status of each parking space by observing occlusion patterns inside each image patch. To be specific, we demonstrate various kinds of patterns inside different projection patches in Figure 2. In total, there are 14 different patterns. Here, owing to the regularity of occlusion patterns among objects, an image patch presents distinguishable textures for vacant space detection. Thus, a direct method to determine the parking statuses is to classify the selected patches into one of the 14 occlusion patterns.

After patch classification, an important step is to relate the classification results to the statuses of spaces. To achieve the goal, we related the classification results to 14 status-related classification labels in the form of "*Typ_Ind*", where "*Typ*" indicates the surface type and "*Ind*" shows the index number of occlusion patterns of this "*Typ*". The correspondence between occlusion patterns and labels are shown in Figure 2. Here, the possible surface types include "side (*S*)", "front (*F*)", "top (*T*)", and "ground (*G*)" of a 3-D cube. For a surface type, it has two or four different occlusion patterns inside the observed patch. Without loss of generality, we assume that the patch of "*T*" surface has two possible patterns because the patch is mainly affected by the parking status of one space in our system. Note that the status of one space could be {vacant (1), occupied (0)}. On the other hand, all the other surface types have 4 possible patterns in that the pattern is affected by the statuses of two neighboring spaces. In other words, the 4 occlusion indexes indicate the 4 statuses of two spaces. Hence, for the *i*th observed patch $o_i$, we classify it as one of the 14 classification labels $\{\{S\_j\}_{j=1\sim4},\{F\_j\}_{j=1\sim4},\{G\_j\}_{j=1\sim4},\{T\_j\}_{j=1\sim2}\}$. The label $l_i$ of the *i*th observed patch $o_i$ then reflects the parking status. For instance, if $l_i$=T_2, it indicates the parking space is vacant. Also, if $l_i$=G_3, the current space and its neighbor are occupied. However, the classification label $l_i$ only provides local decision of the parking status. As mentioned in [3] and [8], the inter-object occlusion makes the status of all spaces highly relevant. To achieve the global optimum, the status of all relative spaces should be inferred at the same time rather than one by one.

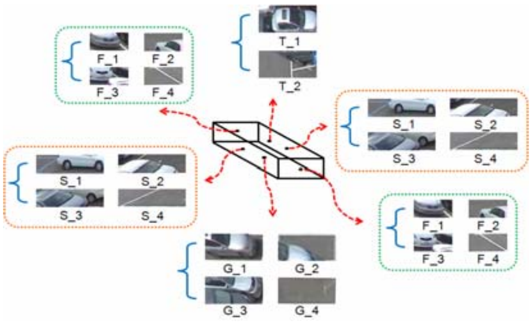


Figure 2. 14 occlusion patterns and their classification labels.

### 3.2 HOG Patch Features and Classification Models

To classify patches, our system trains the likelihood models $p(o_i|l_i)$ for different $l_i$. However, due to the perspective effect of image projection, the shape of image patches appears quite different. To overcome the perspective distortion, we proposed normalizing the size and shape of a given patch before the patch is processed for training or testing. In our system, we normalize an image patch into a rectangle with 64 pixels in length and 32 pixels in width.

After normalization, we extract statistic features from the normalized patches for model training or testing. To be less affected by shadows and the change of illumination, we utilize the HOG feature proposed in [9]. Here, a normalized image patch is regularly segmented into 4x2 cells. Since the patch size is 64 by 32, each cell would contain 16×16 pixels. For each cell, an 8-orientation histogram of gradient is built. By merging the histograms of the 8 cells, we get the HOG feature vector of a normalized patch with 8x8 dimensions.

