PARKING OCCUPANCY DETECTION USING THERMAL CAMERA

Vijay Paidi[1], Hasan Fleyeh[1]
[1] *Dalarna University, School of Technology and Business studies, Borlänge, Sweden*

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Abstract: Parking a vehicle is a daunting task during peak hours. The search for a parking space leads to congestion and increased air pollution. Information of a vacant parking space would facilitate to reduce congestion and subsequent air pollution. This paper aims to identify parking occupancy in an open parking lot which consists of free parking spaces using a thermal camera. A thermal camera is capable of detecting vehicles in any weather and light conditions based on emitted heat and it can also be installed in public places with less restrictions. However, a thermal camera is expensive compared to a colour camera. A thermal camera can detect vehicles based on the emitted heat without any illumination. Vehicles appear bright or dark based on heat emitted by the vehicles. In order to identify vehicles, pre-trained vehicle detection algorithms, Histogram of Oriented Gradient detectors, Faster Regional Convolutional Neural Network (FRCNN) and modified Faster RCNN deep learning networks were implemented in this paper. The detection rates of the detectors reduced with diminishing of heat in the vehicles. Modified Faster RCNN deep learning network produced better detection results compared to other detectors. However, the detection rates can further be improved with larger and diverse training dataset.

1 INTRODUCTION

Parking can be a daunting task during peak hours due to availability of limited number of parking spaces compared to the number of vehicles. It can lead to congestion and increased air pollution. Parking management is an integral component for city planning administrators and this is one of the research themes in a smart city development. It can take up to 14 minutes to find a parking space according to previous studies (Shoup, 2006, Polycarpou et al., 2013). Parking has been an important research area as it enables accessibility to commuters and is capable of enhancing business opportunities (Paidi et al., 2018). Parking problem is applicable to both major and minor cities due to higher demand and limited resources, though there can be a difference in demand between different places. Lack of parking spaces at a retail store can lead to loss of business opportunities. Therefore, stores spend higher expenditure to acquire sufficient number of parking spaces which cover large areas of scarce land resources. Due to space restrictions, in urban areas, new parking areas are being built in multi storey buildings or basements. Another way to address parking problem is to use public transport which might not be a convenient option for everyone.

Parking guidance systems were developed to reduce congestion, fuel costs and air pollution. There are several web and mobile smart parking applications available. Smart parking applications are available for closed parking lots while there are no applications available for open parking lots (Paidi et al., 2018). Demand of parking spaces in an open parking lot is higher compared to a closed parking lot. Therefore, this paper aims to detect parking occupancy in an open parking lot. An open parking lot is also subjected to different environment conditions such as; snow, rain, darkness and sunny. An investment made in parking guidance system or smart parking application for open parking lots cannot be retained directly as the parking spaces are available freely. There are several tools used to identify parking occupancy such as; infrared and ultrasonic sensors, magnetometers, vehicle ad hoc networks (VANET) and microwave radars (Hassoune et al., 2016, Idris et al., 2009). However, sensors, VANET, microwave radars and magnetometers need higher expenditure in installation and maintenance activities. Therefore, usage of camera is a suitable technology to identify parking occupancy which is capable of covering large number of parking spaces with a single camera. However, the number of parking spaces covered by a camera is also dependent on the height and angle of the positioned camera. In this paper, a thermal camera is used for obtain parking occupancy detection in an open parking lot. An open parking lot is subjected to various weather conditions and a thermal camera is capable of detecting objects during such conditions. A thermal camera is expensive compared to a colour camera but it has less privacy restrictions compared to the use of normal colour camera and it is suitable for any environment and light conditions. There is not much previous literature available on the use of thermal cameras to identify parking occupancy. Therefore, this paper aims to address this research gap with this paper. Pre-trained detectors, trained detectors using aggregate channel features, histogram of oriented gradient and deep learning network are implemented for parking occupancy detection. The remaining sections of the paper is organized in the following way. Section 2 discusses relevant literature while Section 3 discusses about the dataset and set of detectors used in this paper. Section 4 presents the results obtained in this paper along with analysis. Section 5 discusses pros and cons of using a thermal camera for parking occupancy detection. Finally the paper is ended with conclusion in Section 6.

