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Sayani Sarkar
University of Louisiana at Lafayette

Michael Totaro
University of Louisiana at Lafayette

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Sayani Sarkar, Michael W. Totaro, Khalid Elgazzar

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Intelligent Drone-based Surveillance: Application to Parking Lot Monitoring and Detection

Sayani Sarkar, Michael W. Totaro, and Khalid Elgazzar

University of Louisiana at Lafayette, 104 East University Avenue, Lafayette, USA

ABSTRACT

Unmanned aerial vehicles (UAVs) or drones are rapidly gaining popularity in the field of remote sensing for capturing images with ultra-high spatial resolution while flying at lower altitudes. Development of highly-efficient miniaturized sensors and the use of geospatial image processing techniques have been immensely helpful in growing this technology as the most sought-after and sophisticated remote sensing technique at a relatively lower cost. Parking lot occupancy detection, one of the current drone based application area, can be used for effective management of parking spaces, to reduce queues, minimize the time required to find an area, and to issue tickets in cases of parking violations. Visual information based parking lot monitoring techniques are mostly tailored for specific applications, and they lack generalization. In this paper, a UAV-assisted quick and efficient monitoring solution is proposed for real-time parking occupancy and car number plate detection. In this approach, a drone-mounted camera has been used to capture images of the parking lot under consideration. Initially, the parking lot is being mapped using drone-coordinates, and then a dynamic programming algorithm is used to determine the shortest route to cover multiple parking lots in minimum time to capture maximum number pictures solved by the Traveling Salesman Problem (TSP). For capturing images, an optimum location is used, such that the drone can cover the maximum area of a parking space in minimum time. Depending on the parking area under investigation, paths altitudes and gimbal angles of the drone is changed dynamically while capturing images. Then a deep neural network based parking lot occupancy monitoring system is used to determine the number of occupied and vacant spots in a parking lot. The drone captured images of each parking spot are then tested with a pre-trained model based on car and non-car images. Then the automatic license plate recognition (ALPR) algorithm is used for parking rule enforcement. Finally, experimental results are verified using a web based application that is connected with a cloud database.

Keywords: Drone, real-time surveillance, parking lot monitoring, route planning, traveling salesman problem (TSP), deep convolution neural network, automatic license plate recognition (ALPR), web application.

1. INTRODUCTION

An unmanned aerial vehicle (UAV) or drone is an aircraft operated without an onboard human pilot. It is an essential part of an unmanned aircraft system (UAS), which is capable of flying through remote control or autonomous programming.[1] Though UAVs were initially developed for military applications, they have since been used for commercial purposes, scientific applications, recreational purposes, policing/surveillance, aerial photography, agriculture and so on.[2] Parking lot occupancy detection is one of the essential area for drone application, has great significance for effective management of car parking lots. The real-time knowledge of the availability of free parking spaces and communicating the same to users can be of great help in reducing queues and the time required to find a parking space. In many parking lots, ground sensors are being used to determine the status (availability) of the various spaces.[3] This requires the installation and maintenance of sensors in every parking space, which might be expensive, especially in parking lots with a high number of available spaces. Recently, various techniques relying on the use of video cameras have been proposed to monitor the occupancy of parking lots.[4,5]However, despite these efforts, parking space detection using only visual information is still

Further author information: (Send correspondence to Sayani Sarkar)
Sayani Sarkar: E-mail: C00270565@louisiana.edu, Telephone: +1(337)806-5484
Michel W. Totaro: E-mail: miket@louisiana.edu, Telephone: +1(337) 482-5697
Khalid Elgazzar: E-mail: elgazzar@louisiana.edu, Telephone: +1(337) 482-6875

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an open problem that needs a practical solution. Most of the approaches developed rely on specialized visual techniques tailored to the specific scenario, and there is a lack of generalization when applied to different parking lots. Automatic detection of car parking occupancy can be used for effective management of parking lots and parking violations. The advent of programmable unmanned aerial vehicles (UAVs) has given rise to a great deal of interest in advanced parking lot monitoring, management and license plate detection using these UAVs. In this paper, a UAV based smart and scalable monitoring solution has been proposed. Initially, a parking lot has been mapped using drone-coordinates and the shortest route to cover the multiple parking lots in minimum time has been determined. Then, a car feature detection based algorithm has been used to identify the existence and location of vehicles in parking lots, and it has been used for developing a suitable classifier. Finally, the classifier has been trained and tested to identify the effectiveness of the system.