By using the HOG feature discussed above, we can train the 14 likelihood models. However, to be more practical, we have to reduce the dimension of HOG feature while keeping all models discriminative. Note the feature dimension is 64. In our system, we adopt the multi-class Linear Discriminant Analysis (LDA) [10] to lower the feature space. In general, it may be difficult to retain the discrimination among 14 likelihood models in a low feature space. Fortunately, with the use of 3-D scene information, we are able to know the surface type of a patch label in advance. Note that each selected patch is related to the projection of one surface of the 3-D cube. Given a patch, its surface type is determined. Thus, while performing patch classification, only likelihood models within the same surface type should compare with each other. This allows us to divide the 14 models into 4 groups based on the surface type and apply LDA to each group independently. Obviously, this is a benefit from 3-D scene information. In our system, we lower the feature space to a 3-dimensional space.

Taking the learning process of the surface type "T" as an example, based on the 3-D scene information, we know and could collect T-type patches. Each patch is normalized and its HOG feature vector is extracted. Furthermore, each patch is manually labeled as either "T_1" or label "T_2" for a 2-class LDA process. Here, for each label, L patches are collected for training. In our experiment, we found 300 patches per label are enough for training. After the LDA process, the feature dimension is reduced from 64 to 3, and we attain two three-dimensional feature sets $\{X_{j|T\_1}\}_{i=1\sim L}$ and $\{X_{j|T\_2}\}_{j=1\sim L}$. Here, we assume the distribution of each class is a Gaussian function. Therefore, the likelihood model of a label is represented as

$$L(\boldsymbol{X};\boldsymbol{\mu},\Sigma)=\frac{1}{(2\pi)^{3/2}|\Sigma|^{1/2}}\exp\left(-\frac{1}{2}(\boldsymbol{X}-\boldsymbol{\mu})^{T}\Sigma^{-1}(\boldsymbol{X}-\boldsymbol{\mu})\right). \quad (1)$$

By using the training sets $\{X_{j|T\_1}\}_{j=1\sim L}$ and $\{X_{j|T\_2}\}_{i=1\sim 3L}$, we can estimate the mean vectors and covariance matrixes for the model $L_{T\_1}(\boldsymbol{X};\boldsymbol{\mu},\Sigma)$ and the model $L_{T\_2}(\boldsymbol{X};\boldsymbol{\mu},\Sigma)$.

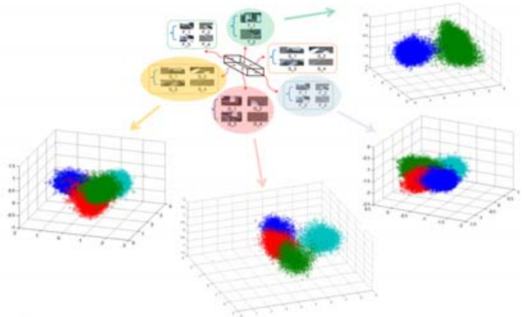


Figure 3. Feature distributions of 14 likelihood models.

For all the other surface types "S", "F", and "G", the training process is similar except that we use a 4-class Linear Discriminant Analysis and learn 4 likelihood models for each surface type. Thus, we totally have learned 14 models for the inference. Figure 3 shows that the feature distributions of the 14 different classes are well-separated after LDA process.

If we denote the feature reduction process from the ith high-dimensional feature oi to the low-dimensional feature Xi as Xi=R(oi), we could define the likelihood model as

$$p(o_i\,|\,l_i)=L_{l_i}(R(o_i);\boldsymbol{\mu},\Sigma)=L_{l_i}(\boldsymbol{X}_i;\boldsymbol{\mu},\Sigma). \qquad (2)$$

