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Computer Vision-based Approaches, Datasets, and Applications of Smart Parking Systems: A Review

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Abstract
Nowadays, smart parking systems (SPS) represent one of the active research areas of intelligent transport systems (ITS). It is an interesting topic and attractive to researchers due to the difficult challenges that are needed to solve it. It enhances city life and plays an important role in reducing gas emissions, air pollution, and traffic congestion while improving the time override for drivers to easily allocate vacant parking lots. In this paper, we discuss and dedicate a review of how computer vision-based approaches can assist in providing wellness solutions for the occupancy of smart parking lots. In addition, we provide an overview of the most common standard datasets and some well-known applications of vacant smart parking lots.

Keywords: Smart Parking System, Computer Vision, Intelligent Transport System, Detection, Smart Cities.

الطرق القائمة على رؤية الحاسوب ومجموعات البيانات وتطبيقات أنظمة وقوف السيارات الذكية: مراجعة

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الخلاصة
في الوقت الحاضر ، تمثل أنظمة وقوف السيارات الذكية (SPS) أحد مجالات البحث النشطة لنظام المرور الذكي (ITS). إنه موضوع مثير للاهتمام، وجذاب للباحثين بسبب التحديات الصعبة اللازمة لحلها. فإنها تحسن حياة المدينة وتلعب دورًا مهمًا في تقليل انبعاثات الغاز ، وتلوث الهواء، والازدحام المروري ويحسن الوقت الذي يتجاوز فيه السائقين نتيجة البحث لتخصيص مواقف السيارات الشاغرة لهم بسهولة. في هذه الورقة، نناقش ونكرس مراجعة حول كيفية مساعدة الطرق القائمة على رؤية الحاسوب في توفير حلول جيدة لوقوف السيارات

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الذكية الغير مشغولة. بالإضافة إلى ذلك، فإننا ندعم نظرة عامة حول مجموعة البيانات القياسية الأكثر شيوعًا وبعض التطبيقات المألوفة لوقوف السيارات الذكية الشاغرة.

1. Introduction

With the complexities and evolution of lifestyles, as well as the world's increasing human population, the vehicle parking lot is one of the most concerning issues that affect the quality of life from both environmental and economic perspectives. Searching in a parking lot leads to time-consuming traffic jams, energy waste, gas emissions, and air pollution factors [1, 2].

However, smart parking systems (SPS) are an interesting topic and are represented as one of the most active areas in computer vision applications. They are also attractive to researchers due to the difficult challenges that are needed to solve them. Many existing parking systems in real environments have been implemented by using several technologies: active wireless sensors, infrared sensors, ultrasonic sensors, inductive loop detectors, radio frequency tags, magnetometers, GPS, vehicular ad hoc networks, microwave radar, multi-agent systems, the Internet of Things (IoT), and vision-based techniques (cameras, artificial intelligence (AI), machine learning (ML), etc.) [3, 4]. In this paper, the aim is to review computer vision-based methodologies, datasets, and applications of the smart parking system. Therefore, the paper investigates six categories as follows:

- Background Subtraction & Frame Differencing Approaches
- Feature-based Approaches
- Statistical Approaches
- Transformation Approaches
- Camera calibration (2D & 3D)
- Machine and Deep Learning Approaches

The remaining part of this paper is structured as follows: A review of vision-based smart parking approaches is presented in Section 2. The datasets are described in Section 3. In section 4, the applications are illustrated. Finally, the conclusion section is summarized in Section 5.

2 Computer Vision-based Smart Parking Approaches

Many research studies for smart parking lot supervision approaches that use computer vision techniques have been widely investigated due to their efficiency, resilience, and economy [5–7]. In the sections that follow, we survey and compare multiple approaches related to computer vision techniques that solve smart parking challenges and issues.

2.1 Background Subtraction & Frame Differencing Approaches

Background subtraction & frame differencing approaches represented the most common methods used in vision-based Intelligent Transportation System (ITS) applications. The background subtraction (BS) method is represented by extracting (subtracting process) the moving foreground objects (input image) from stored (background/static) images or generating images from a series of video frames [8, 9]. Likewise, the Frame Differencing (FD) method is represented by subtracting two subsequent frames from the image series to extract the moving foreground objects from the background image [10]. In this section, we are presenting how the researchers employed BS and FD approaches in the SPS.

According to Wang et al. [11], the authors proposed an innovative vision-based parking space management system for parking lot management. This system consists of three parts: firstly, a multi-feature (edge and color) based background model using YCrCb color space is used, and a foreground feature extraction method is used to detect the unoccupied parking space. Secondly, an adjacent frame difference image is used to find the static state of the parking space (if there are available cars in a parking lot or not).

Finally, adaptive threshold updating is used for the final decision and capture of moving vehicles and to determine if there is a static state available or not for a parking lot. The proposed system shows that it is highly accurate and effective for different monitoring scenes. A semi-automated parking lot management approach was proposed by [12]. This approach used image processing techniques to detect the parking lot. However, the author utilizes the Raspberry Pi camera as hardware to capture the parking images. Then, image preprocessing is represented by using such steps (converting the RGB image to grayscale, background subtraction, and denoise filters) to output a binary image. After that, they are using multiple techniques (pixel segmentation, Hough line, corner detection, fit line, and merge squares) as a structure for the parking lot extraction approach. Despite this approach achieving a promising result, it is needed for future enhancements related to a completely automated car park detection approach.

