PARKING SPACES MODELLING FOR INTER SPACES OCCLUSION HANDLING

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ABSTRACT

Intelligent systems for vacant parking spaces detection present an important solution to facilitate finding an available parking place for the drivers. Many real world challenges can face these vision based systems like weather conditions and luminance variation. In this paper, we are interested in the problem of inter spaces occlusion, where one or more place of a parking can be hidden by another parked vehicle. In order to overcome this problem we propose a new on-street surface based model for parking model extraction and we perform vehicle tracking in order to detect the events of "Entering" and "Leaving" of a car to a parking place.

Keywords

Vacant; Parking; On-street surface model; Tracking.

1 INTRODUCTION

In this project, we are interested in the intelligent systems for vacant parking places detection based on the vision techniques. In practice these systems suffer from many challenging problems like the environmental conditions, the lighting variations and specially the problem of inter spaces occlusion. This problem of occlusion is considered as a major problem that can affect the performance and the precision of our system. This problem occurs when parked vehicles hide all or a part of the parking places next to it because of the scene disposition relatively to the camera.

Several approaches were proposed in the literature trying to overcome this problem. To solve this issue we have to take into our consideration the outdoor context and the fact that the system will be applied for different parkings that can have different types and different dispositions of cars. Our objective is to develop a new approach which can be adapted for several parking cases and overcome principally the problem of occlusion. We introduce a new approach for parking modelling and we adapt the tracking of the foreground objects in the scene in order to detect the car events while "Entering" or "Leaving" a parking lot in real time. So we can decide of the occupancy or vacancy of each parking place.

This paper is organized as follow: Section 2 presents a review of the existent solutions with their different approaches. In section 3, we introduce an overview of our approach with the used techniques. Section 4 evaluates the performance of our approach to overcome the problem of inter spaces occlusion. Finally, section 5 concludes our work and presents ideas for feature ameliorations.

2 RELATED WORK

Many existent researches are dealing with the problem of finding vacant parking places based on vision techniques. Different approaches of presenting the parking model and detecting the vacancies are proposed.

[RFS14] represents the parking spaces as rectangular ground area in order to detect the existent cars by extracting their energy based descriptors. Rectangular regions of interest are also used in [TNK13] and are classified based on their descriptor vectors to decide of the status occupied or vacant.

A two categories classification of the existent methods was proposed in [WHW07], [HTW13]. The authors classify the approaches of parking spaces modelling into : the car-oriented approaches which usually work on the image area where can exist the cars in a parking place and try to extract the characteristics of vehicles within this area, and the space-oriented approaches which rely on the analyse of the ground extracted area of a parking space. Then they present their

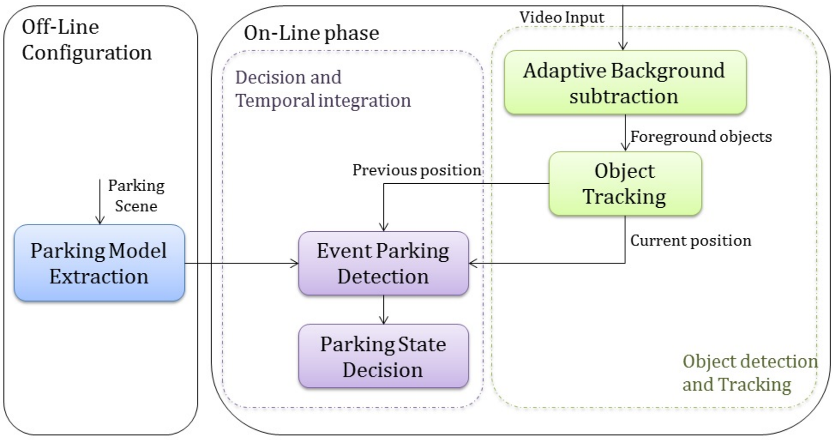


Figure 1: Proposed process.

new surface-based approach as a third category of vacant parking spaces detection system. In this approach they integrate the 3D scene information and consider the parking lot as a set of six surfaces. The method presented in [DDB13] is also based on a 3D model for parking spaces. The volume of each parking lot is estimated with a parallelepiped having a height of half of the average lengths of the four base sides. [Tom13] proposes a probabilistic model that represents all possible positions of a car within a parking space. This approach provides a set of discriminative features and provides a 3D probabilistic model to decide of the presence of a vehicle.

