

Moving Shadow Removal for Object Tracking

Mohamed Taha^{#1}, Hala H. Zayed^{#2}, M. E. Khalifa^{*3}, Taymoor Nazmy^{#4}

[#]Faculty of Computers & Informatics, Benha University, Benha, Egypt

¹mohamed.taha@fci.bu.edu.eg

²hala.zayed@fci.bu.edu.eg

^{*}Faculty of Computer & Information Sciences, Ain Shams University, Cairo, Egypt

³esskhalifa@cis.asu.edu.eg

⁴ntaymoor19600@gmail.com

Abstract— Identifying moving objects from a video scene is a fundamental and critical task in object tracking. However, shadows extracted along with the objects can result in large errors in object localization and recognition. Despite many attempts, the problem remains largely unsolved due to several challenges. Since cast shadows can be as big as the actual objects, their incorrect classification as foreground results in inaccurate detection and decreases tracking performance. Hence, an effective method for shadow detection and removal is required significantly to provide urgent support and to reduce the effects of incorrect object tracking.

In this paper, an efficient method for removing cast shadow from vehicles is proposed. The method works by applying a Gamma decoding followed by a thresholding operation and employing the estimated background model of the video sequence. A number of experiments has been performed. The results revealed the proposed algorithm is efficient and leading to improved tracking process.

Keywords— Shadow Removal, Shadow Detection, Moving Shadow Removal, Object Tracking, Cast Shadow Removal

I. INTRODUCTION

Over the last decade, many interesting applications of traffic monitoring and vehicle tracking using roadside cameras have been proposed and shown to be useful in many situations [1-3]. Vehicle tracking systems are presented in order to solve many traffic problems like vehicle routing [4] and accidents detection [5] to name a few. However, their effectiveness depends on video image processing algorithms that are capable of reducing common problems such as shadows, occlusion, illumination, reflection, and camera shaking. Among of them, shadows have proven to be a large source of error in vehicles detection and classification [6, 7]. Shadow is a region of relative darkness that occurs when an object totally or partially occludes direct light from a light source [8]. Typically, there are two types of shadow: ‘self’ and ‘cast’; self-shadow occurs on the object occluding the light, while cast-shadow is that

generated by the object on the ground or other objects in the scene. Fig. 1 shows the difference between the self-shadow and cast-shadow.



Fig. 9 Self-shadow and cast-shadow

In many computer vision applications, cast-shadow is more important than self-shadow which is usually identified as some pixels of the object itself. Cast-shadow can bring serious problems while extracting moving objects due to the misclassification of shadow points as foreground [9]. In some cases when the shadows stretch, two or more independent objects can appear to be connected together. Shadow can cause merging of objects, object shape distortion and object losses. Fig. 2 shows a merging problem of two objects in a tracking process. It occurs as a result of the fusion of the right vehicle shadow with the left vehicle.

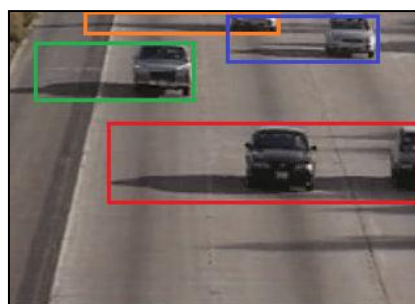


Fig. 2 Two vehicles appear as one object in the tracking process because of shadow stretching

Understanding the content of images and videos requires detecting and tracking moving objects. When the objects of interest have a well-defined shape, template matching or more sophisticated classifiers can be used to directly separate the objects from the image [10]. The difficulties associated with shadow detection arise since shadows and objects share two important visual features: First, shadow pixels are detectable as foreground pixels since they are typically different from the background; second, shadows have the same motion pattern of the objects casting them [8, 9, 11]. In fact, shadow identification is serious for both still images and image sequences (video) and has become an active research area.

It should be noted that the purpose for which shadow removal is utilized determines the restrictions of how the problem is solved. For example if the goal is just image enhancement, it can be allowable to have some guidance by a user to remove shadows. This will simplify the problem. However, in computer vision domain, the purpose is usually to extract meaningful information from an image. The artistic nature of the image is not so important as long as the resulting image is shadow free and keeps the core information of the original image. In this case, the shadow removal should be done automatically without any user intervention.

In the case of still images [12], shadows are commonly analyzed to estimate geometric properties of the objects causing the shadow, and to enhance object localization and measurements. This is helpful in many applications such as in aerial image analysis for recognizing buildings [13, 14], and for obtaining 3-D reconstruction of the scene [15, 16]. In addition, another significant application is in 3-D analysis of objects to extract surface orientations [17] and to determine light source direction [18]. However, in the case of image sequences, Shadows are referred as moving shadows to differentiate it from that in still images [19] and the detection approach and steps are usually different from still images. In addition, the purpose for the shadow detection in image sequences could be change detection, scene

matching or surveillance that is different from a detection purpose for still images. In moving shadow detection methods, generally a background subtraction step is usually present [19, 20]. There are several studies on moving shadow detection [19 - 26]. In vision-based vehicle detection systems, differentiating cast shadows from moving objects is significant and remains largely unsolved [27]. In this paper, a method for removing cast shadow from vehicles is proposed. The method works by applying a gamma decoding followed by a thresholding operation and employing an estimated background model of the video sequence.

