Real-time adaptation to unconstrained lighting for occlusion detection

A. Malla[1], R. Green[2]

[1] University of Canterbury, Dept. Electrical & Electronic Engineering, New Zealand.
[2] University of Canterbury, Dept. Computer Science & Software Engineering, New Zealand.

Abstract

This research introduces a real time algorithm that is invariant to changing luminance levels and tested on classifying the occlusion of spaces in large outdoor regions. The algorithm calculates the correlation coefficients of the grayscale histograms of continually updated template images of a known non-occluded space with the spaces of interest, to determine their occlusion status. The continually updated vacant space template image significantly increased tolerance to the varying ambient conditions. The results suggest that this approach supports a successful occlusion detection method that is robust to unconstrained luminance levels.

Keywords: Computer vision, Histogram, Occlusion, Correlation coefficients

1 Introduction

This project addresses the problem of locating occluded spaces in a large outdoor region using a video data. Prior research is limited to algorithms proven only within constrained laboratory environments [1, 3]. Hence, there is a need for an adaptive system that eliminates varying ambient luminance levels in real world environments. This paper uses techniques that can be employed to adapt to variable ambient conditions.

We propose using a video camera in an elevated position with a birds-eye-view of a large outdoor region to detect occluded spaces. The incoming frames are analysed for correlation with the continually updated template histogram of vacant space to determine the status of each space that are visible within the frame. The preliminary histogram cross correlation results and its performance are discussed in section 4. These results indicate that this algorithm is successful at classifying occluded spaces through varying luminance levels.

2 Related Work

Intel's IrisNET project group has implemented an occluded parking space finder as part of the demonstration of its "wide area sensor network service" project [1]. For this demonstration, they used a controlled tabletop toy car park simulation environment. In the algorithm used by IrisNET, difference between the current image of the indoor occluded space by a toy car and the corresponding stored template image of the same region free of occlusions is taken. The difference image is then threshold to decide if a parking spot is occupied. Although, this method is very robust in an indoor environment with controlled lighting, it is impractical to form a database of a fixed set of template images of each parking space in large outdoor environments with continually changing illumination.

IrisNET literature also suggested improving an algorithm that maintained the different statistical models of each pixel in the background image based on the time of day as described in [2] to compensate for environmental changes. However, acquiring a fixed set of background reference images of each designated space before it could be compared against current images renders this process computationally implausible for a real-time outdoor system.

A similar project with real-world adaptation limitations using the toy car park model has also been investigated [3] by taking the sum-of-square difference between the template image and the current image. This process also imposes an impractically huge burden on the system implementation in real-world situation due to such a large database of images required for all possible variable conditions.

The changing illumination from day to night and changing weather patterns, partial occlusion by the surrounding objects, as in the car park shown in Figure 1, are some of the factors that needs to be considered when implementing an occluded space finder algorithm in a practical situation. However, the variant ambient conditions can be compensated if the template images of free spaces are updated with every new frame. It is assumed that the camera is stationary with the same fixed field of view all the time. Section 3 describes the method to determine occlusion status of a space by comparing initially identified areas in an incoming image to an area of the image that represents not occluded space.

Figure 1 Nighttime lighting condition with the circle illustrating the partial occlusion problem of a free parking space for the given camera angle.

3 Method

3.1 System Model

Figure 2 shows a complete model of occluded space detection system. The first step is the video data acquisition from a stationary web-cam. The ADS TURBO USB 2.0 web-cam was used in this project. The system operated at 30 fames per second at a 640 x 480 pixel resolution. The algorithm is implemented using openCV and Matlab image processing libraries under Windows XP operating system.

