A Low-cost Occlusion Handling Using a Novel Feature
In Congested Traffic Images

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Abstract—Occlusion detection is critical for robust and reliable vision-based systems for traffic flow analysis. In this paper we discuss novel occlusion detection approach. The goal of this algorithm is to detect vehicles in congested traffic scenes with occlusion handling. Also we proposed a new proper feature for vehicle detection to avoid the merging of two or more objects into one and to improve the accuracy of object localization. This feature is strong shadow which exists under any vehicle. Many sequences of real images including noisy images, cluttered, and images containing remarkable shadows and occlusions, taken from both scenes of outdoor highways and city roads, have been taken for evaluating our method.

I. INTRODUCTION

INTELLIGENT traffic surveillance systems are assuming an increasingly important role in highway monitoring and city road management systems. Their purpose, amongst other things, is to provide statistical data on traffic activity such as monitoring vehicle density and signaling potentially abnormal situations. This paper addresses the problem of vehicle segmentation in traffic images including vehicle occlusion.

Some of the related works for analyzing surveillance images, based on background subtraction methods [1], [2]. Also [3-5] have some methods for occlusion handling in the video data stream. Occlusion detection can be performed using an extended Kalman filter that predicts position and size of object bounding regions. Any discrepancy between the predicted and measured areas can be used to classify the type and extent of an occlusion [4], [5]. The early attempts to solve the occlusion problem involved simple thresholding, while later methods applied energy minimization [6] or Markov random field (MRF) models [7]. In order to find the number of motion classes, K-means clustering [8] and mixture models [9] were used. More recently, motion segmentation methods based on active contours [10] have been proposed. The original active-contour formulation [11] suffers from stability problems and fixed topology. These issues can be resolved by embedding the contour into a higher-dimensional function of which it is a zero-level set [12]. An alternative is to consider all intensities in a region, as proposed by Mansouri and Konrad [13], Jehan-Besson et al [14], and Debroue et al.[15]. Some early works using multiple frames includes motion detection using 3-D MRF models [16] and "video-cube" segmentation based on marker selection and volume growing [17]. The other concept of object tracking as spatio-temporal boundary detection has been proposed by El-Feghali et al. [18] and [19]. This new multiple-image framework has lead to interesting space-time image sequence segmentation methods developed by Mansouri et al.[20], [21] and, independently, by the authors [22]. In [23] they employed a straightforward blob tracking algorithm. The advantage of part-based methods is shown in [24], and the algorithm known as predictive Trajectory Merge-and-Split (PTMS) in [25], has been developed to detect partial or complete occlusions during object motion.

Traditionally, shadow detection techniques have been employed for removing shadows from background and foreground but in our work, we used it as a key feature to vehicles detection and occlusion handling. In our approach shadow is a key feature and plays very important positive role. Shadows provide relevant information about the scene represented in an image or a video sequence. Until now shadow was a problem for good object detection and shadows cause the erroneous segmentation of objects in the scene but now we use special type of shadow (strong shadow which exists under vehicle) as a key feature for vehicle detection and occlusion handling. The problem of shadow detection has been increasingly addressed over the past years. Shadow detection techniques can be classified into two groups: model-based and property-based techniques. Model-based techniques are designed for specific applications, such as aerial image understanding [26] and video surveillance [27]. Luminance information is exploited in early techniques by analyzing edges [28], and texture information [29]. Luminance, chrominance and gradient density information is used in [30]. Color information is used also in [31]. A physics-based approach to distinguish material changes from shadow boundaries in chromatic still images is presented in [32]. Authors of [32] proposed Shadow-aware object-based video processing in [37]. A classification of color edges by means of photometric invariant features into shadow-geometry edges, highlight edges, and material changes is proposed in [33]. In [34] cast shadow segmented using invariant color features.

In our method, contrary of previous algorithms, shadow is useful feature to detect vehicles. We use photometric...
characteristic of darkest pixels of strong shadows in traffic images for occlusion handling.