A real-time detection and classification approach for parked vehicles is proposed by [13]. This approach uses a combination of psychological perceptions obtained from human intervention during the detection process and the SVM learner classifier. Moreover, it depends on using multi-reference image streams to adapt to changes in weather conditions. The approach begins by converting the color images to 8-bit grayscale images. Then, apply an edge detection filter and binarization on both reference and current images (r, r´). Finally, the detection is carried out by computing the ratio of matching the intensities reading between r and r' and comparing it to the threshold.

A multi-classifier system was suggested by [14] for the detection of vacant parking. This system is used in both indoor and outdoor settings. It worked by combining three decisions from different methods to achieve more robustness for the detection of parking spaces. The system used the information from vehicle edge detection (edge density and closed contour density), object counting, foreground extraction, and background detection to identify whether the car parking spot is occupied or not. Another proposed method based on background subtraction and transience map analysis techniques was presented by [15]. In this paper, a geometrical calibration of the camera was implemented on the video frames to obtain the real-world coordinates of the parking lots. After that, convert the RGB frame to grayscale for less computational cost. A background model using a mixture of the Gaussian technique (MoG) and a transience map was executed for the detection of parking lots. Moreover, this work treated different complex urban scenarios under poor illumination conditions.

On the other hand, the authors [16] presented a real parking space management system. It is adaptive to climate changes and based on color consistency, background generation, foreground (vehicle) extraction, and shadow detection and removal techniques. They used color information as a pre-processing step to preserve color stabilization. This step is represented as a color-balancing algorithm. The background generation step is used to make an adaptive background model or image with parking spaces determined in advance. During this process, the median filter is implemented to remove the noise of vehicles and pedestrians on the road that is generated from image sequences. Finally, the chromatic information (RGB color space) will be utilized for foreground extraction, detection, and elimination of the shadows from the parked vehicles. The perspective scene is very important in parking lot detection.

In the paper [17], the authors used multiple cameras for the management of parking spaces. They utilized the Affine transformation to link the resultant different images from cameras and merge (or mend) them into one wide-range image. Then, two procedures are used for object detection: background subtraction and removal of foreground noise, respectively. The background subtraction is based on the Codebook technique, which is used to classify the background and foreground pixels. Meanwhile, morphology and connected component techniques are used to overcome and remove the noise of foreground information (vehicles). After that, the parking space detection used the Canny edge detector to detect the line edges of each park. Moreover, this system addressed the occlusion issue between the parked vehicles. Car-Park Occupancy Information System (COINS) is an integrated approach suggested by [18]. Firstly, to determine the exact location of parking lots in the image, we used a manual seeding procedure for the initialization process. After that, the normal four operations of image difference, object detection, edge detection, and voting algorithm were applied to detect occupancy of the smart parking system. This approach was tested using two scenarios: (a) a car park simulation model and (b) real car parking images. Table 1 presents the comparisons between the background subtraction & frame differencing approaches.

Table 1: Summary of the comparison between background subtraction & frame differencing approaches

Approaches	*Hardware & Software Platforms*	*Dataset (Type of Parking)*	*Pros*	*Cons*
Background model and foreground feature extraction method [11]	Surveillance cameras	Own (Indoor)	High accuracy (97.58 %) and robust	Occlusion matter
Background subtraction, Hough line, and corner detection [12]	Raspberry Pi camera, Raspbian Wheezy, GNU C++, and OpenCV	Own (Outdoor)	Robust	Occlusion matter
Psychological perceptions, edge detection filter, and SVM classifier [13]	Surveillance cameras, Microsoft C#, and AForge.NET	Own (Outdoor)	High efficiency and accuracy (97%)	3 parking lots for benchmarking
Foreground extraction, background detection, and object counting, [14]	Camera (Canon 600D)	Own (Indoor & Outdoor)	Efficient in indoor and outdoor environments	No benchmarking with other previous works
Geometrical calibration, Mixture of Gaussians (MoG), and transience map [15]	Internet Protocol (IP) cameras, C++, and OpenCV	Own (Outdoor)	Flexible, good detection (FN 20%), and handling occlusion	High complexity
Background generation, and shadow detection and removal techniques [16]	Surveillance cameras	Own (Outdoor)	Different illumination conditions, and shadow detection	Occlusion matter, and no benchmarking with other previous works
Affine transformation, Codebook, and Canny edge detector [17]	Surveillance cameras	Own (Outdoor)	Accuracy (99.310%), handling the occlusion, and shadows	Low detection accuracy and illumination change scenarios matter
Image difference, object, and edge detection, and voting algorithm [18]	Surveillance cameras and MATLAB	Own (Outdoor)	Real-case scenarios under different weather conditions, and accuracy (93%)	Occlusion and shadow problems, and no benchmarking with other previous works

2.2 Feature-based Approaches

Generally, this section is a survey about the researchers investigating, collecting, and analyzing the set of features or sub-features like the edges, corners of vehicles, etc. to use for detecting the process of the occupancy of parking spaces. Management of the parking space system is suggested in [19]. This system used small, distributed wireless cameras based on the Raspberry Pi Zero platform and computationally well-organized algorithms for vacancy and occupancy detection processes based on the histogram of oriented gradients (HOG) feature descriptor and support vector machine (SVM) classifier. For the validation of the results, the system was tested on the standard publicly available PKLot dataset and two small databases of parking images, which were collected by the authors of the article, namely PKSlots and FELSlot, respectively.

