Vision based System for Vacant Parking Lot Detection: VPLD

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Abstract: The proposed system comes in the context of intelligent parking lots management and presents an approach for vacant parking spots detection and localization. Our system provides a camera-based solution, which can deal with outdoor parking lots. It returns the real time states of the parking lots providing the number of available vacant places and its specific positions in order to guide the drivers through the roads. In order to eliminate the real world challenges, we propose a combination of the Adaptive Background Subtraction algorithm to overcome the problems of changing lighting and shadow effects with the Speeded Up Robust Features algorithm to benefit from its robustness to the scale changes and the rotation. Our approach presents also a new state "Transition" for the classification of the parking places states.

1 INTRODUCTION

Parking is becoming a major problem especially with the increasing number of vehicles in the metropolitan areas. The search for an available parking space through the roads is usually a waste of time principally in the pic periods when the parking are crowded or almost full. Hence the need to a parking lot management system to efficiently assist drivers to find empty parking lots and identify their positions over time. Many existent systems are using sensor-based techniques such as ultrasound and infra-red-light sensors. But this type of systems may requires high costs for installation and maintenance. Therefore, there is a growing interest in the use of vision-based systems in recent years thanks to its high performances with a low cost solution. These solutions can cover a large number of parking places with a minimal number of cameras, in addition to many other services which can be provided, like driver guidance and video surveillance.

In this context, our work aims to introduce a vision-based system for vacant parking space detection. It can provide an intelligent solution that reliably counts the total number of vacant places in a parking lot, precisely specifies their location and detects the changes of status in real time. The development of a robust solution must face many challenging issues. In practice, the major challenges of such a system come from lighting conditions, shadow, occlusion effects and perspective distortion. To overcome these challenges we propose a new approach combining a set of treatments. A homography transformation is ensured in preprocessing phase to change the point of view of the scene and reduce the effects of perspective distortion. Then two algorithms are explored, the Adaptive Background Subtraction for the detection of objects in motion in the scene and the Speeded Up Robust Features SURF for the features extraction which can serve in later step of the decision.

This paper is organized as follow: Section 2 is a summary of the existent systems in the field of vacant parking spaces detection based on video. In section 3, we present an overview of our approach with a detailed explanation of the used techniques. Section 4 evaluates the performance and the obtained results throw several achieved measurements. Finally, section 5 concludes our work and presents ideas for feature researches.

2 RELATED WORK

Many parking systems that aim to automate the occupancy detection based on image processing are already available. We can classify these approaches into two main classes that differ with the used technique to decide on a parking space state: Recognition based approaches and appearance based approaches. The

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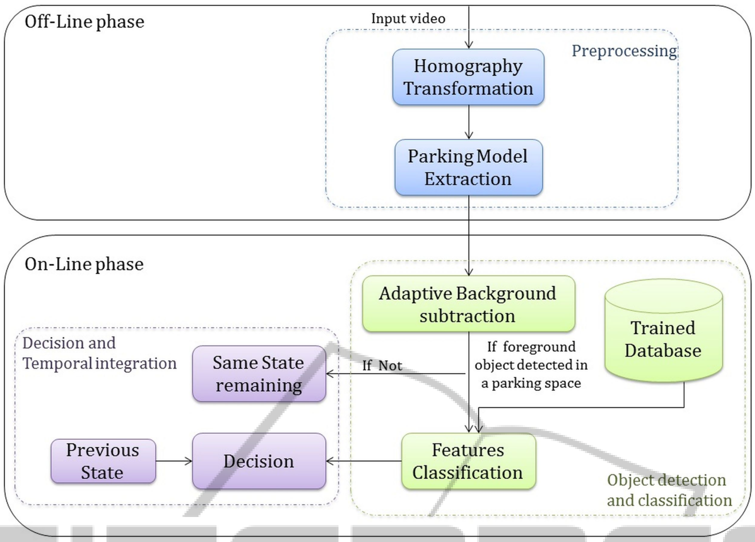


Figure 1: Proposed process.