2 LITERATURE REVIEW

Since, parking occupancy detection is performed using a camera, relevant algorithms or detectors are discussed in this section. The use of a thermal camera for identifying parking occupancy is not discussed in previous literature. However, when it comes to colour camera, there are several studies available in the literature. Edge detectors such as Canny and Sobel can be used to identify vehicles (Bao et al., 2005) (Maini and Aggarwal, 2009). Edge detectors perform efficiently when the vehicles can be recognized. However, when using thermal cameras, due to loss of heat in the vehicle over a period of time, vehicles can become dark and can be challenging to recognize or detect. In such scenarios edge detectors might not be a suitable option for vehicle detection. Histograms of Oriented Gradient (HOG) descriptors and Viola Jones are efficient human or pedestrian detectors (Dalal and Triggs, 2005) which can also be used for vehicle detection. HOG detector trains using positive and negative images using a linear Support Vector Machine (SVM) classifier (Mao et al., 2010). HOG detector is invariant to geometric and photometric transformations (Xu et al., 2016) and is therefore, one of the detector tested in this paper.

Neural networks is an evolving data processing system used for classification purposes. It is inspired by the human brain nervous system. In one study, neural networks are used for efficient recognition of license plates (Villegas et al., 2009). Convolutional neural networks is a deep learning method for classification of images which can be used for object detection and it can also be adapted for identifying parking occupancy (Amato et al., 2017). Deep learning is capable of handling complex object detections and is therefore one of the method tested in this paper. Increased performance normally requires higher computational costs and in order to maintain accuracy with lower computational costs a binary sliding window detector also called aggregated channel feature (ACF) detector was developed (Dollár et al., 2014, Liu and Mattyus, 2015). An image is computed to multiple channels and then sum every block of pixels to generate lower resolution channels. A multi scale sliding window is employed and boosting is performed to identify object in ACF.

Kalman filter is used to identify and classify night time traffic surveillance (Robert, 2009). Headlight and visible vehicle features are used to detect vehicles. Similarly in another study, (Fleyeh and Mohammed, 2012) vehicles during night time were detected using blob properties which were classified by an SVM classifier and Kalman filters were invoked to track the detected vehicles. In another study, infrared thermal camera was used to study traffic flow by using Viola jones detector. The tires and windshield of the vehicles were used to identify the vehicles (Iwasaki et al., 2013). Based on the chosen features, positive and negative images were used to train the detector. However, since the vehicles are moving on the road, heat can be captured by the windshield or by the tires which might not be applicable to this paper since the vehicles are stationary in a parking lot. In a similar study, an unmanned aerial vehicle with help of a thermal camera is deployed for detection of people and cars (Gaszczak et al., 2011). Detection of people and cars are performed using multiple cascaded Haar classifiers. Haar uses a set of weak classifiers to form a strong classifier. However, the position and angle of the vehicle affected the detection using this classifier.

(1.1) Sunny in winter morning
(1.2) Dark snowy winter morning
(1.3) Dark winter evening
(1.4) Dark snowy winter afternoon