All these presented methods are different in their used techniques but they are all based on the extraction of a parking model and provide their results according to a local treatment for each extracted parking lot in the model. These techniques where classified in [MWJ14] into recognition based approaches and appearance based approaches, but there is another category of methods which relies on the learning and the classification of trajectories or events. In [LSW11] and [WWA12] the authors extract feature vector for each trajectory of object in motion and detect the vacancy or occupancy of a parking space based on a combination of a pedestrian event followed by a car event or the opposite. [NC12], [WAK10] and [WA10] presents a trajectory analysis approach for activities recognition. An event is trained according to a features vector containing motion trajectory and contextual informations describing its size and velocity. The classification of an input event is by evaluating its similarity to the definition of the events in the training phase.

In our paper we aim to introduce a new solution to provide robust results for the parking vacancies and to face the problem of inter places occlusion. For the parking model extraction we propose a new model based on the on-street surfaces as it is the less occluded model. Then we proceed with an Adaptive Background Subtraction algorithm for foreground objects detection. These detected objects are then tracked based on the Kalman filter in order to follow their trajectories and detect the events car "Entering" or car "Leaving" a parking place.

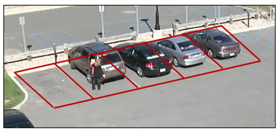
3 PROPOSED PROCESS

Our process is presented in Fig.1. It proposes a first phase of off-line configuration in which a new approach for defining a parking model is presented. The on-line phase of parking states detection relies on the adaptive background subtraction algorithm for motion detection then on the tracking of detected objects over time. The real time tracking of the vehicles allows us to detect when a car cross an on-street surface of our extracted model and to decide of the vacancy and occupancy of the parking places.

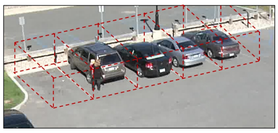
Parking Model Extraction

The phase of defining the parking model is a crucial step that can influence the results of our work. The Fig.2 presents firstly the main two used model in the existent researches.

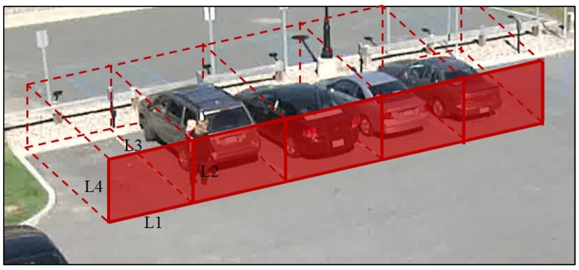
The first presented model is a basic model for parking lots extraction based on the ground tracing of the places. The use of such a model can cause different problems of inter spaces occlusion. As shown in Fig.2.(a), a parked car can cover an important part of its adjacent place next to it. The second model, presented in Fig.2.(b), is a 3-d model used in order to evaluate the hole volume of each parking place presented as a cube. In Fig2.(c), we present our proposed model, which is partially inspired from the 3-d model. But we are only interested in the on-street surface of the parking place in order to detect the vehicle's events. The idea is to preserve from the hole 3-d cube presenting a parking place, the most important area that can give us reliable results with a great reduction of the inter car occlusion problem. Whatever is the position of the camera and



(a) Ground Model



(b) 3-d Model



(c) Proposed Model

Figure 2: Different parking models presentation.

the disposition of the cars in the scene, these parking places on-street surfaces presented in the Fig.2.(c) with red area, can represent the parking model with the less possible occlusion and provide good performances for parking events detection. The extraction of this model can be performed independently of the position of the installed camera according to the parked cars, it was tested even with a parking disposition where the rows of the parked cars are completely parallel to the camera direction as presented in Fig.3.

Figure 3: Case of Parking Model Extraction.