approaches based object recognition aim to detect and classify the vehicles present in the parking lot. They rely on a first performed step of learning the characteristics of cars and then detect and recognize objects in the scene having similar properties. In (Ichihashi et al., 2010) the authors proposed a method using fuzzy c-means clustering and Principal Component Analysis PCA for data initialization to classify single parking spaces.(Wu et al., 2007) defined patches of 3 successive parking spaces and classify them into 8 classes using a multi-class Support Vector Machine SVM in order to reduce the conflicts caused by inter space occlusion. (Huang and Wang, 2010) proposed then a three-layer Hierarchical Bayesian Model and extracted the region of interest as an entire row of car park spaces which will be then treated to decide the status of each parking place individually. Huang performed his researches and presented a new approach in (Huang et al., 2012) which is a surface based method extracting 14 different patterns to modelize the different sides of a parking space. (Tschentscher et al., 2013) performed a comparison of several combination of algorithms and opted for the extraction of features using the Histogram of Oriented Gaussian HOG algorithm and the training using SVM with a temporal integration to perform the results of classification. These approaches based on the learning of characteristics can be generally problematic because of the complexity and the large variety of the target objects. This needs a huge amount of data for training the positive images with all possible views and the negative objects. Also the results of these approaches can be affected if we aim to install the solution in different environments and divers parking lots cross the cities.

The appearance based approaches rely on the comparison of the current appearance of a parking place with an original appearance of the vacant state. This comparison leads to the decision of the occupancy of the parking lot. Many approaches were proposed in this model and they are generally simple methods such as background subtraction, or even using reference images to perform a difference with the current frames. (Lin et al., 2006) used an adaptive background subtraction algorithm for each parking place to detect the foreground objects newly entered to a parking place. (Fabian, 2008) used a segment-based homogeneity model assuming that a vacant parking place has a homogeneous appearance. while (Bong, 2008) combined two streams of process to obtain his results. He used a gray scale threshold to recognize the occupancy of a parking place combined with an Edge detection process and the final result is obtained based on an AND function. The major problem that can face these approaches is the perspective distortion which affects the quality of results for the distant places. To overcome this issue, (Sastre et al., 2007) proposed a top-view of the original parking scene coupled with a texture properties extraction with Gabor filter. But the still persisting problem is the variation of luminosity.

In this paper we aim to provide a robust solution facing the most common problems of lighting variations, shadow, occlusion and perspective distortion. So, we proceed with a homography transformation to change the view point of the scene and facilitate the extraction of parking model and the elimination of the perspective distortion, then we combine the adaptive background subtraction algorithm with the classification of the SURF features to overcome the problem of lighting variation and the detection of shadow over the scene.

3 SYSTEM OVERVIEW

Our proposed vision based approach for Vacant Parking Lot Detection: VPLD is presented in Fig.1. The process is composed mainly of five modules: Homography transformation and Parking model extraction which correspond to the off-line phase of preprocessing For the on-line phase, the step of classification of the parking places is performed using the Adaptive background subtraction and SURF for features extraction and classification. And finally the step of decision of the state of each parking place in the model.

3.1 Homography Transformation

The first pre-processing step that was performed in our process is the Homography transformation which has the objective to change the point of view of the input video stream. Samples of obtained results can be shown in Fig. 2. Another objective of this transformation is to reduce the effects of the perspective distortion caused by the long distances to the camera which can affect the quality of vision of the parking places such as the car shapes or size. This transformation will also facilitate the next step of parking model extraction and try to reduce the inter-places occlusion problem.

Figure 2: Samples of Homography Transformations.

In the off-line phase of preprocessing, and in order to perform the Homography transformation, the user should select manually at least four required points and their corresponding real world coordinates. This transformation is an invertible mapping of points on a projective plane. In a given input image I, a point (i, j) may be represented as a 3D vector p = (x, y, z) where $i = \frac{x}{z}$ and $j = \frac{y}{z}$. The idea is to provide a clearer view point of the parking places than the initial view of the scene. The top-view model is performed using a Homography transformation which ensures a projective correspondence between two different image planes(Dubrofsky and Woodham, 2008) (Lin and Wang, 2012). For an image I, This correspondence between two points p (x, y, z)^T and p' (x', y', z')^T is illustrated in (1) with the relationship:

$$p' = Hp \tag{1}$$

where H is a 3x3 matrix named the homogeneous transform matrix. This equation can be expressed in terms of vector cross product, we obtain:

$$p' \times Hp = 0 \tag{2}$$

If we express the matrix H as:

$$H = \begin{pmatrix} h^{1T} \\ h^{2T} \\ h^{3T} \end{pmatrix} \tag{3}$$

Then, the equation (2) may be written as:

$$\begin{pmatrix} y'h^{3T}p - z'h^{2T}p \\ z'h^{1T}p - x'h^{3T}p \\ x'h^{2T}p - y'h^{1T}p \end{pmatrix} = 0 \tag{4}$$

The equation (4) can be expressed in term of the unknowns since $h^{iT}p = p^T h^i$

$$\begin{pmatrix} 0^T & -z'p^T & y'p^T \\ z'p^T & 0^T & -x'p^T \\ -y'p^T & x'p^T & 0^T \end{pmatrix} \begin{pmatrix} h^1 \\ h^2 \\ h^3 \end{pmatrix} = 0 \tag{5}$$

3.2 Parking Model Extraction

After the performed step of the Homography transformation, we obtain a new disposition of the rows of the parking spaces facilitating the extraction of the patches of each place individually. To do so, the idea is to extract the places of each row based on the position of the first place and a measure of width w. According to the Fig.3, we can specify the coordinates of the first two corners of the first parking place in the row, then we specify a fixed distance of width that represents the large of each parking place. So we can iterate this step and extract automatically the rest of the parking places belonging to this specified row.

This phase allows the extraction of the patches representing the parking places with an important reduce of the problem of the inter-places occlusion. Also the normalisation of the patches into equal rectangles may decrease the effects of the perspective distortion.

Figure 3: Extraction of parking model.

3.3 Adaptive Background Subtraction

The main objective of this phase is to dissociate the foreground objects that are in motion in the scene from the background model. For this, we opted for the Mixture Gaussian Model MGM (Ju and Liu, 2012) which is an adaptive model based on the principle of permanently re-estimates the model of background. It is efficient, reliable and sensitive and can incorporate illumination changes and low speed changes in the scene. These powerful properties allow to overcome the problems of lighting variations along the day time caused by the different whether conditions and to be adapted to the variation of shadow throw the ground. This algorithm subtracts the background of the video and separates its first plane in order to extract the existent objects in the foreground. This leads to the separation of the new objects that are in motion in the video from all the other parts of the background which are static. 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

$$p(I(x)) = \sum_{k=1}^{N} \omega_k \mathcal{N}(I(x), \mu_k(x), \Sigma_k(x)). \quad (6)$$

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.

$$\mathcal{N}(I(x), \mu_k(x), \Sigma_k(x)) = c_k \exp\left\{-\frac{1}{2}(I(x)-\mu_k(x))^T \Sigma_k^{-1}(x)(I(x)-\mu_k(x))\right\}. \quad (7)$$

and c_k is a coefficient defined by

$$c_k = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_k|^{\frac{1}{2}}}. \quad (8)$$

Each mixture component k is a Gaussian with mean μ_k and covariance matrix Σ_k

This model is updated dynamically according to a set of steps. It starts by checking if each incoming pixel value x can be attributed to a given mode of the mixture, this is the operation of correspondence. If the pixel value is within the confidence interval of 2.5 of standard deviation, then the pixel is matched and the parameters of the corresponding distributions are updated.

Ones the foreground model is extracted according to the MGM algorithm, we can then extract each foreground object separately. The idea is to consider only the foreground objects overlapping with the patches in the extracted model. This leads to the detection of cars in two cases, while entering to or leaving the parking places.

3.4 Features Extraction and Classification

The previous performed step leads to the detection of moving objects overlapping with parking places. This motion can be detected while a vehicle is entering to a parking space or while living it. The first used algorithm of MGM can't provide this crucial information for the rest of our decision. So we opted for the combination of this obtained result with a classification of the state using a recognition based method. Many algorithms are used in the literature. In this section we will focus on the two algorithm for features extraction SURF (Sec.3.4.1) and HOG (Sec.3.4.2) , then we present in (Sec.3.4.3) two used methods for the phase of classification. The objective of this section is to evaluate and compare these algorithms in order to decide of the convenient one to be used.