### 3.3 3-D Scene Information

Based on the local image features, we could classify image patches and extract the parking status implied by the labeling results. However, the extracted statuses from relevant patches may sometimes happen to report inconsistent statuses for the same space. In Figure 4, we use a three-space case to explain the inconsistency. In this example, after patch classification, the top patch of space "c" is labeled as T_2, which implies space "c" is vacant (1). On the other hand, the ground patch of space "c" is labeled as G_3, which implies both space "b" and "c" are occupied (0). Here, the reported statuses of "c" are inconsistency. To resolve the inconsistency, we use scene information. Based on the scene model, we can generate status hypotheses $S$. In our 3-space example, we have 8 hypotheses for spaces "a", "b", and "c". Given a hypothesis, such as $S$=(1,0,0), its corresponding expected label set $L^S$ could be generated. Since $L^S$ and $S$ are one to one mapping, to determine the statuses of the three spaces, we only need to measure the likelihoods of 8 expected label sets and pick the optimal one. Here, for status inference, we only check the possible expected label sets, which the labels are always consistent. Obviously, we do not measure the likelihood of inconsistent labeling combinations. Thus, the inconsistency is resolved. As for the likelihood measurement, the detail is given in the next section.

In summary, with the 3-D scene information, we have two benefits. First, the image patches for analysis are systematically selected by geometric projection. Note that those patches are overlapped. Second, once 3-D surfaces and image patches are related, the expected classification labeling passed from the scene layer could be used to reduce the inconsistency of patch labeling and enhance the performance.

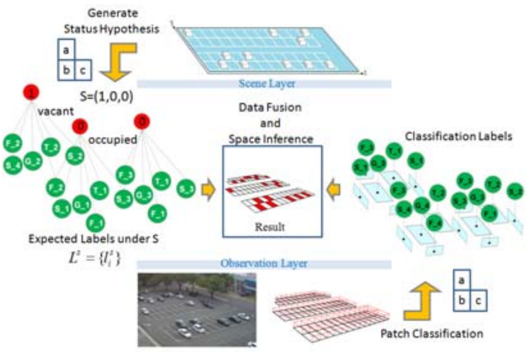



Figure 4. A three-space example to illustrate the information from observation layer and scene layer for status inference.

### 3.4 Information Fusion and Problem Solving

In our system, we need a mechanism to fuse image texture and scene information for the optimal inference of the parking status. Here, we propose a surface-based structure to achieve the goal. In the structure, as an example in Figure 4, the scene layer includes many nodes which denote the statuses of all parking spaces. Each status node is supported by six labeling nodes, and each labeling node denotes the classification of the corresponding image patch in the observation layer. Using the proposed structure, we could fuse local image observations and global 3-D scene information to infer the statuses of multiple spaces with the consideration of inter-object occlusion.

In our method, we denote a status hypothesis ($S$) as a combination of the statuses of the parking spaces. If we also denote our image observation, which is the set of patches, as $O=\{o_i\}_{i=1\sim N}$, the inference of the optimal parking statuses is equivalent to maximizing (3).

$$S^* = \arg\max_S p(S \mid O) \cdot \tag{3}$$

Here, $N$ is the total number of patches and $i$ is the patch index. However, the relation between $S$ and $O$ is not straightforward and hence the solution of (3) is not trivial. To solve (3), we treat the set of classification labels $L$ as a hidden layer in order to bridge the gap between $S$ and $O$. Under the proposed framework, the expected labels of $N$ patches $L^S = \{l_i^S\}_{i=1\sim N}$ can be directly generated if a hypothesis $S$ is given. Here, the superscript of $L^s$ indicates that $L^s$ belongs to the limited labeling space under the status hypothesis $S$. In our system, this one to one mapping, denoted as $L^s=f(S)$, means that the scene information is completely inherited by $L^s$. Therefore, we could assume $p(O|S)=p(O|L^S)$. Thus, with $L^s$ standing between $S$ and $O$, we may rewrite (3) based on Bayesian rule as:

$$\begin{aligned} S^* &= \arg\max_S \left[p(O|S)p(S)\right] \\ &= \arg\max_S \left[p(O|L^S)p(S)\right] \end{aligned} \tag{4}$$