I. THE PROPOSED APPROACH

During occlusion, visual features of the occluded objects are not observed and the objects cannot be tracked. We propose a two step approach to handle the occlusions. The first step detects the novel feature for detecting vehicle, and the second step convert picture format to binary with morphologic techniques and suitable filters.

A. Novel Feature

Our approach is directly based upon the physical characteristics of shadow pixels. The part of pixels that are observable under vehicle and between wheels of it is proposed as a novel feature. This strong shadow is the darkest part of image and other shadows doesn't influence in our algorithm because we use an intelligent low-cost approach to determine useful shadow. Fig.1 shows the shadow feature existent in any vehicle image taken from a camera which is used for traffic monitoring.

Fig.1. (a) and (b), two different views of our proposed shadow feature

In Fig.2 we distinguished this feature in traffic images

Fig.2. the shadow feature is observable in real traffic images

B. Theoretical Background

What is a shadow?

A shadow occurs when an object partially or totally occludes direct light from a source of illumination. Shadows can be divided into two classes: self and cast shadows. A self shadow occurs in the portion of an object which is not illuminated by direct light. A cast shadow is the area projected by the object in the direction of direct light. In the following, the relationship between shadows and lit regions is formalized in order to derive relevant shadow properties.

Photometric and spectral properties of shadows

To describe the spectral appearance of a surface in shadow, let us consider the physics of color generation. The appearance of a surface is the result of the interaction among illumination, surface reflectance properties and the responses of a chromatic mechanism. This chromatic mechanism is composed of three color filters in a color camera. To model the physical interaction between illumination and surface of objects, let us consider the Dichromatic Reflection Model [34]-[35]. The radiance [34-36] of the light, \( L_r(\lambda, p) \), reflected at a given point \( p \) on a surface in the 3D space, given some illumination and viewing geometry, is formalized as [34]

\[
L_r(\lambda, p) = L_a(\lambda) + L_b(\lambda, p) + L_s(\lambda, p)
\]

(1)

Where \( L_a(\lambda) \), \( L_b(\lambda, p) \), and \( L_s(\lambda, p) \) are the ambient reflection term, the body reflection term, and the surface reflection term, respectively and \( \lambda \) is the wavelength. The ambient illumination term is assumed to account for all the light indirectly reflected among surfaces in the environment and does not vary with geometry. If there is no direct illumination because an object is obstructing the direct light, then the radiance of the reflected light is

\[
L_r(\text{shadow})(\lambda, p) = L_a(\lambda)
\]

(2)

Which \( L_r(\text{shadow}) \) represents the intensity of the reflected light at a point in a shadow region. Let \( SR(\lambda) \), \( SG(\lambda) \) and \( SB(\lambda) \) be the spectral sensitivities of the red, green, and blue sensors of a color camera, respectively. The color components of the reflected intensity reaching the sensors at a point \( (x, y) \) in the 2D image plane are

\[
C_i(x,y) = \int E(\lambda, x, y) S_i(\lambda, x, y) d\lambda
\]

(3)

Where \( C_i \in \{R, G, B\} \) are the sensor responses, \( E(\lambda, x, y) \) is the image irradiance [36] at \( (x, y) \), and

\[
\{S_R(\lambda), S_G(\lambda), S_B(\lambda)\}
\]

(4)

The interval of summation is determined by \( S_i(\lambda) \), which is non-zero over a bounded interval of wavelengths \( \lambda \). Since image irradiance is proportional to scene radiance [34],[36], for a pixel position \( (x, y) \), representing a point \( p \) in direct light, the sensor measurements are

\[
C_i(x,y)_{\text{ds}} = \int \alpha(L_a(\lambda) + L_b(\lambda, p) + L_s(\lambda, p)) S_i(\lambda) d\lambda
\]

(5)

Giving a color vector \( C(x, y)_{\text{ds}}(R_{ds}, G_{ds}, B_{ds}) \), \( \alpha \) is the proportionality factor between radiance and irradiance. For a

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point in shadow the measurements are

\[ C_i(x,y)_{\text{shadow}} = \int \alpha (L_i(\lambda)) S_{\text{ct}}(\lambda, x, y) d\lambda \]