3.4.1 Speeded Up Robust Features

Speeded Up Robust Features (Bay et al., 2008), is a detector and a descriptor of key points, Fig.4. It has the advantage of being invariant to the scale variation. It uses a very basic approximation of the Hessian matrix based on the integral images which reduces greatly the computing time. The entry of an integral image $I(x)$ at a location $x = (x,y)^T$ represents the sum of all pixels in the input image I within a rectangular region formed by the origin and x.

$$I_\Sigma = \sum_{i=0}^{i \le x} \sum_{j=0}^{j \le y} I(i,j) \quad (9)$$

The detector is based on the determinant of the Hessian matrix because of its good performance in accuracy. A Hessian matrix for a continuous function $f(x,y)$is defined by

$$H(f(x,y)) = \begin{pmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial x \partial y} & \frac{\partial^2 f}{\partial y^2} \end{pmatrix} \quad (10)$$

By analogy with this definition, the Hessian matrix for an image $I(x,y)$ at a given scale σ is computed using the second derivatives of the intensity of its pixels. These derivatives are obtained by the convolution of the image I by a Gaussian kernel $\frac{\partial^2 g(\sigma)}{\partial x^2}$. Given a point $X = (x,y)$, we obtain :

$$L_{xx}(X,\sigma) = \frac{\partial^2 g(\sigma)}{\partial x^2} * I(x,y). \quad (11)$$

$$L_{xy}(X,\sigma) = \frac{\partial^2 g(\sigma)}{\partial x \partial y} * I(x,y). \quad (12)$$

$$L_{yy}(X,\sigma) = \frac{\partial^2 g(\sigma)}{\partial y^2} * I(x,y). \quad (13)$$

These derivatives are known as "Laplacian of Gaussian. The determinant will be calculated for each point of the image and it will be possible to determine the key points as the maximum and minimum.

$$\det H(X,\sigma) = \left(L_{xx}L_{yy} - L_{xy}^2\right) \quad (14)$$

Gaussians are optimal for scale space analysis, but in practice they must be discretized and cropped. Bay proposed to approximate the filters of the algorithm Laplacian of Gaussian using D_{xx}, D_{xy} and D_{yy} to improve the performance. The proposed filters are 9x9 approximations for Gaussian with $\sigma = 1.2$. They represent the lowest scale that means the highest spatial resolution.

Figure 4: SURF features extraction.

3.4.2 Histogram of Oriented Gradients

Histogram of Oriented Gradients (Dalal and Triggs, 2005) is a features descriptor providing information about the distribution of the local gradients in a normalized image. It represents the appearance and the shape of an object based on the distribution of the intensity of gradients or the directions of the edges. Like shown in Fig.5, HOG divides an image into small connected cells and for each one it computes a histogram of gradients directions. The final descriptor is a combination of all these histograms. So, having an image I, we compute the I_x and I_y the horizontal and vertical derivatives using an operation of convolution given by:

$$I_x = I * D_x \quad (15)$$

$$I_y = I * D_y \quad (16)$$

where:

$$D_x = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}, D_y = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}^T \quad (17)$$

Then we can calculate the gradient using:

$$|G| = \sqrt{I_x^2 + I_y^2} \quad (18)$$

and the orientation of the gradient is given by:

$$\theta = \arctan \frac{I_y}{I_x} \quad (19)$$

In this phase, each pixel of a cell casts a weighted vote for an orientation based histogram. Then the gradient will be normalized and the cells are grouped into larger connected blocks. Hence, the HOG descriptor is obtained from the normalized histograms from all the blocks.

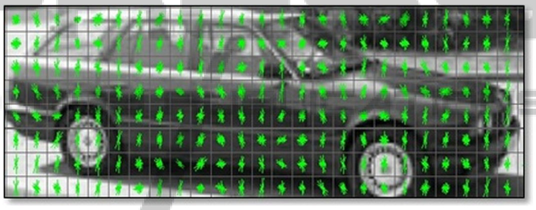


Figure 5: HOG features extraction.