In our system, $p(O|\ L^s)$ is further reformulated as:

$$p(O \mid L^S) = \prod_i^N p(o_i \mid l_i^S) \tag{5}$$

in which we assume the observation nodes $O=\{o_i\}_{i=1\sim N}$ are conditionally independent if the status of the labeling layer is given; in addition, as shown in Figure 4, we assume the connections between the patches and the labeling nodes are one-to-one. These connections can be modeled by a likelihood term $p(o_i \mid l_i^S)$, which represents how likely the $i$th patch $o_i$ can be observed if $l_i^S$ is given. Note that $l_i^S$ is the expected label of the $i$th patch under the status hypothesis $S$. Also, $p(S)$ in (4) represents the prior knowledge of the parking space status. In our system, we assume $p(S)$ is uniformly distributed. Under this assumption, the $p(S)$ term in (4) can be ignored and we have the final formulation in (6).

$$\begin{aligned} S^* &= \arg\max_S \left[\prod_i^N p(O_i|l_i^S)p(S)\right] \\ &= \arg\max_S \left[\prod_i^N p(O_i|l_i^S)\right]. \end{aligned} \tag{6}$$

To assess the likelihood term $p(o_i \mid l_i^S)$, we use the trained models in equation (2). To solve the optimal problem in (6), an exhaustive search of $S$ is workable. However, in our system, we adopt the standard graph-cuts technique [11-12] to speed up the inference of the parking status.

## 4. EXPERIMENT RESULTS

### 4.1 System Evaluation

In our experiments, we evaluate our system in the outdoor parking lot. Here, we set up an IP camera on the roof of a building near the parking lot. The camera was geometrically calibrated beforehand and monitored the status of parking spaces both day and night. In the parking lot, there are three major blocks and 72 parking spaces. Figure 5 shows some images of the parking lot and the detection results. To evaluate the performance of our system, we calculate false positive rate (FPR), false negative rate (FNR), and accuracy (ACC).

$$\mathrm{FPR} = \frac{\hat{N}_{\mathrm{PV}}}{N_P} \tag{7}$$

$$\mathrm{FNR} = \frac{\hat{N}_{\mathrm{VP}}}{N_V} \tag{8}$$

$$ACC = \frac{\hat{N}_{\mathrm{VV}} + \hat{N}_{\mathrm{PP}}}{N_V + N_p} \tag{9}$$

where $N_P$ denotes the number of total parked spaces, $N_V$ denotes the number of total vacant spaces, $\hat{N}_{\mathrm{PV}}$ denotes the number of parked spaces being detected as vacant, $\hat{N}_{\mathrm{PV}}$ denotes the number of vacant spaces being detected as parked, $\hat{N}_{\mathrm{VV}}$ denotes the number of vacant spaces being detected as vacant, and $\hat{N}_{\mathrm{PP}}$ denotes the number of parked spaces being detected as parked.

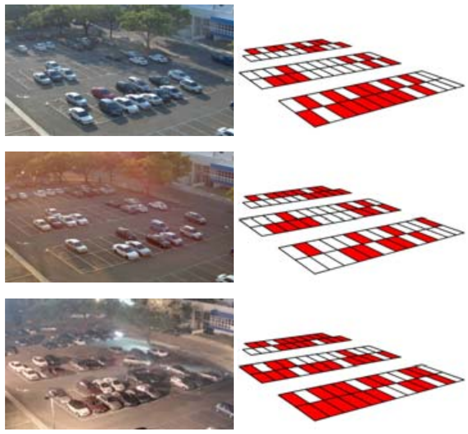
(a)
(b)
(c)


Figure 5. Results of vacant space detection.

As aforementioned, there are four challenges for vision- based parking space detection: occlusion effect, shadow effect, perspective distortion, and fluctuation of lighting condition in both day time and night time. To evaluate our system under those conditions, we firstly divide a whole day into the day period (5:00~19:00) and the nigh period (19:00~5:00). For day time, we used four testing video sequences, including a sunny day, a cloudy day, a normal day, and a rainy day, to test our system. Each sequence presents challenging occlusion effect, shadow effect, perspective distortion, and lighting change. Moreover, we also evaluated the performance of detection over different blocks to evaluate the influence of perspective distortion. In Table I, we list the experimental results including the detection result of each parking block and the performance in a normal day, a sunny day, a cloudy day, and a rainy day. In our experiments, perspective distortion and weather changes cause little degradation. For the night time, we used another three video sequences for evaluation, which include unpredictable lighting change caused by car headlights as shown in Figure 5(c). The performance of detection over different blocks was also evaluated. The detection result is shown in Table II. With the surface-based method, our system can deal with the occlusion problem, shadow effects, and lighting changes effectively in both day time and night time. Please check our website [13] for the complete detection result.