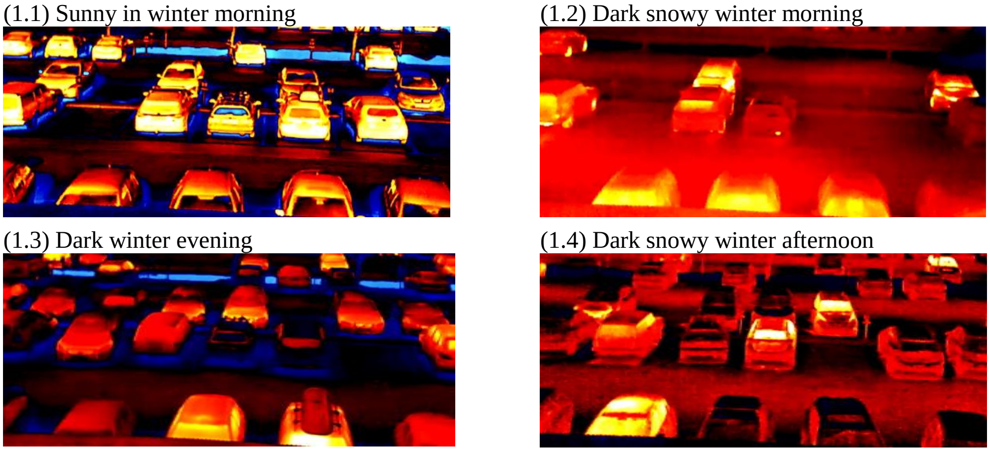

Figure 1. Images of parking space from thermal camera

3 METHOD

The data for parking occupancy detection for this paper is captured using a thermal camera. Thermal camera is normally deployed for surveillance purposes where objects are identified using heat signatures (Robert, 2009). The thermal camera installed in this paper is equipped with 19mm focal length objective on top of a two storey building. Since the camera was not placed at sufficient height the entire parking lot was not covered. Therefore, due to height and focal length limitations of the camera, only first four rows of the parking lot were selected to identify parking occupancy. The data was collected in different weather conditions such as snow, rain, dark and bright conditions. In Scandinavian countries or other similar countries, daylight is shorter during winter and longer during summer. Snow can be seen for three to four months during winter. A colour camera can face issues with low light levels and snow conditions which are common in Scandinavian countries. Based on the privacy policy guidelines in Sweden, it is restricted to use video surveillance in open public areas where individuals can be recognized or identified (Datainspektionen, 2018). Therefore, the use of thermal camera had helped to avoid these restrictions where no individuals can be identified or recognized. There are multiple parking spaces in the parking lot selected for this study. However, the first four rows of the parking lot is identified as the region of interest which is marked by the green rectangle as shown in Figure 2. The vehicles outside region of interest are small and majorly occluded which was the reason for exclusion. The thermal camera records videos based on motion detection which lead to collection of several small interval videos. The videos were collected in bright, dark and snowy weather conditions. Videos from various weather conditions were selected and one frame from each video was collected. In this way 60 images were collected from 60 videos.

Figure 2. Area of parking spaces

In the morning, vehicles are warm and can be easily identified during winter or sunny conditions. However, when the heat in the vehicles reduce over a period of time, they appear to be dark and are hard to be recognized as shown in Figures 1.3 and 1.4. The thermal camera uses pseudo colours to display data as shown in Figures 1 and 2. Therefore, the data is converted to grey scale for further processing. Since there were no pre-labelled dataset available, occupied and vacant parking spaces were labelled manually as shown in Figure 3. Occupied spaces were labelled as cars and unoccupied spaces were labelled as empty. Diversity between the images was maintained to improve feature detection. Due to limited number of training images, all the images were used for training. Testing was performed with a different set of images which are not part of the training dataset. In order to check the performance and accuracy of the detector, images of different environmental conditions were tested. There are free online databases such as PKLot providing hundreds of parking lot images which can be used to test performance of various algorithms (De Almeida et al., 2015).

Table 1. Detectors description

S.No	Detector	Description
1	Pre-trained Aggregate Channel Features (ACF) detector	A trained vehicle detector based on aggregate channel features. The detector is trained with unoccluded images of vehicles (ACFdetector, 2018, Liu and Mattyus, 2015).
2	Pre-trained Faster RegionalConvolutionalNeuralNetwork (Faster RCNN) detector	A pre-trained deep learning convolutional neural network trained using unoccluded images of vehicles. It consists of modified version of CIFAR-10 architecture. (FasterRCNN, 2018)
3	Trained ACF detector	A detector using ACF is trained using the dataset of 60 images captured by thermal camera. A new detector is trained since, pre-trained detector is trained using colour and unoccluded images. (ACFdetector, 2018)
4	Cascade detector	A cascade detector is trained using the dataset of 60 images. Features are trained using HOG which are efficient in detecting objects compared to Haar or Binary Patterns. (detector, 2018, Dalal and Triggs, 2005)
6	Faster RCNN	A Faster RCNN is trained using the thermal camera dataset of 60 images. Since a pre-trained network is trained using unoccluded images of vehicles, a new detector is trained. The Faster RCNN is created using 11 layers. (Fan et al., 2016). This detector is capable of producing better results with less number of training images.
7	Faster RCNN from Resnet50	A Faster RCNN is created using a 50 layer deep learning network (resnet50, 2018). Resnet is a trained deep learning network which can classify 1000 objects. The network is re-trained with the training dataset.

However, the images were collected by a colour camera and the use of such images are not appropriate for this paper. Therefore, only the images from the thermal camera were used in training the detectors.

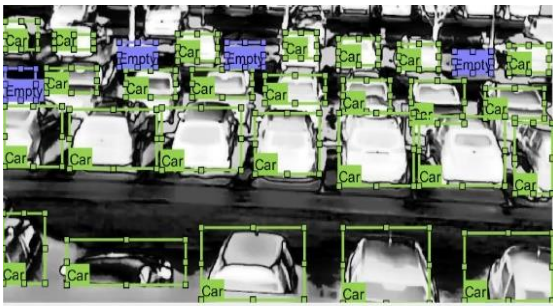

Figure 3. Labelled image

4 RESULTS AND ANALYSIS

This section discusses and analyses the results obtained from implementing the detectors.