2. BACKGROUND STUDY

One of the earliest works on drone-assisted license plates recognition of vehicles in a parking lot and empty parking place detection has been carried out by V. Ganesh.[6] In this work, an autonomous parking lot surveillance system was developed using inexpensive hardware and open-source software without affecting the traffic flow, while offering the mobility of patrol vehicles. The authors used a quadrotor drone (Parrot AR Drone 2.0) was used in this work and captured video and navigation data (including GPS) were communicated to a host computer using a Wi-Fi connection. The host computer analyzed navigation data using a custom flight control loop to determine control commands to be sent to the drone. Analysis and detection of license plates from videos captured using a moving camera presented a novel challenge to the task of license plate recognition. In this work, the Viola-Jones face detection algorithm[7] was used for license plate detection along with the AdaBoost learning algorithm.[8] From experimental results, it was identified that the average recognition rate for the license plate was 85.54%. The processing time for each of these license plate was 250 milliseconds (ms) with a system accuracy rate 73-77%. The quality of captured videos was not very good, and the drone was able to detect license plates only from one side of the car. Since some of the cars had their license plates in the front, this method failed to provide a consistent and conclusive result on the number plate detection. In another approach on parking space detection, DAloia [9]used a marker-based image processing technique. In this approach, all parking lots were labeled with a proper marker so that the UAV captured images could be used directly to detect available parking spots. This approached showed improved results in terms of robustness and reliability (with a cross-correlation coefficient of 0.9916), and thereby paved the way for improved management of urban spaces.

In research work carried out by Dasilva et.al,[10] drones ware used as programmable aerial eyes for an efficient and cost-effective surveillance process. In this work, electronic drone surveillance was used to detect illegal parking, as well as parking of unregistered vehicles in reserved areas at Barry University. The authors used a Litchi flight app[11] on a DJI Phantom 3 Professional drone for further optimization of various aspects of the flights. For license plate detection and processing, an open source Automatic License Plate Recognition library was used. During the experimentation process, the authors were able to capture only two pictures per second using the Litchi app. In another work on parking lot management,[12] 12 mini-drone video data-set has been used. In this work, an open source license plate recognition system Tesseract was used employed for recognition of various characters, after which a lookup table approach was used to get better performance on the character recognition. This technique was able to provide a performance accuracy of up to 70.7%. In a recent work carried out by Cheng-Fang Peng et al.,[13] a drone-based method for vacant parking space detection used aerial images. In this research, the RANSAC scheme was used to estimate the homography relation between the captured image and the reference parking space. Then, three novel features were extracted from each parking space for occupancy condition judgment, i.e., vehicle color feature, local gray-scale variant feature, and corner feature. Subsequently, a deep neural network was trained to determine the occupancy status of each parking space based on the above three features. Finally, the performance of the system was evaluated on various parking lots under different lighting and weather conditions. The average accuracy of this method was to be up to 97% based on multiple trials.

3. WORK-FLOW AND METHODOLOGY

In order to develop a UAV-based smart and scalable monitoring solution, a pilot experiment was designed. The scheme of the pilot experiment is shown in Figure 1. Using the onboard camera of the drone, images of the