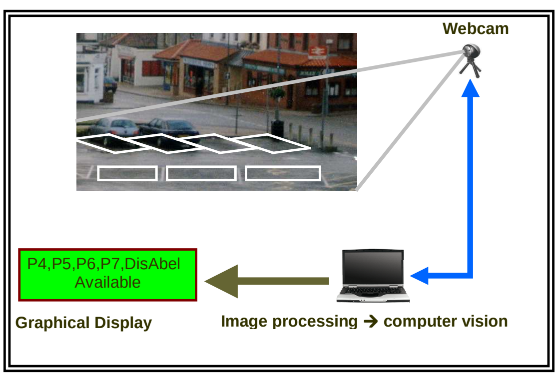

Figure 2 Block diagram of the occlusion detection model in a car park application

3.2 Occluded space detection algorithm

3.2.1 Histogram correlation

The system is initialised using a birds eye-view of the outdoor region as captured by the stationary mounted camera. This initialisation process involves manually allocating each region of interest in an image that represents the space to be analysed for occlusion. The image coordinates for each allocated space is stored and used for identifying the space. The coordinate for one of the allocated spaces is assigned as a non-occluded space template. It is assumed that the template space assigned will never be occluded. The system initialisation needs to be carried out only once for each view. However, if the camera is moved for any reason the system must be reinitialised.

In each frame, eight-bit greyscale histograms of 255 bins for each assigned parking space are calculated. The greyscale histogram of each space is then compared to the template histogram of assigned spaces that is not occluded. The histograms are compared by calculating their correlation coefficients (CC). The CC provides a convenient normalised quantitative single number result [8] of the difference between the two histograms. A threshold for the CC is then assigned to decide whether the space is empty or occluded.

Histograms CC for the space of interest and the template space images in the same frame makes the system invariant to the changing ambient lighting and weather conditions. Hence, the template image is continually updated to provide a dynamic reference.

$$CC = \frac{\sum_x \sum_y (S_{xy} - \bar{S})(P_{xy} - \bar{P})}{\sqrt{\left(\sum_x \sum_y (S_{xy} - \bar{S})^2\right)\left(\sum_x \sum_y (P_{xy} - \bar{P})^2\right)}} \qquad (1)$$

Where: $\bar{S}$ and $\bar{P}$ are the means of two histograms.

The correlation coefficient of two histograms can be obtained using Equation 1, where an eight bit greyscale histogram of a template image is $S_{x,y}$ and the histogram for the image of the space to be investigate is $P_{x,y}$ over the same greyscale.

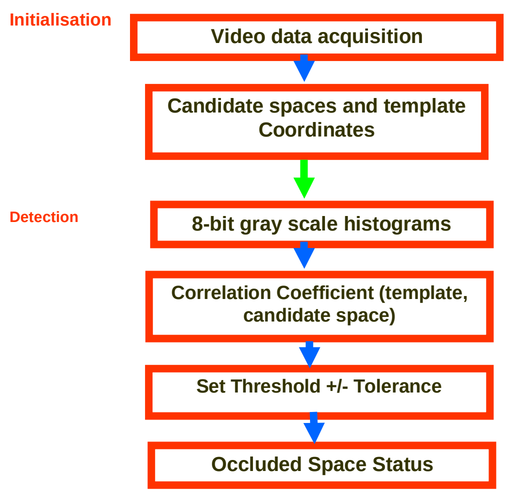

Figure 3 Occlusion detection algorithm's flow chart

The correlation coefficient will tend towards 1 when there is an empty space and towards 0 when a space is occluded. Hence, the CC obtain gives a single value decision parameter. With the determination of a CC values for occlusion decision threshold and tolerance, detecting occlusion in a given space is straightforward. A simple flow chart of the algorithm developed for the implementation of occluded space finder is shown in Figure 3.

4 Performance

Figure 4 shows an image of a car park that has been converted to greyscale. The two selected regions in Figure 4 represents a typical empty parking space and an occluded parking space. The respective histograms of these two selected sub-images are computed and shown in Figure 5.

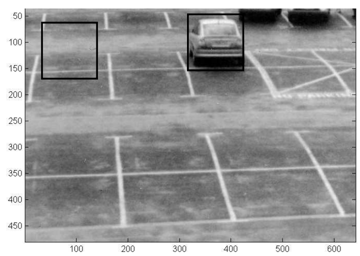

Figure 4 the grayscale of the original sample car park frame.