4.1 Pre-trained ACF detector

The pre-trained ACF detector was not able to detect many vehicles as shown in Figure 4. Only one vehicle was detected with a low score using the pre-trained ACF detector. The vehicle in the middle of the parking lot was only detected due to clear visibility.

Figure 4. Pre-trained ACF detector

4.2 Pre-trained Faster RCNN detector

The pre-trained Faster RCNN detector performed better compared to ACF detector as shown in Figure 5. Approximately 33% of vehicles were detected using this detector. Additional training needs to be done to improve detection rate.

Figure 5. Pre-trained Faster RCNN

4.3 Trained ACF detector

The ACF detector was trained using the images

Figure 6. Trained ACF detector

available in the dataset. 60 images with two labels i.e. cars and empty were used to train the ACF detector. The ACF classifier was trained with 702 positive images, 1404 negative images and 2048 weak learners. However, due to limited number of training images and noise, the detector was not able to detect vehicles accurately. Large number of small areas with high scores were detected which can be due to noise as shown in Figure 6.

4.4 HOG based cascade detector

The cascade detector was trained with 671 positive images and 1342 negative images. People, trees, etc. were used as negative images for the training. Only vehicle bounding boxes were selected for training. However, as shown in the Figure 7, only one vehicle is detected successfully while three vehicles were partially detected. Therefore, detection rate of vehicles with HOG detector is approximately 16%. The position and angle of the parked vehicle is also affecting the detection rate.

Figure 7. HOG based cascade detector

4.5 Trained Faster RCNN detector

The Faster RCNN deep learning network is trained

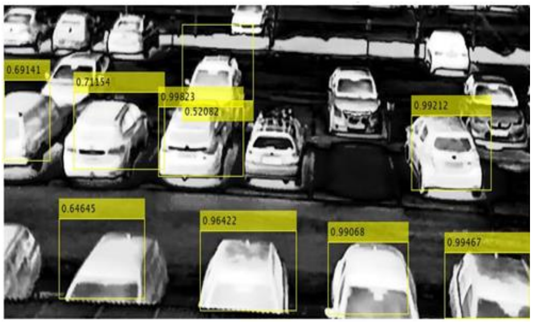

Figure 8. Faster RCNN

with the same training dataset. The network consists of 11 layers and as shown in Figure 8, successful detection rate is approximately 50%. Compared to the previous algorithms, Faster RCNN achieved better detection results. However, the network is newly created and the available dataset is considered to be small to achieve higher detection results. In order to achieve better detection results, higher number of images needs to be used for training.

4.6 Modified Faster RCNN detector

Since, large number of labelled images are not available for training purposes, a Faster RCNN network is updated from pre-trained deep learning network. The pre-trained deep learning network is Resnet-50 which consists of 50 layers and is trained with thousands of images. Since the network is already trained, it is experienced in extracting features from images. Therefore, the last three layers were modified and trained the network with available dataset images. The results can be found in the three images of Figure 9.

Figure 9(a). Detection results from sunny winter morning

This detector performed better than the previous detectors tested in this paper as shown in Figure 9(a). The detection rate of vehicles achieved approximately 88% while detection rate of empty spaces is approximately 66%. Since the results were considerable better, the deep learning network was also tested on other environment conditions such as winter afternoon and winter evening. In winter afternoon, the cars became a bit cold and were not as clear as in the morning. The detection rate of vehicles is approximately 62% while detection rate of empty spaces is approximately 33% as shown in Figure 9(b).

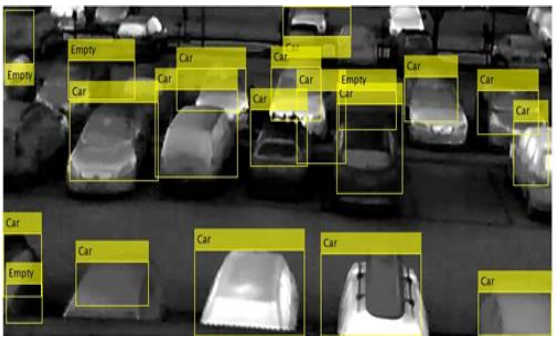

Figure 9(b). Detection results in winter afternoon

In the evening, few vehicles were colder and appeared darker leading to difficult detection results as shown in Figure 9(c). The detection results of vehicles in Figure 9(c) is approximately 42% while there no successful detection of empty spaces. The modified Faster RCNN performed better than other algorithms tested in this paper. Pre-trained detectors did not perform well as they were trained with unoccluded colour images of vehicles. The ACF detector aggregates blocks of pixels from various channels such as; gradient histogram, gradient magnitude and RGB channels.