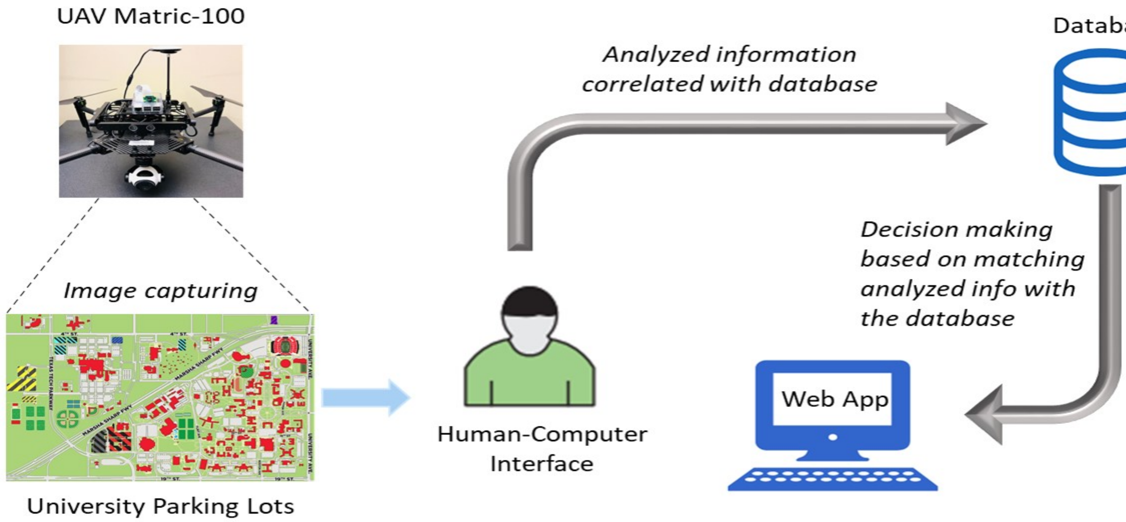

Figure 1. This figure demonstrates the schematic of the pilot experiment for smart UAV-based parking lot monitoring system. The drone captured image of the our university's parking lot is correlated with a comprehensive library stored in the database, the result of which is then used to determine parking lot monitoring and authorization.

parking lot under investigation were captured such that maximum area could be covered. A car detection based algorithm was used on the captured pictures, to identify the existence and location of vehicles in parking lots. Subsequently, these data were compared with a cloud database to check for parking vacancy, or to determine a parking lot violation. Detailed experimental steps and various experimental results are discussed in the following subsections.

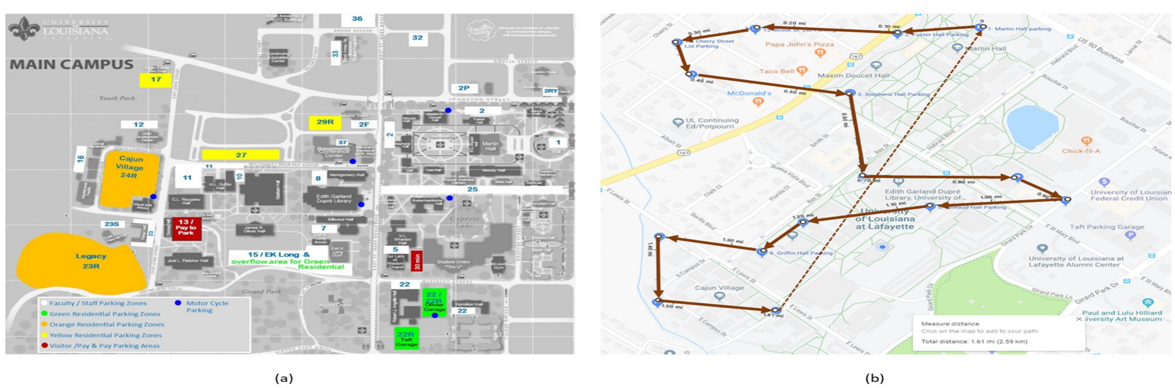

Figure 2. (a) University parking map, (b) Drone route superimposed on Google maps, obtained by application of TSP.