In which \( C(x, y)_{\text{shadow}} = (R_{\text{shadow}}, G_{\text{shadow}}, B_{\text{shadow}}) \). It follows that each of the three RGB color components, if positive and not zero, decreases when passing from a lit region to a shadowed one, that is

\[ R_{\text{shadow}} < R_{\text{lit}} \quad G_{\text{shadow}} < G_{\text{lit}} \quad B_{\text{shadow}} < B_{\text{lit}} \]

Ambient light can have different spectral characteristics with respect to direct light [32, 34]. The intensity differences between shadow and other parts of surface is one of the photometric characteristics. In traffic scenes, sun is the light source and vehicles are strong obstacles against sun. We can model the under-vehicle region which does not receive any direct sun light with above formulas.

It means that pixels of shadow in under-vehicle region have just \( L_a(\lambda) \) and have very low intensity. All other surfaces in a traffic scene, even surfaces of dark objects such as black or dark color vehicles, have the body reflection \( L_b(\lambda, p) \) and the surface reflection \( L_s(\lambda, p) \). So this region has different spectral properties. Also other shadows in traffic scene have \( L_s(\lambda, p) \) and more intensity than under vehicle shadows. We will show in the paper that these shadows will be eliminated properly.

The size and direction of shadow varies as a result of movement of the light source (sun) in daytime and traffic images are affected therein. So, we need a robust approach to vehicle detection and occlusion handling that effectively works regardless of light source position. The region under vehicle has a very strong shadow since vehicles are very strong obstacles and this region has only ambient light. Therefore because of the low dependency of this feature to light source, sun position doesn't have any effect on it and this region always has the lowest intensity among image pixels. This property has been shown in Fig.3.

Fig.3. Very low dependency of novel feature to light source position

The key element in detection of this region is the camera viewpoint. The camera is assumed to be calibrated suitably to detect the strong shadow of the vehicle. A view of the camera position is shown in Fig.4.

Fig.4. Camera viewpoint for feature detection

For determining our mentioned feature and detecting vehicles in traffic scenes, viewpoint of camera is very important and effective. If its angel with horizontal line (\( \theta \)) is 90 degree, this algorithm can not work properly. Therefore we should regulate camera position and viewpoint angle so that this feature can be observable.

For internal camera calibrating, we can modify the detection region by regulating \( \alpha \) angle which is a property of CCD Camera and for external calibrating, height and \( \theta \) angle should be regulated. Most of the cameras used for traffic monitoring or controlling satisfy these conditions.

C. Colormaps

Because of very low intensity of feature region, image format converting from index to gray with specific colormap can find out this feature.

A colormap is equivalent to paint-by-numbers and is a table which contains a small set of color definitions. These colors are the only ones that are used in the image being produced and the application maps some value at a pixel to an allowed color from the colormap.

Matlab has several colormaps that have 64 levels, each level containing the RGB values that define the color. In Fig.5 cool colormap of Matlab has been shown.

Fig. 5. Cool colormap of Matlab

Colormap is a common scalar visualization technique that maps scalar data to colors. Colormaps provide a convenient method for specifying colors through their RGB components. If intensity of some pixels is very low, we can find out these pixels with colormap converting.

Many default colormaps are available in Matlab and also we can customized them. Colormaps can be modified or created with Matlab Colormap Editor. Scalar values serve as
indices into a color look up table, i.e., colormap

\[
i = \begin{cases} 
0 & s_i < \text{min}, \\
 n - 1 & s_i > \text{max}, \\
(n - 1)(s_i - \text{min}) / (\text{max} - \text{min}) & \text{otherwise}.
\end{cases}
\]

Where \( n \) is the length of colormap, typically \( n = 256 \), the scalar is in \([\text{min}, \text{max}]\). Our experiments demonstrated that the best method to show different spectral properties of novel feature (strong under-vehicle shadow) is format conversion with specific colormap. Because, pixels of this part of image have the lowest intensity of image pixels. After converting, it can be shown with minimum peak of colormap. In section B we proved that

\[ R_{\text{shadow}} < R_{\text{lit}} \quad G_{\text{shadow}} < G_{\text{lit}} \quad B_{\text{shadow}} < B_{\text{lit}} \]

Therefore pixels of strong shadow have minimum amount of RGB values and they are in down part of Index image table. When we convert traffic image form Index format to Grayscale format, minimum values of Index image will be mapped with minimum peak of colormap. So we can distinct the region which includes our feature. For showing this fact, we set some of our experiments result in Fig. 6.