Figure 9(c). Detection results from dark winter evening

The images captured from the thermal camera are based on the heat emitted from the object and does not represent visual aspects of the image. Therefore, aggregation of channel features method on pseudo colour images or videos is not suitable for object detection based on the Figure 4 and 6. The modified Faster RCNN deep learning network performed better in sunny or bright conditions where vehicles were detectable. However, with diminishing of heat in vehicles, the detection rate of vehicles and empty spaces was reduced. The detection rate of vehicles in bright conditions is nearly 88% while it is 42% in dark conditions as shown in Figure 9(a) and 9(c). The vehicles were largely occluded which also impacted the detection rate. When the heat in the vehicles is diminished, windshield, tires and headlights also appear to be dark as shown in Figure 9(c). The vehicles were detected in any environment if there is heat in the vehicles as can be shown in Figure 9.

5 DISCUSSION

The training dataset used for the algorithms in this paper consists of only 60 labelled images. Higher number of training images can lead to better detection results. Darker vehicles with less heat are also detected using the modified Faster RCNN algorithm as shown in Figure 9. However, only the first two rows which consists of unoccluded vehicles were detected successfully. The occluded vehicles in the third and fourth row were not detected in dark winter evening conditions where vehicles were colder and darker. The pre-trained networks did not perform efficiently on thermal images since they were trained on colour images. The results clearly show that deep learning network is capable of good detection results in any environment if the vehicles are unoccluded. The detection rate can be improved with occluded vehicles as well with higher number of training images. Since the number of training images in this paper is considered to be low, the detection results of occluded vehicles and empty spaces was low. If the position of the camera is placed at an increased height or placed on top of the parking lot, unoccluded images of vehicles can be obtained which can lead to better detection rate in any environment or lighting conditions.

A thermal camera can be used with less restrictions compared to colour visual camera. Privacy rules do not enable the free use of camera at public places. The main drawback and advantage of using a thermal camera is that the vehicles can be recognized based on emitted heat. A vehicle can be recognized during anytime or any environmental conditions if there is sufficient amount of heat emitted by the vehicle. This is one of the advantage of using a thermal camera instead of a colour visual camera. If a vehicle is stationary for a period of time, the heat in the vehicle diminishes gradually and the vehicles cannot be recognized easily which is disadvantage in using thermal camera. The heat in the vehicle is preserved in warm conditions while it diminishes faster in cold conditions. Therefore, vehicles can be recognized for a longer period of time in warmer climate environments. It would be a challenge to detect a vehicle without any heat in colder environments based on the results. However, the results might vary with larger training dataset. A thermal camera does not work as a normal camera, therefore, any algorithm or deep learning network should be trained with the images or videos obtained from the thermal camera which is also evident based on the results obtained from the pre-trained detectors. Training a deep learning network with many layers take considerable amount of time. It took approximately 8 hours to train the modified FasterRCNN deep learning network with a single CPU. The training time can be reduced with the use of a graphical processing unit. There is also difference between successful detection rates of vehicles and empty spaces. In snowy conditions, vehicles which are warm are successfully detected while few of the empty spaces which are occluded are not detected even in bright conditions. The lines of empty spaces were not visible during snowy or dark conditions making the detection of empty spaces challenging. The empty spaces in third and fourth rows are occluded and could not be detected in winter evening or dark conditions.

6 CONCLUSION

The paper aims to identify parking occupancy using a thermal camera. The first four rows of the parking lot were considered to identify parking occupancy. Pre-trained detectors, ACF detector, HOG based cascade detector, Faster RCNN deep network and modified Faster RCNN deep learning network algorithms were used to identify parking occupancy. The modified Faster RCNN deep learning network performed better compared to other detectors. Even with limited number of training images, modified deep learning network achieved 88% successful detection of vehicles while it achieved 66% of detection rate of empty spaces. The future work can be focused on improving the detection rate and to acquire real time parking occupancy detection using thermal camera. This paper addresses the first step in identifying parking occupancy information and the next step would be to train the detector with additional training images and get the positional information of the vacant parking space which can be fed to a parking guidance system.

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