3.1 Multiple Parking Lot Coverage using Traveling Salesman Problem

A typical application of the vehicle routing add-in is to plan routes for the drone which can cover a maximum number of parking spots within the smallest geographic area. The scale of this problem can be diverse and variable. In this regard, the method of selection of various routing points of the drone was carried out by

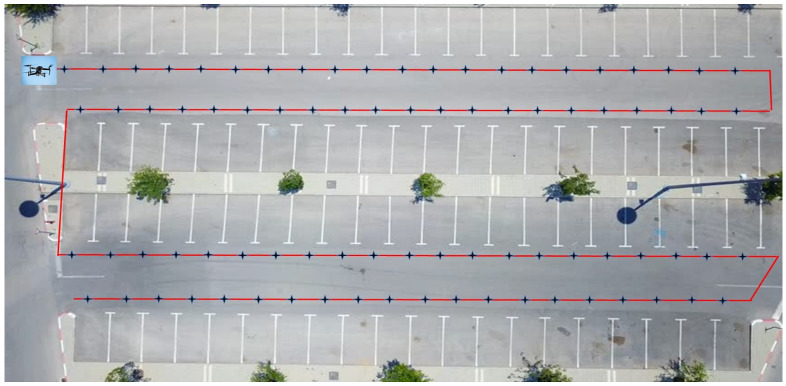

Figure 3. Actual representation of the drone flight over a single parking lot to capture car images. The blue points indicate the locations where the drone stops to capture the license plate image of the car.

using well-known Traveling Salesman Problem (TSP)[14] involving visits to various parking lots in and around our University campus, covering a total distance of 1.61 miles. Figure 2(a) shows various parking spots in and around the university campus. The drone starts from one of the parking spots and travels through each parking spot and finally returns to the starting point, the goal of which is to reduce the total travel route. The optimum traveled path is showing in Figure 2(b). For each parking lot, the drone captures pictures of every parking space allotted for vehicles. Figure 3 demonstrates the drone route in each parking lot. If there is a vehicle parked, the drone captures pictures of the license plate. As per the university parking rule, " front plate required if backed into space ", else the vehicle receives a parking ticket. The blue points on the images correspond to the points where the drone stops to capture images during its travel. The drone is flying at an altitude of 10 meters to distinctly and adequately capture the images. Those captured pictures are then analyzed further to determine parking spot occupancy and parked vehicle authorization monitoring.

3.2 Parking spot occupancy monitoring

Parking space occupancy has been determined using a convolution neural network (CNN).[15] A total of 17800 car and non-car images ware used to train the model. Here, for the model, we use 1000 training pictures captured by drone itself and the remaining taken from an available online dataset.[16] The model is shown in Figure 4. All training images have been reshaped, and image features have been extracted by convolution and rectifier linear unit (ReLU). These convoluted images were passed through the pooling layer, where the number of parameters of large images was reduced. In this model, max pooling was used, which takes the largest element from the rectified feature, map pool-size. The model consists of three convolution and pooling layers. The image matrix was then flattened into a vector and fed into a fully connected layer similar to a neural network.[17] These features

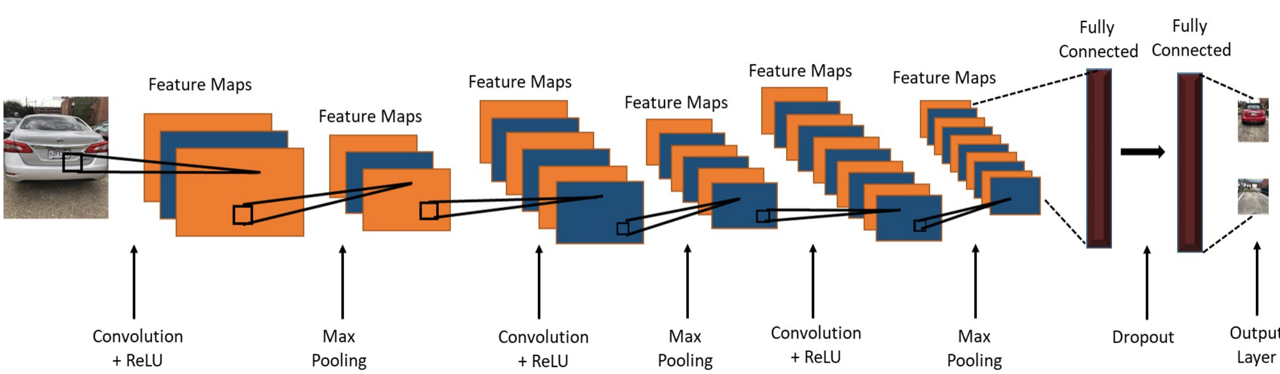

Figure 4. Schematic representation of the parking space occupancy monitoring by a convolution neural network. The diagram indicates how the captured car license plate image is processed by the neural network system so as to match with the database and provide the correct judgment.