3.4.3 Features Classification

This phase of classification is performed firstly for the learning of the dataset of images presenting car images and no car images because in our case, we have to perform a binary classifier for the two cases of vacant or occupied place. Then this learnt classifier will be used in the real time scenario with the input images to decide on the state of the concerned parking place. For this purpose we studied two classifiers which are the K-Nearest Neighbor KNN and the Support Vector Machine SVM.

KNN (Hamid Parvin and Minaei-Bidgoli, 2008), is a classifier categorized as a "Lazy learner". In the classification phase, the input data is classified by assigning the class which is frequent among its k nearest neighbors. While SVM (Zhang et al., 2001), is a discriminative classifier presenting a supervised learning model. SVM predicts for each input data which of the two given classes is the output. The performance of this classifier depends on the hyperplane that divides the learned data into two categories.

3.5 Decision

To decide of the state of a parking model we have to combine the results of the two main used algorithms:

Adaptive Background Subtraction and the Features classification. The main idea of our proposed approach is to verify the new state of a parking place only if this place is overlapped with a moving car detected in the first step of the background subtraction. Also to overcome the confusions that can appear in transitions of state, we achieve a temporal integration.

The first phase of Adaptive Background Subtraction is performed to detect any changes occurred in the scene. So we can detect any car that is in motion in the two cases of entry or exit. Fig.6 presents an example of a car in motion detected as a foreground object. Now we should determine if this car in motion is overlapped with any parking place in the model. If it is the case we pass to the next step and decide of the state of these concerned places. To perform this step, we rely on the chosen appearance based method to classify the patches of the parking places whether it is vacant or occupied.

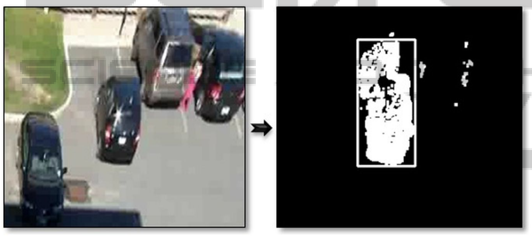


Figure 6: Car in motion detection.

As we tested our approach, we noticed that while a car is in motion inside a parking space the results may be affected and may appear a confusing inference between the two cases vacant and occupied. That's why we propose a third state which represents the phase of transition from occupied to vacant or the inverse. This intermediate state of transition s_t is based on a temporal integration and rely on the two previous states of the same place s_{t-2} and s_{t-1}. The Table.1 represents some of the considered cases for the detection of a transition state with s_{t-0} is the actual returned classification results before we make the decision of s_t.

Table 1: Temporal integration for "Transition" state.

s_{t-2}	s_{t-1}	s_{t-0}	s_t
Occupied	Vacant	Occupied	Transition
Vacant	Occupied	Vacant	Transition
Occupied	Transition	Vacant	Transition
Transition	Vacant	Occupied	Transition

This introduced state of transition can reduce the false classifications and improve the performance of our approach. The Fig.7 presents a case where a car is living the first parking place. In the Fig.7(a) the car is detected in motion and the parking place is marked as "Occupied". Fig.7(b) is a "Transition" state presented in yellow while the decision of the occupancy of the parking place is still not final. Finally Fig.7(c) shows the car after living the parking spaces whose state is now "Vacant".

4 EXPERIMENTAL RESULTS

To evaluate the effectiveness of our approach, we perform several tests based on the database of video VIRAT (Oh et al., 2011). Our evaluation is based on the measurements of the Recall R and the Precision P. The recall reflects the fraction of the relevant instances that are retrieved by our approach and reveals its completeness and quantity. The recall is defined as:

$$R = \frac{TP}{TP+FN} \tag{20}$$

The Precision presents the fraction of the retrieved instances that are relevant and can be seen as a measure of exactness. It is presented as:

$$P = \frac{TP}{TP+FP} \tag{21}$$

where TP is the number of true detections, FN is the number of false negatives representing the number of occupied places not detected and finally FP is the number of false positives which is the number of places detected as occupied although they are vacant.