The histogram for an occluded space has distinctive characteristics to that of an empty space. In the histogram of the empty space image, relatively uniform ground shows a narrow band high peak values at the mid-range of the 8-bit grayscale. Whereas, an occluded space has a wide spread histogram with lower peak values. These histogram characteristics were consistently observed through out all sample images.

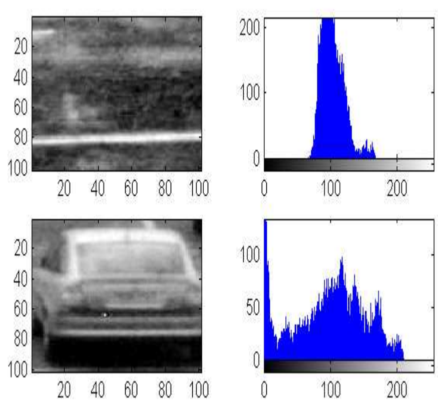

Figure 5 Comparison of the histogram of free space with a histogram of occupied space

The subsequent rows of images in Figure 6, represents the image of an empty parking space assigned as the template empty space, an empty space, an occupied space and a partially occluded space respectively. In order to detect an occlusion status, the histograms of each images (in Row 2, Row 3 and Row 4) are compared with the histogram of know free space template image (Row 1). The CC of the histograms for each occluded space scenario images were computed and listed in Table 1.

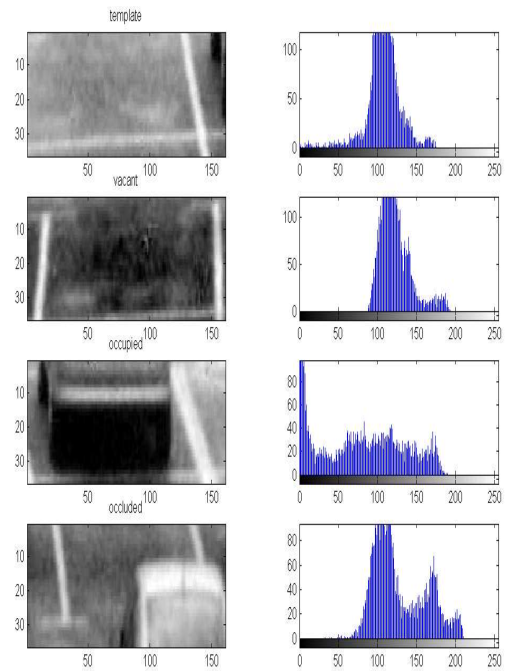

Figure 6 Comparing the histogram of chosen template image to different situation in a car park. Row1: empty space template image. Row2: different empty space. Row3: occluded space Row4: empty space partially occluded.

The CC for the empty parking space and the partially occluded parking space is much higher (tending towards 1) than for the occluded parking space. Using the CC of the car park images, the presence of the vehicle in a parking space can be easily decided. The distinct mid-peak in the histogram of the partially occluded space resulted with high CC when compared with the template histogram of the empty space. This high CC, suggests that the algorithm is tolerant to partial occlusion of the space.

Table 1 The correlation coefficient for the histogram of different parking space scenarios

Scenarios	**Histogram *CC***
Empty space	0.8451
Occluded space	0.1343
Partially occluded space	0.8803

In Figure 6, the image of the occluded parking space in the third row has a distinctive high value peak at the lower bins of its grayscale histogram. These high values at the lower bins are contributed by the shadow of the vehicle on the ground. The shadows of the adjacent objects, like surrounding buildings and vehicles on the vacant space can give misleading results when taking the CC of histograms. Often the shadows of adjacent objects are hard to track, as they are dependent on the angle of the sun. However, lower bins of the histogram of a space can be filtered out for shadow removal.