create a model with the fully connected layers. To reduce overfitting, 50% of the neurons were randomly turned off. Finally, an activation function is obtained, such as " Sigmoid ", which helps to classify the outputs into two classes: Positive (1) for the car and Negative (0) for the non-car image. The performance of our model tested by the confusion matrix shown in Table 1.[18] Here the columns represent the instances of predictive classes and rows represent an instance of actual classes. If a car is detected, then the to the next workflow continues which is checking for parked vehicle authorization. If the model detects that the parking spot is empty, then that picture is discarded, the picture for the next parking slot is processed.

		Predicted	
		No	Yes
Actual	No	True Negative	False Positive
	Yes	False Negative	True Positive

Table 1. Confusion matrix to evaluate model performance.

3.3 Automatic license plate recognition

Parked vehicle authorization monitoring relies on license plate detection. A successful license plate detection involves two steps. Firstly, it involves the detection of the location of the plate in the picture. This is followed by the detection of the characters on the plate. Therefore, to detect an authorized car, the images are shown in Figure 5(a) are converted into gray scale images, and all the contours are calculated Figure 5(b). Based on a standard license plate shape and size, all the probable rectangle contours are extracted. Then the license plate contours were determined by evaluating inner contours of a rectangular plate. As license plate characters have a particular size, if the inner contours of the rectangular plate match the character shape criteria, the number plate is extracted showed in Figure 5(c). Subsequently, the number plate was converted into grayscale as demonstrated

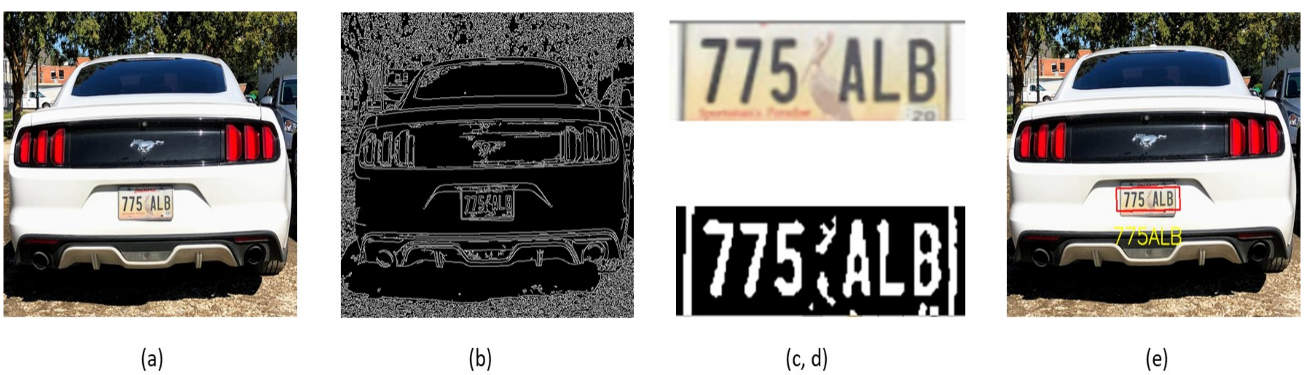

Figure 5. Automatic License Plate Recognition system. (a) An authorized vehicle located at the parking lot. (b) Grayscale conversion of the image captured of the vehicle. (c) Contour matching with the captured license plate image using the kNN classification system. (d) super-imposition of the printed number to match the car license plate.

in Figure 5(d). The plates were then segmented into the detected contours. Each contour is classified using a k-Nearest Neighborhood (kNN) algorithm.[19] The role of this classification is to assign a class to 36 different alphanumeric characters composed of 26 letters and 10 numerical digits, and the training of the algorithm used a plate number font template.[20] In Figure 5(e), the final result was shown by printing the number plate in the figure. The plate information was further validated using a web application.