However, the predicted designated system of parking spaces has achieved well-accurate and reliable tests in the presence of a wide range of lighting conditions; the accuracies are 90.7% for the PKLot dataset, 93.2% for the PKSlot dataset, and 92.2% for the FELSlot dataset, respectively. Also, a new parking lot supervision system called Autonomous Valet Parking (AVP) is suggested by [20]. This system is designed to detect the vehicle parking space using height and salient-line probability maps. The authors used image sensing to recognize the parking lots. It encompasses three parts. Firstly, the height map technique is carried out in a spatial analysis that is based on dense motion stereo. Secondly, a new salient-line feature extractor with a probability map is utilized to model the road markings. Finally, the parking lots are localized by using a Bayesian classifier. This system showed good performance results, as represented by a recognition rate of over 99% and an execution time of up to 10 ms (milliseconds).

Another parking lot detection system was suggested by [21]. It is named VPLD (Vacant Parking Lot Detection). The authors used homography transformation as a preprocessing step for several reasons: (1) to change the projection (point of view) of the video stream image, (2) to enhance the quality of vision (car shape or size) by reducing the effects of viewpoint falsification at long distances from the camera, and (3) to reduce the occlusion issue. After that, the parking lots were localized manually via determined vehicle coordinates. The foreground object (car) is then separated from the background (road) using the adaptive background subtraction technique (Mixture Gaussian Model (MGM)). Therewith, two feature extraction techniques are used: speeding up robust features (SURF) and histograms of oriented gradients (HOG).

They made a comparison between them to find out which one is better for deciding and classifying vacant or empty vehicle parking spaces. An alternate approach for the Vacant Parking Space Detection (VPSD) system was proposed by [22]. This approach is decomposed into four stages: parking space region allocation, pre-processing (creating the color histogram by converting the RGB to L*a*b color spaces, color histogram classification by using k-Nearest and SVM classifiers to classify vacant parking spaces), vehicle feature detection by using the Harris corner interest point detection algorithm, and merging the results to form the final decision of parking space classification). In addition, this system achieved good detection outcomes and was tested on its dataset with day and night scene images.

Another proposed work is by [23]. They proposed a vision-based framework to manage parking lot surveillance. It breaks down into four steps: object tracking, event representation (feature extraction), training, and event recognition. Firstly, the object tracking used the Adaptive Gaussian Mixture Model (GMM) to label the foreground pixels and segment them from the background. Secondly, the spatial-temporal information is represented as the moving object event that was detected at a temporal interval of time. Using connected-component analysis, the centroids of moving objects are used and characterized as a feature vector of behavior and the trajectory of their movement, providing dynamic information for event analysis. Third, during the training phase, the feature vectors of moving objects are collected, and events are classified accordingly. Finally, the principal component analysis (PCA) statistical method is used to arrange these collected events (training data), which are denoted as a chart for event recognition.

A video-based parking lot management algorithm was suggested by [24]. This algorithm is implemented in two stages: pre-processing and vehicle separations. The input color image is converted to grayscale, which contains the parking spaces and background scene. The pre-processing handled the image by using a high-pass filter (Sobel edge detection operator) with an adaptive threshold to get essential edges and parking-space masks. At this moment, the Hough transformation is used to separate the vehicles' spaces from the background scene. After that, the algorithm decided which parking lot was occupied or free. However, it was tested on its own dataset of 1078 images and demonstrated a high detection accuracy rate.

On the other hand, a promising video-based parking space detection system was developed by [25]. The system used a wide-angle lens camera to capture parking images. Intrinsic calibration is used to configure the images to minimize radial distortion by using a direct linear transformation. At that time, a pre-processing step is implemented; each parking lot is marked manually and labeled as a region of interest (ROI). The rest of the image is neglected. Next, the feature extraction step is utilized for the mixing of color histograms, gradient histograms, difference-of-Gaussian (DoG) histograms, and Haar-like feature information extracted from the image. Following that, several classification algorithms (k-nearest neighbor (k-NN), linear discriminant analysis (LDA), temporal integration exponential smoothing, and support vector machines (SVM)) are used to determine whether the parking lots are occupied or empty.

The authors [26] developed an algorithm for detecting unoccupied parking spaces using the image-processing abilities of the OpenCV platform. During the pre-processing, they used image resizing and grayscale conversion to reduce the processing time. Then, the Gaussian Blur technique is utilized to reduce image noise, enhance sharpness, and create a smooth blur view. The subsequent stage is image thresholding and segmentation, using the Canny edge detector to discriminate the edges of objects and thresholding the processed image into binary form.

Here, the morphological transformations (erosion and dilation) are applied to the image to enhance the existing contour features of vehicles. Furthermore, false contour removal and module classification are efficient algorithms for noise removal and classifying the contours, which are based on the outline features such as the area and angle of the contours in the image. The area and Y-axis position features are used for classifying the contours. So, the extracted contour is determined by the position and cropped from the image by using accurate bounding box dimensions as a final stage. Another on-street smart parking spot system was suggested by [27].