### 4.2 System Performance Comparison

Moreover, we tested the daytime dataset released by Huang et al. [8] for performance comparison. In this dataset, there are 46 parking spaces in the parking lot and three video sequences captured in a normal day, in a sunny day, and in a cloudy day. In Figure 6, we plot the Receiver Operating Characteristic (ROC) curve of their method and the proposed method for comparison. Comparing with Huang et al.'s work, our method achieves comparable performance in the day period. However, Huang's method is more complicated and needs to dynamically model the lighting condition and estimate sunlight direction for the pixel-based classification. Those processes can be avoided in our system due to the use of texture information. Also, since it is more difficult to model the complex nighttime lighting condition, Huang et al.'s method could not be directly applied in the night time. For performance comparison in night time, we compare our method with Wu's method [3] by using our nighttime video sequences. In Figure 7, we plot the ROC curve of Wu's method and the proposed method for comparison. Here, our method achieves better accuracy if comparing with Wu's work in night time.

## 5. CONCLUSIONS

In summary, we proposed a vacant parking space detection system working day and night. In practice, the challenges come from occlusion effect, shadow effect, perspective distortion, and lighting change. To overcome the problems, we proposed the surface-based modeling that regards the parking lot as a structure consisting of plentiful surfaces. With the structure, we are able to import the texture information and 3-D scene information simultaneously for space detection. Experiments have shown that our approach performs well in the complicated parking lot environment in both day time and night time.

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TABLE I. SPACE DETECTION RESULTS IN **DAY** TIME

| | #of tested spaces | | | Proposed method | | |
|---|---|---|---|---|---|---|
| | vacant | parked | total | FPR | FNR | ACC |
| Normal | 4937 | 7519 | 12456 | 0.0028 | 0.0097 | 0.9945 |
| Sunny | 8259 | 3405 | 11664 | 0.0012 | 0.0115 | 0.9915 |
| Cloudy | 5774 | 6250 | 12024 | 0.0022 | 0.0002 | 0.9988 |
| Rainy | 3668 | 6916 | 10584 | 0.0078 | 0.0049 | 0.9932 |
| Block_1 | 6857 | 10017 | 16874 | 0.0012 | 0.0004 | 0.9986 |
| Block_2 | 8701 | 8173 | 16874 | 0.0020 | 0.0064 | 0.9955 |
| Block_3 | 7080 | 5900 | 12980 | 0.0034 | 0.0145 | 0.9905 |

TABLE II. SPACE DETECTION RESULTS IN **NIGHT** TIME

| | #of tested spaces | | | Proposed method | | |
|---|---|---|---|---|---|---|
| | vacant | parked | total | FPR | FNR | ACC |
| Seq_1 | 4592 | 3112 | 7704 | 0.0135 | 0.0294 | 0.9770 |
| Seq_2 | 4659 | 2631 | 7200 | 0.0049 | 0.0282 | 0.9803 |
| Seq_3 | 4540 | 2588 | 7128 | 0.0232 | 0.0172 | 0.9806 |
| Block_1 | 4480 | 3476 | 7956 | 0.0147 | 0.0221 | 0.9811 |
| Block_2 | 5051 | 2905 | 7956 | 0.0048 | 0.0123 | 0.9904 |
| Block_3 | 4170 | 1950 | 6120 | 0.0256 | 0.0434 | 0.9623 |