Figure 7 shows a plot of CC varying with time for the video data as a space becomes occluded. The closest empty parking space relative to the camera is taken as template free parking space. Initially when the space is vacant the CC is high at approximately 0.8. However, after five seconds, the space is partially occluded and this is depicted by the decrease in CC to approximately 0.5. After thirteenth seconds, the space is occluded and the correlation between the template and the space of interest is almost zero, indicating the space is now occluded. On the other hand, Figure 8 shows the increase in CC as the car pulls out of the parking space. By the fifteenth second the parking space is empty and the CC is high at approximately 0.8. For the illustrations in Figure 7 and Figure 8, if the occlusion decision threshold is set at CC of 0.5, the occlusion status of the space could be correctly determined.

Note that the empty space template image is extracted from the same frame as the frame being analysed. Taking the template from the same frame adapts the algorithm to the effects of rapidly changing illumination conditions.

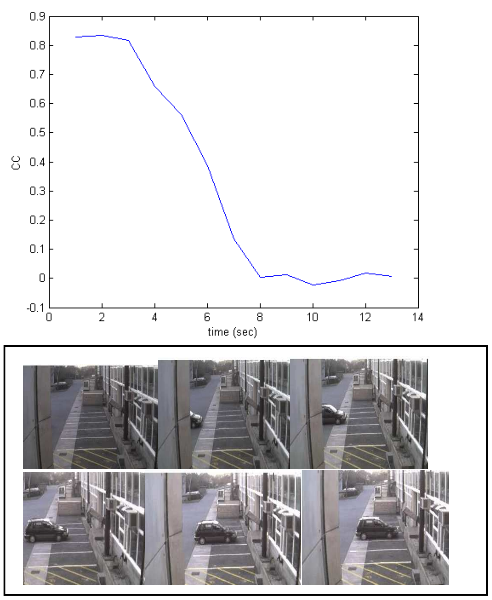

Figure 7 Illustration of decrease in correlation coefficient when a space becomes occluded. From left to right: frames at 1sec, 2sec, 3sec, 5sec,7sec, 13sec.

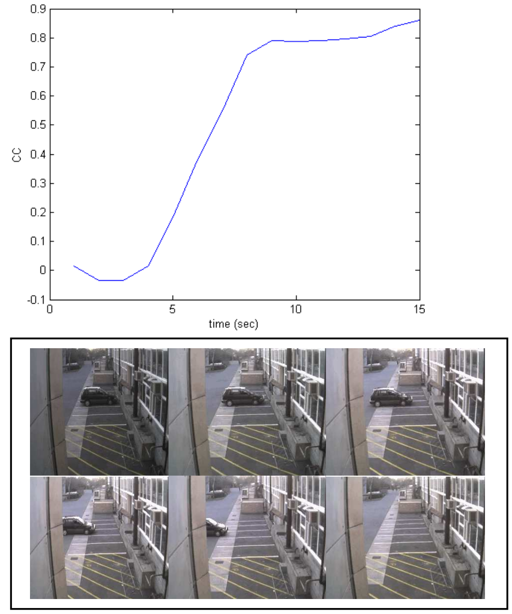

Figure 8 Illustration of increase in correlation coefficient when a vehicle pulls out of the parking space. From left to right: frame at 1sec, 4sec, 6sec, 8sec, 10sec, 15sec.

5 Conclusion and future work

A histogram correlation coefficient algorithm was used to detect occluded spaces in an outdoor environment. The updated template image of vacant spaces is used to adapt to changing lighting levels. The histogram of an image forms a parameter for the space whose correlation coefficient with the histogram of the template image gives the single value decision marker. The research outcome using adaptive algorithms to identify occlusion in an outdoor region was supported by encouraging results of 87% correct occlusion classification.

More field trials are needed to further verify the occlusion detection algorithm. For example, effects from shadows, which vary throughout the day depending on the sun's direction and the reflection of night-lights from wet ground, can cause the algorithm to give false positive results. These variables need to be further investigated as discussed in [5] to make the algorithm more adaptable to such conditions. Further statistical analysis of the histogram correlation coefficient for various occlusion scenarios should be conducted to identify a suitable occlusion decision thresholds and relative tolerance values. For practical implementation of the system, optimal camera geometry, such as a higher camera position with wide-angle lens, needs to be investigated to minimize partial occlusions.

6 References

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