This system consists of two parts: the setup phase and the exploitation phase for vehicle motion detection, tracking, and the visual recognition pipeline. During the setup process, the system starts by training images, data collection, and annotation from the parking camera and external database. In addition, visual recognition is performed by using FAST corner detection and then SURF algorithms for feature extraction and description. After that, the K-means algorithm is applied to cluster and group the resultant features. Finally, the parking spots are classified by utilizing the K-NN classifier. Besides, the exploitation phase is used to detect vehicle motion and track it in the parking spaces by using the background subtraction and Kalman filter techniques, respectively.

Additionally, the visual recognition step mentioned before is also used in the exploitation phase. Textual descriptors such as local binary patterns (LBP) and local phase quantization (LPQ) were also utilized for parking space detection. The authors [28] used LBP and LPQ techniques as descriptors for the feature extraction process. After that, the SVM classifier was applied to distinguish the occupancy of parking lots. The results show the lowest rate of error of 0.16% on the public database PKLot, which is comprised of 105,837 images of parking lots, compared with many related previous works on their private databases. In addition, the authors [29] presented a marker-based image processing method to detect the free parking spaces by using images from unmanned aerial vehicles (UAVs), which can handle the automatic supervision of traffic. The onboard camera is installed on the UAV, which is used to capture an image, and the authors suppose all parking spaces are labeled with markers (a white characteristic shape drawn on asphalt) to recognize the vehicles from the background image. However, the comparison between feature-based approaches is mentioned below in Table 2.

Table 2: Summary of the comparison between feature-based approaches

Approaches	*Hardware & Software Platforms*	*Dataset (Type of Parking)*	*Pros*	*Cons*
HOG feature descriptor, and SVM classifier [19]	Raspberry Pi Zero platform	Own & PKLot (Outdoor)	The efficiency with accuracy (90%), and tested on multi datasets under different illuminations changes	High complexity, and occlusion & shadow problems
Height and salient-line probability maps, and Bayesian classifier [20]	Four 1.3 Megapixel Point grey blackfly cameras and C/C++	Own (Outdoor)	High recognition rate (99%), and low complexity	Occlusion and shadow problems
Homography Transformation, MGM, SURF, and HOG [21]	Surveillance cameras	VIRAT (Outdoor)	Handling the lighting variation and shadow effects	Occlusion and shadow problems, and no benchmarking with other previous works
Color histogram, k-Nearest, and SVM classifiers [22]	Cannon Power Shot A540 hand-held camera	Own (Outdoor)	Good detection results (85.2%)	Occlusion problem, and no benchmarking with other previous works
Adaptive GMM, spatial-temporal, and PCA [23]	Surveillance cameras	Own (Outdoor)	Good detection results (92%)	pedestrians occlusion problem
Sobel edge detection, Hough transformation [24]	Surveillance cameras	Own (Outdoor)	Good accuracy detection rate (80 %)	Illumination changes, and shadow problem
DoG histogram, Haar, K-NN, LDA, and SVM [25]	Surveillance cameras	Own (Outdoor)	High accuracy detection rate (99.8 %)	Illumination changes
Gaussian blur, thresholding, canny edge detector, false contour removal, and module classification [26]	Raspberry PI surveillance camera, OpenCV, and dropbox	Own (Outdoor)	High accuracy detection rate (99.64 %)	Occlusion and shadow problems, and no benchmarking with other previous works

FAST corner detection, SURF, k-means, K-NN classifier, and Kalman filter [27]	Surveillance cameras, ViPER Ground Truth Authoring Tool, and MATLAB R2013a	Own (Outdoor)	High accuracy (99%), and create a new annotated video database for the outdoor parking lot	Occlusion matter
LBP and LPQ, and SVM classifiers [28]	Microsoft LifeCam (HD-5000 USB HD	PKLot (Outdoor)	Low error rate (0.16%), and create a new huge common standard database for the parking lot	Occlusion and shadow problems
Otsu, Sobel edge detection, morphological processing (edge linking, filling, and labeling) [29]	Surveillance cameras	Own (Outdoor)	High result (A cross-correlation coefficient value greater than 0.9916)	Occlusion & shadow problems, and Illumination changes

2.3 Statistical Approaches

Additionally, statistical methods such as mean, variance, histogram, principle component analysis (PCA), etc. are utilized for the management of SPS. However, the Smart Parking Guidance System (SPGS) is suggested in [1]. This system is implemented under different weather conditions. It involved three different models: (1) a pre-localized coordinate configuration that is used to determine the parking lot coordinates manually; (2) a new efficient and simple technique is implemented to analyze the chromatic gradient of parking area pixels by using an adaptive weather analytic technique under different weather conditions; and (3) an inspection model used to detect and classify the pixels of parking lots. This system was tested on the common standard dataset (PKLot) with the promised results.

Furthermore, the authors [30] present a car parking statistical analysis method based on neural networks to determine occupancy situations using the chromatic features extracted from parking lots. Moreover, this method tackles three scenarios: Firstly, it solves the fluctuating brightness and non-uniformity problems in the daytime. Secondly, it solves the limited light problem in the early morning and evening. Finally, it solves different light pattern problems at night. In addition, the proposed method showed 97.9% accuracy in the detection of non-empty and empty parking spots 24 hours a day.