3.4 Web Application

The authorized car information is stored in a cloud-based database by name, university id, car model and license plate number as shown in Figure 6(a). While checking this information, an operator can insert the license plate information and search. If the license plate number is in the database, the display will be as shown in Figure 6(b); otherwise, the display bar will be empty as shown in Figure 6(c).

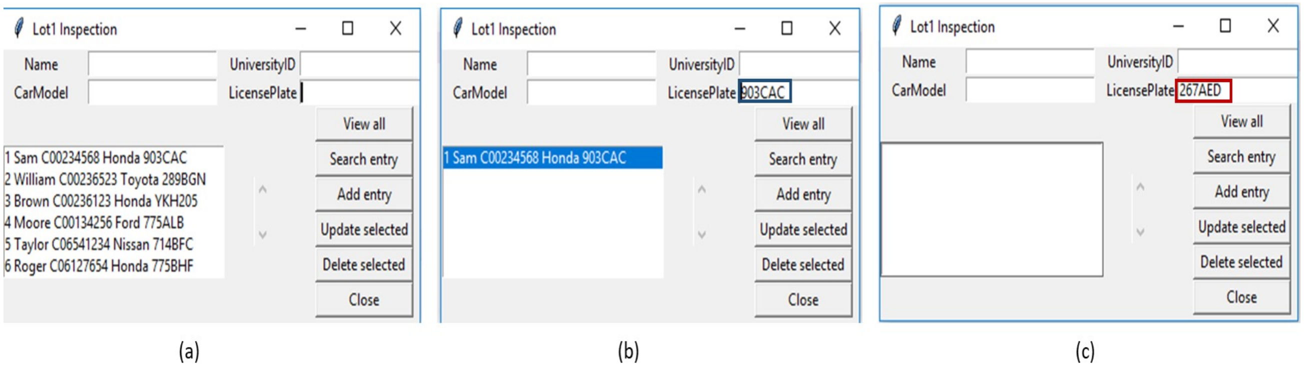

Figure 6. Application to display parked vehicle authorization.

4. EXPERIMENTAL RESULTS

The images are captured by DJI Matric 100 drone with Zenmuse Z3 camera with a 7x zoom attached to it. The drone contains a guidance system which continually scans the nearby environment and detects obstacles in real time. For the best image capture of cars, the drone was flown at an altitude of 10-meter. A Dell Probook, consisting of an I7 processor, 8GB ram in the Linux operating system processed the images. From Table 2, it is observed that the test images are correctly classified and recognized by our model. The routing path between

Experiment	Number of test samples	Number of correct prediction				Efficiency
		TP	TN	FP	FN	
Parking space occupancy	120	57	58	2	3	95.83%
License plate recognition	120	103				85.83%

Table 2. Experimental Results indicating efficiency of the parking spot occupancy model and the license plate recognition system over the number of samples tested.

the different parking lots is shown in Figure 2(b), set by waypoints. In each waypoint, the drone hovers for a specified duration and collects the car pictures for further processing. The waypoint feature helps to save a flight path for future monitoring. For parking space occupancy monitoring, the model has 115 accurate predictions (True positive (TP) and True negative (TN)) out of 120 test samples with reference Table 1. In the case of number plate detection, 17 false predictions are observed out of 120 samples. It was noticed that, occasionally, the number plate recognition model had difficulties in distinguishing between 0/O, 8/B and 1/I. The efficiency of both models was calculated based on the results obtained. The parking spot occupancy model has a 95% efficiency in determining whether a parking spot occupied or not, whereas the license plate recognition model is 85% effective to determine a parked license plate.

5. CONCLUSIONS AND FUTURE WORK

In this paper, a drone-routing approach for different parking lots was used. Parking space occupancy monitoring was also observed by a deep neural network with 96% accuracy. The license plate of parked vehicles is detected with 86% accuracy and displayed by a web application. We intend to implement the parking spot occupancy monitoring and license plate detection in real time so that an onboard computer attached with the drone will process the captured image on the spot and give results on vehicle authorization. For that purpose, the drones software development kit (SDK) will be controlled by an onboard computer, thereby converting the drone into a smart drone. That prototype will be customizable according to needs.

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