The extraction of this model is performed in an off-line phase. Using a graphical interface, the user is able to draw the corners of each on-street surface. This model is saved and can be reloaded for in-line use.

Foreground Objects Detection and Tracking

Our objective is to provide a new solution that can be adapted with several outdoor parking contexts and dispositions. To achieve this objective we avoid the methods based on a training phase or the methods that treat locally the parking places and we propose an event based detection approach.

We use the adaptive background subtraction algorithm in order to detect the moving vehicles extracted as foreground objects. The use of this technique is possible as we are exploring the video stream from the video-surveillance cameras that are already installed in the street. So we can benefit from the fact that we are dealing with scenes with fixed background. The adapted algorithm for the adaptive background subtraction is the Gaussian Mixture Model as presented in [MAA13] . The MGM presents each pixel with a mixture of N Gaussians. It is used to estimate parametrically the distribution of random variables modeling them as a sum of several Gaussians called kernel. In this model, each pixel $I(x) = I(x,y)$ is considered as a mixture of N Gaussian distributions, namely

$$p(I(x)) = \sum_{k=1}^{N} \omega_k \mathcal{N}(I(x), \mu_k(x), \Sigma_k(x)). \quad (1)$$

with $\mathcal{N}(I(x), \mu_k(x), \Sigma_k(x))$ is normal distribution multivariate and ω_k is the weight of the k th normal.

$$\mathcal{N}(I(x), \mu_k(x), \Sigma_k(x)) = c_k \exp\left\{-\frac{1}{2}(I(x) - \mu_k(x))^T \Sigma_k^{-1}(x)(I(x) - \mu_k(x))\right\}. \quad (2)$$

and c_k is a coefficient defined by

$$c_k = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_k|^{\frac{1}{2}}}. \quad (3)$$

Each mixture component k is a Gaussian with mean μ_k and covariance matrix Σ_k. This model is updated dynamically in order to affect each pixel to its corresponding distribution. This allows to separate the foreground mask of the scene from the fix background. The Fig.4 represents the extraction of the foreground mask of the scene extracted using the GMM model and presenting the foreground scene in motion.

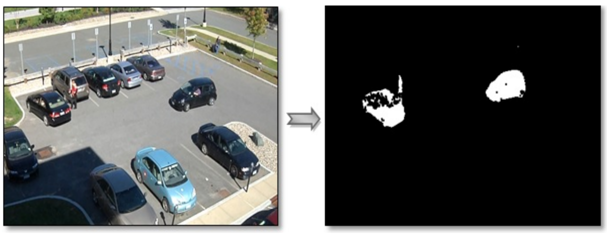


Figure 4: Foreground Mask Extraction.

The generated foreground mask is a binary image with a black background presenting the foreground objects in white pixels. We can detect one or more objects in the same foreground image. The Fig.5 shows the case where the foreground presents two different vehicles in motion and each object will be extracted separately based on the white blobs detection. then we are able to track these detected objects throw the scene in order to explore their behaviour for the detection of the state of the parking places.

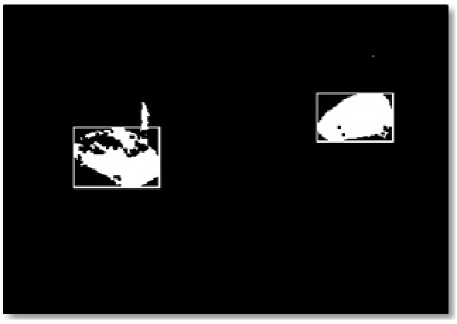


Figure 5: Foreground Objects Detection.

The phase of object tracking is performed using the Kalman filter which is a recursive solution to estimate the state of a given process. It consider that a real state x_t of a process at a time t is obtained from its previous state x_{t-1}.

$$x_t = F_t x_{t-1} + B_t u_{t-1} + w_t \quad (4)$$

with F_t the transitional state model applied to the state x_t, B_t the control-input model applied to the control vector u_t and w_t the process noise to be drawn from a zero mean multivariate normal distribution with covariance Q_t.

$$w_t \sim N(0, Q_t) \quad (5)$$

An observation z_t of the true state of the system x_t is measured based on

$$z_t = H_t x_t + v_t \quad (6)$$

H_t is the model which maps the true state space into the observed space and v_t is an observation noise assumed to be zero mean Gaussian white noise with covariance R_t.

$$v_t \sim N(0, R_t) \quad (7)$$

Decision and temporal integration

The final phase of our process is to make a decision about the vacancy of the parking lots based on several detected events. This phase relies on the already extracted model of the parking and the results of the previous step of vehicles tracking.