Also, an image-based framework called Smart Parking System (SparkSys) was used to detect parking spaces [31]. The authors implemented the Haar-Cascade and AdaBoost learning algorithms to classify cars and parking lots. The framework has been implemented using the OpenCV software platform and tested on its dataset. A robust parking lot detection system was proposed by [32]. This system consists of four stages. To begin, pre-processing is used to normalize the parking areas using perspective transformation. Secondly, to extract the critical features, the authors used a color histogram analysis and PCA. Thirdly, a multi-class SVM model is used for the recognition process. Finally, the Markov Random Field (MRF) method is implemented for optimizing the results of SVM. The following table is a summary of the comparison between statistical approaches.

Table 3 : Summary of the comparison between statistical approaches

Approaches	*Hardware & Software Platforms*	*Dataset (Type of Parking)*	*Pros*	*Cons*
An adaptive weather analytic technique that depends on first statistics (i.e. the mean & variance) criteria [1]	Microsoft Visual C# 2017	PKLot (Outdoor)	Efficient and simple	Occlusion problem, and no benchmarking with other previous works
An adaptive reference pavement pixel technique [30]	Surveillance cameras	Own (Outdoor)	High accuracy detection rate (99.9%)	Occlusion problem, and no benchmarking with other previous works
A Haar-Cascade and AdaBoost algorithms [31]	Surveillance cameras, Python, and OpenCV	Own (Outdoor)	Good detection rate	Occlusion and illumination changes
A color histogram analysis, PCA, SVM, and MRF [32]	Surveillance cameras	Own (Outdoor)	Good detection rate (FAR 1.25% and FRR 3.56%)	Occlusion & shadow problems, and illumination changes

2.4 Transformation Approaches

Here, transformation approaches such as Fourier and wavelet are used for detecting and classifying empty or non-empty parking spots. A unified framework to detect the occupancy of parking spaces is suggested by [33]. It uses the Radon transform and SIFT descriptor to classify empty and non-empty parking spaces. The authors used geometric constraints over the Radon transform with spatial constraints for more accurate and simultaneous detection of multiple parking spaces. Also, in this paper [34], the authors suggest a system to evaluate parking lot occupancy by implementing a custom FPGA-based camera to capture real images of numerous outside parking scenarios. They used the 2-D discrete wavelet transform (DWT) and masking algorithms to produce the binary images. Then, pixel counting is applied to enumerate the pixels of the regions of interest (ROIs) and determine the percentage of parking space occupancy. Another work was proposed by [72] that solved the issue of real-time multistep estimation of parking lots. The author presented a new idea by combining the Fourier transform (FT) and least squares support vector regression (LSSVR) techniques together to propose a new algorithm called Fourier transform–least squares support vector regression (FT–LSSVR). This algorithm detected single-step and multi-step parking lots with low complexity and high accuracy. The authors [73] proposed a prediction algorithm that is based on Fourier transformations to detect parking spaces for trucks. First, they analyzed the parking data to detect the recurrent behaviors of trucks. Second, they applied the Fourier model to estimate the truck parking lot occupancy. Finally, this model calculated the detection error and used mixed correction approaches to manipulate it if it exceeded a predefined threshold. Hereinafter, a comparison between transformation approaches is illustrated in Table 4.

Table 4: Summary of the comparison between transformation approaches

Approaches	*Hardware & Software Platforms*	*Dataset (Type of Parking)*	*Pros*	*Cons*
Radon transform and SIFT [33]	Canon G7 10 megapixel camera	Own (Outdoor)	Accurate (95%) and robust against noise, clutter, and lighting changes in images	Occlusion and shadow problem
DWT [34]	FPGA-based camera, and GAlib C++ library	Own (Outdoor)	Good detection rate with an average error of 6.8% and maximum error of 25.8%	Occlusion & shadow problems
FT–LSSVR [72]	-	Own (Outdoor)	Good prediction error (absolute prediction error >3%) and computing time (0.01919s)	Occlusion & shadow problems
Discrete Fourier Transform (DFT) [73]	-	Own (Outdoor)	Good Root Mean Square Error (RMSE 5%) and computing time	Occlusion & shadow problems

2.5 Camera calibration (2D & 3D) Approaches

Camera calibration or configuration is a vital process for good results in ITS applications and is set up semi-automatically or manually [35]. A vision-based smart parking framework was presented by [36]. This framework obtained a live stream video of the parking lot arena's top view. The video is segmented into frames when a car enters the parking lot or leaves it. Besides, the RGB images (frames) are converted to grayscale images. The parking lots were then assigned from the image by cropping the extra space in the parking lot, which was then calibrated. Secondly, it selected the coordinates of every single parking lot and made the number of slots equal in size. Afterward, every block (individual parking lot coordinates) was converted from grayscale to binary, and an inverse binary process would be done to get the white (vehicle area) and black (parking lot) colors. Finally, a specific threshold is calculated in every block to detect car occupancy or not. This framework presented good results, but its efficiency decreased in the presence of occlusions and fewer lighting effects.

In addition, another work was proposed by [37] to detect outdoor vacant parking spaces using an approximate inverse perspective transformation and Pyramid Histogram of Oriented Gradients (PHOG) feature analysis. This work consists of image acquisition, context modeling, object detection, and activity description. In the image acquisition stage, the system processed and corrected the stream of images acquired by a camera located in the proper position to remove the radial distortion. After that, the context modeling begins by making the parking zone initialization and 2D/3D mapping using a pinhole camera model. A 3D coordinate model used two types of features (feature analysis): edge density and PHOG, to create a database of training samples to distinguish between vehicles and empty parking lots during object detection and activity description. Finally, the experiments show encouraging results for the proposed system to detect vacant parking spaces.