無研發成果推廣資料

# 100 年度專題研究計畫研究成果彙整表

| 計畫主持人：王聖智 | 計畫編號：100-2221-E-009-149- |
|---|---|
| 計畫名稱：戶外停車場空位自動偵測系統 | |

| 成果項目 | | | 量化：實際已達成數（被接受或已發表） | 量化：預期總達成數(含實際已達成數) | 量化：本計畫實際貢獻百分比 | 單位 | 備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等） |
|---|---|---|---|---|---|---|---|
| 國內 | 論文著作 | 期刊論文 | 0 | 0 | 100% | 篇 | |
| | | 研究報告/技術報告 | 0 | 0 | 100% | | |
| | | 研討會論文 | 0 | 0 | 100% | | |
| | | 專書 | 0 | 0 | 100% | | |
| | 專利 | 申請中件數 | 0 | 0 | 100% | 件 | |
| | | 已獲得件數 | 0 | 0 | 100% | | |
| | 技術移轉 | 件數 | 0 | 0 | 100% | 件 | |
| | | 權利金 | 0 | 0 | 100% | 千元 | |
| | 參與計畫人力（本國籍） | 碩士生 | 0 | 0 | 100% | 人次 | |
| | | 博士生 | 0 | 0 | 100% | | |
| | | 博士後研究員 | 0 | 0 | 100% | | |
| | | 專任助理 | 0 | 0 | 100% | | |
| 國外 | 論文著作 | 期刊論文 | 1 | 0 | 100% | 篇 | |
| | | 研究報告/技術報告 | 0 | 0 | 100% | | |
| | | 研討會論文 | 1 | 0 | 100% | | |
| | | 專書 | 0 | 0 | 100% | 章/本 | |
| | 專利 | 申請中件數 | 0 | 0 | 100% | 件 | |
| | | 已獲得件數 | 0 | 0 | 100% | | |
| | 技術移轉 | 件數 | 0 | 0 | 100% | 件 | |
| | | 權利金 | 0 | 0 | 100% | 千元 | |
| | 參與計畫人力（外國籍） | 碩士生 | 5 | 0 | 100% | 人次 | |
| | | 博士生 | 0 | 0 | 100% | | |
| | | 博士後研究員 | 0 | 0 | 100% | | |
| | | 專任助理 | 0 | 0 | 100% | | |

| | |
|---|---|
| 其他成果<br>(無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。) | 無 |

| | 成果項目 | 量化 | 名稱或內容性質簡述 |
|---|---|---|---|
| 科教處計畫加填項目 | 測驗工具(含質性與量性) | 0 | |
| | 課程/模組 | 0 | |
| | 電腦及網路系統或工具 | 0 | |
| | 教材 | 0 | |
| | 舉辦之活動/競賽 | 0 | |
| | 研討會/工作坊 | 0 | |
| | 電子報、網站 | 0 | |
| | 計畫成果推廣之參與（閱聽）人數 | 0 | |

# 國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

■達成目標

□未達成目標（請說明，以 100 字為限）

□實驗失敗

□因故實驗中斷

□其他原因

說明：

2. 研究成果在學術期刊發表或申請專利等情形：

論文：■已發表 □未發表之文稿 □撰寫中 □無

專利：□已獲得 □申請中 ■無

技轉：□已技轉 ■洽談中 □無

其他：（以 100 字為限）

本計畫之部份成果已經整理為學術論文, 前期成果發表在 IEEE Transactions on Circuits and Systems for Video Technology 期刊論文, 後期成果發表在 International Conference on Intelligent Transport Systems Telecommunications (ITST). 此外也正進一步整理為期刊論文.

本計畫之成果正與業界廠商進一步洽談技轉之可能性

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）

在本計畫中，我們提出了一套戶外大型停車場空位偵測系統。此一系統可以有效克服戶外光影變化, 車輛間的遮蔽現象，影像中的透視失真等問題, 也可以克服光照不佳的狀況. 即使是夜間也能正常工作。此一系統具有技術之創新性及實用性, 可以廣泛應用在各種戶外停車場中.