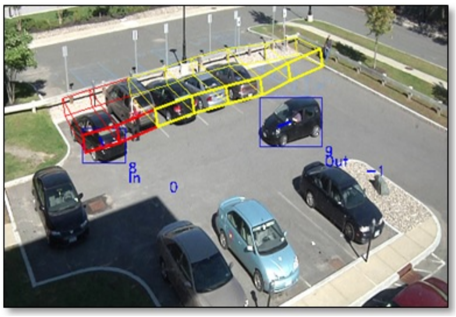


Figure 6: Simultaneous Events Detection.

Each detected foreground object is extracted and tracked separately. At an instant t we can obtain the position p_t of the object defined by the center of the bounding box delimiting the object. Based on this position we can verify if the object is overlapping with the parking model or not. The Fig.6 presents the case of the already detected vehicles in motion. In this sample we verify the case of each vehicle separately and we determine if it is out of the parking or it is overlapping with one of its lots.

Assuming that an on-street surface of a parking place is represented by four segments of lines (L_1, L_2, L_3, L_4), as shown in Fig. 2.(c), we can decide if a tracked object is inside this surface or not by comparing its position $p_t(x,y)$ relatively to these representative lines. A position of a given point (x,y) to a line $L_1(p_{11}, p_{12})$ is given by:

$$\begin{aligned} d_1 = (p_{12}.x - p_{11}.x) \times (y - p_{11}.y) - \\ (p_{12}.y - p_{11}.y) \times (x - p_{11}.x) \end{aligned} \quad (8)$$

With the same manner we can calculate d_2, d_3 and d_4, and a tracked object is considered crossing a parking surface only if the measurements of these four distances are all positive.This solution can give us an idea about its behaviour in real time and we can define and detect several events according to the model of the parking. The main four events in which we are interested in our case are:

(a) A car is "Entering" to a parking space.

(b) A car is "Leaving" a parking space.

(c) A car is "In" a parking space.

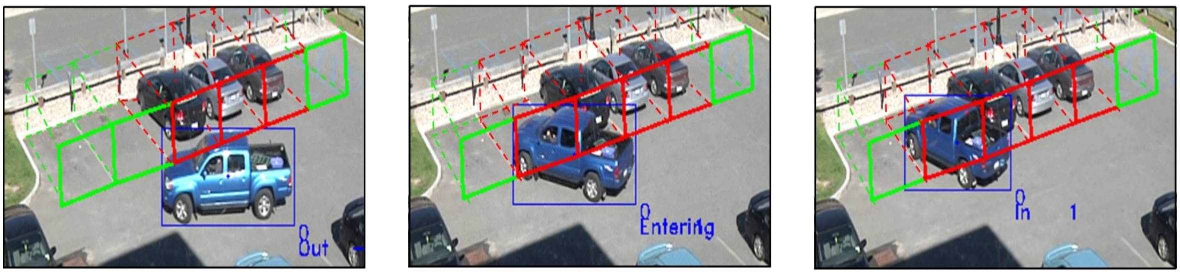
(d) A car is "Out" of all the parking spaces.

The definition of these events is closely related to the tracked positions of the object over time, so we perform a temporal integration of the previously extracted positions p_{t-2} and p_{t-1}, like presented in Table.1, in order to decide of the current event. The "Entering" state of a car to a parking space is detected when the vehicle passes from the state "Out" of the parking model to the state "In" a defined parking lot. The same logic is applied for the state "Leaving" which is detected when a vehicle passes from the state "In" to "Out".

p_{t-2}	p_{t-1}	Event
Out	Out	Out
Out	In	Entering
In	In	In
In	Out	Leaving

Table 1: Temporal integration for events definition.