The authors [38] presented a new trajectory analysis for the detection of vacant parking lots. In this system, a real-time solution is provided for reserved parking lot detection in crowded cities. It is encompassed by two stages: offline configuration and an online phase. Firstly, during the camera installation and system setup, a configuration setup was implemented just once, represented by ground spaces and 3D parking modeling of parking lots.

However, a novel framework was proposed by [39] for the detection of parking lot occupancy from lamp-post camera views. It is working on calculating the geometry of parking lots to model the 2-D and 3-D volume of each parking space. Then, the Probability Density Function (PDF) performs the pixel classification by using a vehicle detector on the acquired image(s); this process distinguishes the likelihood that a pixel belongs to a vehicle or an empty parking lot. This framework was evaluated on different datasets and showed an 80% detection rate. Also, this paper [74] presents an automatic parking scheme for a self-driving car. First, the authors constructed a 3D model to segment the parking spaces of the stopped car, which represented a preprocessing stage. Second, an improved random tree algorithm (RRT) is used to plan the parking path. Moreover, they designed two fuzzy logic controllers to regulate the brake and accelerator of the vehicle's steady speed. Table 5 summarizes the comparison between camera calibration (2D & 3D) approaches.

Table 5: Summary of the comparison between camera calibration (2D & 3D) approaches

Approaches	*Hardware & Software Platforms*	*Dataset (Type of Parking)*	*Pros*	*Cons*
A calibration process, inverse binary process, and thresholding [36]	Surveillance cameras, and MATLAB	Own (Outdoor)	Well average detection rate (98%)	Shadow problem, and no benchmarking with other previous works
PHOG, and 2D/3D mapping using a pinhole camera model [37]	Two IP cameras: an AXIS-211 CCD camera, and AXIS P3346/-VE camera	Own (Outdoor)	Good detection rate (87%)	manual configuration, and tested on two different parking scenes
Off-line configuration, and online phase [38]	OpenCV	VIRAT (Outdoor)	Good performance with accuracy (94.15 %) and Computation Time (154 ms)	Tested on a few parking lots
2-D and 3-D models, and PDF [39]	Surveillance cameras	Own (Outdoor)	A new parking lots dataset is collected at the University of California Santa Barbara (UCSB) and good accuracy (80%)	Amelioration of the accuracy, efficiency, and robustness of the performance against numerous weather and environmental circumstances
3D model and RRT [74]	HDL-32E LiDAR sensor	Own (Outdoor)	Automatic parking of a self-driving vehicle	Shadow problem, and no benchmarking with other previous works

2.6 Machine and Deep Learning Approaches

Over the past several years, machine learning (ML) and deep learning (DL) approaches have played an important and pivotal role in the enhancement and development of many computer applications and systems for many research fields such as computer vision and pattern recognition, big data, etc. [40-43]. This section presents how the researchers implement ML and DL techniques to get optimal results for parking lot occupancy detection.

The authors [44] compared supervised and semi-supervised learning approaches to explain the problem of empty vs. non-empty parking lot classification in their paper. Specifically, they implemented a deep convolutional neural network architecture called AlexNet (supervised) and a recent deep neural network approach called pseudo-label (semi-supervised) on two popular PKLot and PSD datasets. The experiment results in this paper show that AlexNet outperforms pseudo-label during evaluation performance in all cases.

Additionally, a new approach using deep learning for car parking occupancy detection is proposed by [45]. The authors of this paper use mAlexNet, a convolutional neural network (CNN) architecture, to create a mini AlexNet classifier that runs on a Raspberry Pi smart camera with limited resources. Moreover, this work provided a further contribution by collecting and making a public dataset, which is named CNRPark-EXT. It contains images taken by nine smart cameras with different weather conditions, illuminations, and perspectives. They tested and assessed their approach on a previously mentioned dataset. Additionally, they tested it on a very large, free, and public standard dataset, namely PkLot. Finally, the presented approach is compared with other state-of-the-art non-deep learning approaches tested on the PKLot dataset. However, this approach showed very high accuracy even if there were noises such as light condition variation, shadows, and partial occlusion.

A parking-vacant image-based framework was developed by [46]. The authors used the VGGNet CNN model as a deep learning technique and a binary Support Vector Machine (SVM) classifier to identify and categorize empty and non-empty outdoor parking spots from images. This framework was tested on the PKLot dataset as well as a dataset created by authors named Barry Street. However, a deep learning framework was suggested by [47]. The authors inferred the status of the occupancy of parking spots from two contributions. Firstly, crop the local area image according to the size of the parking space and car by using a convolutional spatial transform network (STN). Secondly, the problem of inter-object occlusion that occurs between cars is solved by grouping three neighboring spaces that are used in the neighbor's hypotheses prediction network (NHPN), which is considered a unit, and also by using a multi-task function to estimate the status of the occlusion problem. The framework produced good results by lowering the detection rate error.