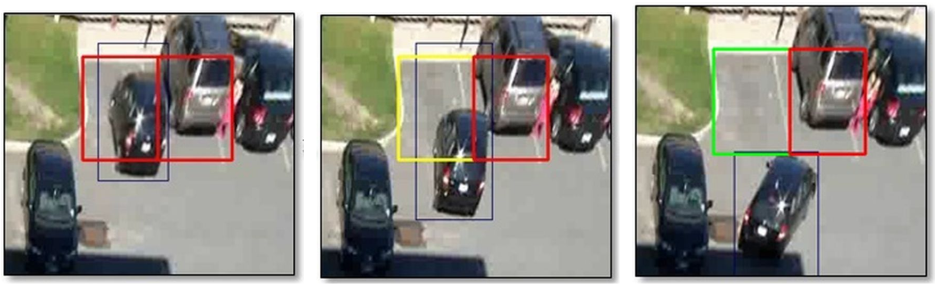
The first measurements that we achieved are to prove the effects of the Homography Transformation HT initially adapted for the preprocessing of the input video. The Table.2 demonstrates the improvement of results and accuracy especially in the case of use of the SURF algorithm.

Table 2: Measurements for Homography transformation.

	SURF	HOG
Without HT	R=0,89 - P=0,98	R=0,77 - P=0,81
With HT	R=0,92 - P=0,89	R=0,8 - P=0,89

Then, in order to decide on the algorithms to be adopted for the Features extraction and classification, we opted for a comparative study for the possible combinations that we can use. The Table.3, presents a set of results obtained while testing the different combinations. Our performed tests prove that in our case, the application of the algorithm SURF as a features extractor and the SVM as a classifier, we obtain more pertinent results than the other combinations and the average of recall measurement can reach 0,92.

Once we adopt this configuration of methods, we can test the performance of our proposed approach



(a) Occupied (b) Transition (c) Vacant

Figure 7: Transition in parking space state.

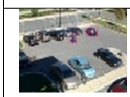
Table 3: Comparative study of methods.

	SURF	HOG
SVM	R=0,92 - P=0,89	R=0,8 - P=0,89
KNN	R=0,87 - P=0.86	R=0.76 - P=0.85

under different parking dispositions. We can also introduce the F-measure which combines the measurements of Recall and precision previously introduces and presents a weighted average.

$$F - measure = 2 * \frac{Recall * Precision}{Recall + Precision} \quad (22)$$

Table 4: Tests for different parking dispositions.

	F-measure	Recall: R	Precision: P
	0.88	0.89	0.87
	0.98	0.97	0.99
	0.95	0.99	0.92
	0.95	0.98	0.93

Our approach was tested with four different dispositions of parking. For each parking we perform the measurements for several number of video sequences. The results in Table.4 presents an average measurement for each parking. the results show that the performance of our approach remains stable under different lighting and weather conditions of the tested parking and that the measurements of Recall and Precision maintain a value above 0,92 for the case of three parking disposition. In the case of parking one, the measures have an average of 0,88. This decrease of performance is principally caused by the problem of the inter spaces occlusion. An other problem that can affect the results is the passing of pedestrians or other type of vehicles throw the parking places without tacking a place.

5 CONCLUSIONS

This paper presents a new approach for vision based vacant parking places detection based on a combination of a properties based method which is the Adaptive Background Subtraction for foreground objects detection and a recognition based method which is the SURF algorithm for features extraction. The choice of these techniques helps to reduce the problems of lighting variation and shadow effects. Ordinarily, the parking places are classified as ”Vacant” or ”Occupied”. To better the performance of our approach we introduce a new transitional state ”Transition” which represents the passing of a parking space from a state to another. This leads to improve the accuracy of the obtained results and prevents the confusions.

Our proposed approach provides good results but still suffer in case of unexpected scenario like the presence of pedestrians or the inter objects occlusion. Our future work will focus on the amelioration of our used techniques to propose novel approach and overcome these problems and better the performance.

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