Fig. 6. influences of format conversion from Index to Grayscale with different colormaps of Matlab, (a) four object which is created with Matlab under four different lighting styles (none, flat, Phong, Gouraud), (b) Index to Grayscale conversion with Winter colormap, (c) Index to Grayscale conversion with Pink colormap, (d) Index to Grayscale conversion with Hot colormap,

When a RGB image is converted from Index to Grayscale using a specific colormap, the different spectral property of under-vehicle region can be precisely observable. We executed this process on traffic scenes in Fig. 7.

Fig. 7 (a) Original RGB image, (b) Grayscale image using JET colormap (Index \( \rightarrow \) Grayscale)

After determining this strong shadow, the resulted image is converted into a binary image using a proper threshold. Then a noise suppression algorithm is applied on the binary image and blobs are counted. Due to perspective, the shadows in the end of image are too small or segmented. This problem can be resolved by filling the holes, removing the narrow protrusions and applying morphologic techniques such as Dilation, Erosion, Closing and Opening. Also instead of converting RGB image from Index format to Grayscale format, we can directly convert RGB into Grayscale, Fig. 8.

Fig. 8 (a) Original RGB image, (b) Grayscale image using JET colormap (RGB \( \rightarrow \) Grayscale)

As it is obvious in Fig. 7 and Fig. 8, the under-vehicle shadow can be used as an effective feature in vehicle detection. This feature is also useful in occlusion detection. Our detection is more reliable when using customized colormaps. Colormaps can be modified or created by Matlab Colormap Editor. In Fig. 9 the final result of algorithm is illustrated. In this figure we have used a customized colormap, which is modified from VGA colormap.

Fig. 9 (a) Original RGB image, (b) Grayscale image using customized colormap, (c) Final result of algorithm
D. Experimental Results

To demonstrate the effectiveness of our algorithm, we have applied it to several real images. The input images are masked to determine the framework field. There may be situations where two vehicles in close proximity were first segmented correctly, but later segmented as one blob, due to partial occlusion or errors in the background image. Also, there may be cases where parts of a large vehicle (for example, a container carrier) are represented by separate blobs. These and similar situations cause inaccuracies in measured traffic parameters. Therefore, in order to have more accurate detection, first we increase image contrast then morphologic techniques are applied.

Long sequences of real images (noisy, cluttered, and containing remarkable shadows and occlusions) taken from both scenes of outdoor highways and city roads have been considered. The first image in Fig.10 shows a single vehicle along a road, whereas the second one Fig.11 shows two vehicles under occlusion that our approach could detect them and in Fig.12 there is a group of occluded vehicles in congested traffic which are detected accurately. Finally, Fig.13 shows a bus in a road that is detected such as other vehicles.

II. Conclusion

In this paper we discuss novel occlusion detection approach. We proposed a new proper feature for detecting vehicle and improving the accuracy of object localization. This feature is strong shadow which exists under any vehicle. Our novel approach to detecting occluded vehicles has following simple and efficient steps:

1. preprocessing (increasing image contrast)
2. Convert image format from Index to Grayscale
3. Convert image format from Grayscale to Binary
4. Perform suitable morphologic techniques

This approach has several advantages. It is very simple and low-cost and can help other detection algorithms for occlusion handling. Accuracy of this approach in real images including noisy images, cluttered, and images containing remarkable shadows and occlusions, is very good.
FUTURE WORKS

Future work involves making the algorithms more robust for occlusion and improving its performance. The current results are encouraging and further work is being done to make the system more practical. Work can be done for enhancing the algorithms more suited to the non-static cameras in intelligent vehicles. This system if coupled with other algorithms for detecting and classification, can help in solving occlusion problem and thus help in accurate traffic monitoring and controlling.

REFERENCES