Car Parking Space Prediction (CPSP) is another proposed model that is suggested in [48]. In this model, three layers are used to detect parking spaces. First, the data acquisition is collected from a standard car dataset. Second, pre-processing is applied to refine the data from car parking images. Finally, the application layer is executed by utilizing an enhanced Deep Extreme Learning Machine (DELM) method, which encompasses two parts: prediction and performance, to determine the parking occupancy. The simulation results showed the highest accuracy rate of 91.25%.

Furthermore, a real-time parking occupancy detection method was proposed by [49]. In this work, an Internet Protocol (IP) camera is installed to capture car parking images in real-time. Moreover, this method was implemented on the CNRPark + Ext standard dataset. The authors used four architectures: LeNet (proposed by Yann LeCun et al.), AlexNet (designed by Alex Krizhevsky), Mini LeNet, and Mini AlexNet, to achieve a precise CNN paradigm. Also, the results of the proposed method presented well, with classification rates up to 93.15% and 0.5 seconds of computational time for each parking lot.

The authors [50] suggested a computer-vision smart parking lot system using low-complexity deep learning architecture for outdoor environments. This system utilized a Raspberry Pi3 model B (RPi3) linked to a camera and a low-complexity deep neural network (DNN) called mAlexnet to detect the empty locations of parking spaces. They also used the standard PKLot-Test dataset and the SWUPark dataset, which were created specifically for this research, to evaluate system performance.

In this paper [51], the author proposes two approaches to developing an automated parking spot system. First, a binary CNN classifier and the stochastic gradient descent (SGD) method are used to label the occupied or empty spaces. Second, a multi-classifier is used to return the number of empty parking lots over the entire image. Moreover, this work utilized the torch framework to build and train the proposed CNN approaches and used the PKLot dataset to evaluate the system's performance. An alternative solution is suggested by [52]. They used CNN techniques (AlexNet, LeNet, SGD, Adaptive Gradient Descent (AdaGrad), and Nesterov's Accelerated Gradient (NAG)) by applying them to the Caffe and Nvidia DiGITS frameworks. However, a DiGITS model would be used to train the proposed approach, and a Caffe model would be used to predict/detect the parking spot occupancy automatically in real-time. Table 6 compares machine learning and deep learning approaches.

Table 6: Summary of the comparison between machine and deep learning approaches

Approaches	*Hardware & Software Platforms*	*Dataset (Type of Parking)*	*Pros*	*Cons*
AlexNet (supervised) and pseudo-label (semi-supervised) [44]	Surveillance cameras, and Python	Own & PKLot (Outdoor)	High accuracy result (96%), and a new parking lots dataset which is called Parksmart dataset (PSD)	This study requires defining computational complexity and benchmarking with other previous works
mAlexNet [45]	Raspberry Pi smart camera and OpenCV	CNRPark-EXT & PKLot (Outdoor)	High accuracy results, and a new huge common standard database for the parking lot	This study requires defining computational complexity
VGGNet CNN model, and SVM [46]	DSLR camera, and MATLAB	Barry Street & PKLot (Outdoor)	High accuracy result (99.7%), and a new huge common standard database for the parking lot	Occlusion and shadow problems, and no benchmarking with other previous works
STN, and NHPN [47]	-	Own (Outdoor)	High accuracy result (99.25%)	Shadow problems, and illumination changes
DELM [48]	-	Baroffio (Outdoor)	High precision rate (91.25%)	Occlusion and shadow problems, and illumination changes
Four architectures LeNet, AlexNet, Mini LeNet, and Mini AlexNet [49]	IP camera and Python	CNRPark-EXT & own (Outdoor)	High accuracy result (93.15%)	Occlusion and shadow problems
mAlexnet [50]	Raspberry Pi3 model B (RPi3)	SWUPark & PKLot (Outdoor)	High accuracy result (88%), and a new database for the parking lot	Occlusion and shadow problems
A binary CNN classifier, and SGD [51]	Torch framework (DeepMind's torch-hdf5 package) & Python with NumPy	PKLot (Outdoor)	High accuracy result (81%)	Occlusion and shadow problems
AlexNet, LeNet, SGD, AdaGrad, and NAG [52]	GoPro Hero 4 Black camera	PKLot & own (Outdoor)	High accuracy result (99%), and a new database for the parking lot	No benchmarking with other previous works

3 Datasets

3.1 PKLot

This dataset is the most common standard dataset for smart parking systems [53]. It encompassed 12,417 images of parking lots and 695,899 segmented images, which were labeled manually and under different weather conditions (sunny, cloudy, and rainy). Also, these images were collected from the parking lots of the Federal University of Parana (UFPR) and the Pontifical Catholic University of Parana (PUCPR), both located in Curitiba, Brazil. Figure 1 shows samples of the PKLot dataset.

Figure 1: PKLot dataset samples [53]

3.2 CNRPark+EXT

Another common dataset for visual detection of parking lot occupancy was suggested by [45, 54]. It roughly encompassed 150,000 labeled images (patches) of occupied and vacant parking spaces. This dataset is an extension of CNRPark, which contains 12,000 images of parking lots. Moreover, CNRPark+EXT captured images under different scenarios of illumination conditions and involved partial occlusions due to partially or globally shadowed cars and obstacles (street lights, trees, other cars). Figure 2 illustrates samples from the CNRPark+EXT dataset.