The Fig.7 shows a case where a new entering vehicle in the scene is detected as a foreground object. The car is tracked over the time and kept the same identifier of object. The sample presents a succession of detected



(1) Car "Out" (2) Car "Entering" (3) Car "In"

Figure 7: Car event detection.

events for the moving car. First (1) the object is "Out", then in (2) it is "Entering" to a parking space and finally in (3) it is "In" the parking lot.

By defining and detecting these events, we can conclude on the change of states for the parking places defined in the parking model. In the case we detect the event "Entering" of a car in a parking space, we can conclude that this place is being "Occupied" and it is presented in Red color in 7. In the same way, when we detect the event of w car "Leaving" a parking space, then this place is being "Vacant" and it is presented in Green color.

4 EXPERIMENTAL RESULTS

To evaluate the performance of our proposed solution, we are interested in the evaluation of the advantages of the new introduced parking model based on-street surfaces and the new approach based event detection.

The implementation of our approach was performed based on the library OpenCv [BK08] and the tests were performed using the database of videos VIRAT [OHP11], which includes five different video scenes presenting five different parking dispositions.

(a) case a (b) case b

Figure 8: Case of inter spaces occlusion.

The Fig.8 presents a case of parking disposition where a parked car can occlude the parking spaces next to it. For studying this case, we perform our tests based on the Method 1 which is the approach proposed in [MWJ14] and the Method 2 which is our new presented approach. In this sample we are interested in three successive parking places, and we present their states with "O" if the place is occupied and with "V" if it is vacant.

The Table.2 shows the obtained results for these two methods and presents for each case the measures of FP: False Positive, FN: False Negative, TP: True Positive and TN: True Negative. We notice that the results given by the method 1 in this case are confused and that each parked car hides the place next to it. But we can conclude that our proposed approach can handle this case and overcome the problem of occlusion. Because our state decision relies on the detection of the on-street surface that was overlapping with the vehicle on motion.

Method	Occupancy	FP	FN	TP	TN
Method 1	(a) O,O,O	0	2	1	0
	(b) O,O,O	0	1	2	0
Method 2	(a) O,V,V	0	0	1	2
	(b) O,O,V	0	0	2	1

Table 2: Event detection for occlusion handling.

Our approach was also tested in different parking dispositions. The tests for each parking were performed using several number of video sequences presenting different parking scenarios. In this part we will be interested in the comparison of our results with those given by the method 1 in the case where there are a lot of inter spaces occlusion cases.

	F-measure	Recall: R	Precision: P
Method 1	0.88	0.89	0.87
Method 2	0.91	0.93	0.90

Table 3: Tests and results comparison.

The results in Table.3 recapitulates the average measurements performed for each method for several parking cases. We perform our study based on the measurements of Recall,

$$R = \frac{TP}{TP+FN} \tag{9}$$

The measures of Precision,

$$P = \frac{TP}{TP+FP} \tag{10}$$

And Finally the F-measure which combines the Recall and the precision previously calculated and presents the weighted average.

$$F-measure = 2 * \frac{Recall * Precision}{Recall + Precision} \tag{11}$$

The results show that our proposed approach provides better performance and can handle the problem of occlusion and returns reliable results for the real time parking spaces vacancy. Our new approach improves to measurements of the precision and recall of the system in the presence of the problem of occlusion. It better the results up to 0.90 of precision in comparison of 0.87 given by the Method1.

5 CONCLUSIONS

The purpose of this paper is to provide a new solution to prevent the problem of inter spaces occlusion in the vision based systems for vacant parking lots detection. Our proposed approach is based on an on-street surface model which was considered as the less occluded model to represent a parking model independently of its disposition. The tracking approach of each vehicle in motion allows the study and the detection of the vehicle behaviour. It can detect the events of car "Entering" or "Leaving" a parking space when it is crossing a parking place surface. This approach was proposed in order to reduce the effects of inter spaces occlusion and to improve the performances of the system and the obtained results shows that it improves the accuracy of the system and prevents the confusions.

6 ACKNOWLEDGMENTS

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