Figure 2: CNRPark+EXT dataset samples [45, 54]

3.3 VEDAI

This dataset consisted of 1200 images and was offered by [55] for vehicle detection in aerial imagery. It is represented as a tool to evaluate and benchmark automatic target recognition algorithms in different environments such as illumination/shadow variations, occlusions or obstacles, and various directions. Furthermore, each image in this dataset is available in numerous resolutions and spectral bands. Samples of the VEDAI dataset will be shown in Figure 3.

Figure 3 : VEDAI dataset samples [55]

3.4 OIRDS

Also, a collection of open-source annotated overhead images is provided for computer vision researchers, as suggested by [56], and it is called the Overhead Imagery Research Data Set (OIRDS). This dataset included 1000 images with overhead labels that were dedicated to Automatic Target Detection (ATD) algorithms. In addition, these images encompassed 1800 labeled targets. Figure 4 depicts samples from the OIRDS dataset.

Figure -4 OIRDS dataset's samples [56]

3.5 VIRAT

A large-scale surveillance video benchmarking dataset was presented by [57]. This dataset is called Video Image Retrieval and Analysis Tool (VIRAT) and is famous for event recognition. It was divided into two parts: the VIRAT Ground Video Dataset and the VIRAT Aerial Video Dataset. However, it is included in outdoor parking lot videos captured within 24 hours of a day. Figure 5 demonstrates samples of the VIRAT dataset.

Figure -5 VIRAT dataset samples [57]

3.6 COWC

Additionally, a large dataset of an annotated car from overhead images is provided by [58]. This dataset is called Cars Overhead with Context (COWC). It's composed of six large, different images, which are covered for each set in a diverse geographical position. For more information, these images covered regions from Potsdam and Vaihingen, Germany [59], Toronto, Canada [60], Utah [61], Columbus, United States [62], and Selwyn, New Zealand [63], as shown in some samples in Figure 6.

Figure -6 COWC dataset samples [58]

3.7 CARPK

[64] A new large dataset for parking lots has been proposed. This dataset contains 1448 images and approximately 90,000 cars, which were captured by a drone (PHANTOM 3 PROFESSIONAL) from 4 different parking lot images. Furthermore, the cars are annotated with bounding boxes for each image set. This dataset is dedicated to object detection, counting, and further investigations with the labeling setup in the bounding box. Figure 7 displays some samples from this dataset.

Figure -7 CARPK dataset samples [64]

3.8 RSOC

Also, the authors [65] created a large-scale remote sensing dataset for object counting (RSOC), which consisted of 3057 images and a total of 286,539 instances. However, it encompassed four extensively deliberate object sets, including buildings (2468 images), small vehicles (280 images), large vehicles (172 images), and ships (137 images). Figure 8 demonstrates samples from this dataset.

Figure -8 RSOC dataset samples [65]

3.9 DOTA
Likewise, the annotated huge dataset for oriented object recognition in aerial images was introduced by [66]. This dataset is composed of 15 public object classes and 2806 aerial images collected from different stages and sensors. Moreover, it included 188282 instances from annotated aerial images. Some samples from the DOTA dataset are shown in Figure 9.

Figure 9: DOTA dataset samples [66]

4 Applications
4.1 ParkingRhino
It is a smart parking lot management platform that combines the supremacy of artificial intelligence, machine learning, mobile, big data analytics, and IoT techniques to deliver parking services and facilities to clients. This software is available on the Apple Store and Google Play platforms [67].

4.2 4Park - Smart Park App
In addition, the smart parking system is another robust and easy-to-manage application [68]. It uses precisely designed sensors that are inhumed under every road surface and smart cameras for inspection of vehicle activities to give more accurate real-time information about parking bay status.

4.3 The SmartPark system
Another smart parking application uses Google Maps as guidance to find a car park, directions, and live information. Furthermore, this application is a complete, end-to-end solution that uses the SmartCloud platform, an intelligent IoT services platform, a network of sensors, and live gateways for providing real-time smart parking and giving flexible facilities to customers [69].

4.4 AI-based Smart Parking Solutions
A complete, efficient, and fully-fledged smart parking management platform is provided by the Parking Telecom company [70]. It is an AI-based smart parking solution that uses hardware and software to analyze parking spaces. It consisted of four AI applications in parking management. First, automated license plate recognition (ALPR)/automatic vehicle identification is used to identify a vehicle and provide automatic access for parking occupants

to decide who enters or exits. Second, a real-time parking occupancy and availability solution is utilized to count the vehicle parking lot occupancies by using Internet of Things (IoT) tools. Third, an automatic algorithm is used to predict and forecast the parking state and forthcoming parking residence rate. Finally, using a dynamic pricing solution for parking lots to calculate the pricing changes of real-time parking.

5. Conclusion

This paper provides a comprehensive study of computer vision-based approaches, datasets, and applications of SPS. In this paper, six categories of approaches are used for smart parking lot detection and classification. In addition, we introduced a comparison table for all approaches mentioned before to show the pros and cons of each of them and how they are implemented and tested on several smart parking datasets under different weather conditions. The most common standard datasets will be examined in this survey. Moreover, an overview of some familiar applications of the vacant smart parking lots was illustrated. More specifically, this study will yield a dedicated survey that highlights and focuses on the issues, challenges, and solutions of smart parking lots by using computer vision techniques.

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