For clarity of presentation, the paper is organized as follows: Section 2 explores the related work found in the literature concerning cast shadow detection. Section 3 presents the proposed method in detail. Section 4 discusses the experimental results and the performance evaluation of the proposed method. Finally, the conclusion is presented in Section 5.

II. RELATED WORK

There has been significant work done recently that deals with the problem of moving cast shadows. In 2003, Prati et al. [11] conducted a survey on moving shadow detection algorithms. They categorized shadow detection methods in a two-layer taxonomy as shown in Fig. 3. The first layer classification is algorithm-based taxonomy. It considers whether the decision process in the algorithm introduces and exploits uncertainty. The second layer classification is feature-based taxonomy where they mentioned the types of features used by each method among three broad classes: spectral, spatial and temporal features. Their main conclusion was that only the simplest methods were the one convenient for generalization. Moreover, to detect shadows efficiently in a specific environment, more assumptions yield better results. Consequently, there was no single robust shadow detection technique and it was better for each particular application to develop its own technique according to its nature.

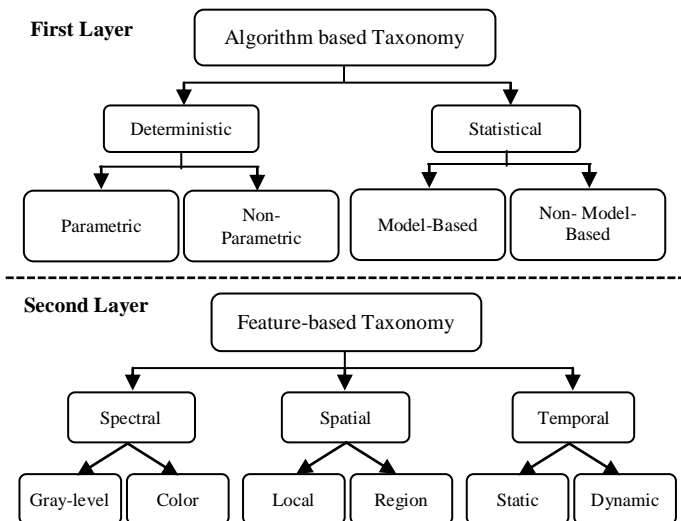


Fig. 3 Prati taxonomy of shadow detection algorithms

Sanin et al. [10] conducted a more recent review of shadow detection and removal techniques in 2012. The survey follows the work of Prati et al. [11] but with more recent publications, and a more comprehensive set of test sequences and experiments. In contrast to Prati review, Sanin review categorized shadow detection methods in a feature-based taxonomy into six classes: intensity, chromacity, physical properties, geometry, textures, and temporal features (see Fig. 4). They observed that the choice of features has greater impact on shadow detection results compared to the choice of algorithms.

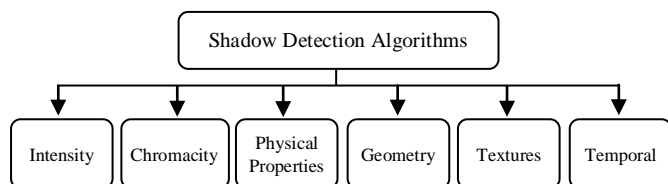
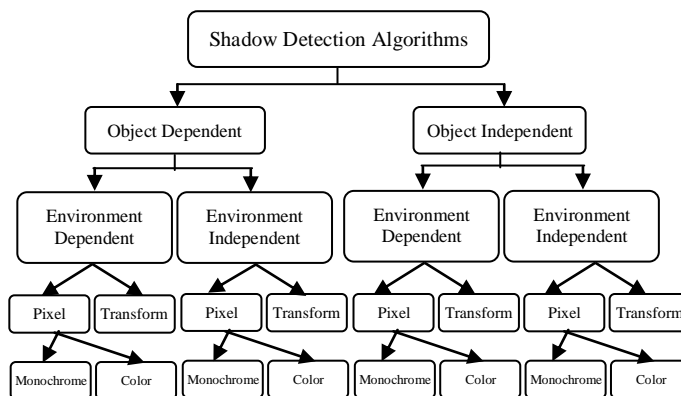


Fig. 4 Sanin taxonomy of shadow detection algorithms

Sanin evaluation [10] indicates that all shadow detection approaches have individual strengths and weaknesses. Out of these methods, the geometry-based technique has severe assumptions and is not generalizable to various environments, but it is an obvious choice when the objects of interest are easy to model and their shadows have different orientation. The chromacity-based method is simple to implement and computationally inexpensive, but it is sensitive to noise and less effective in low saturated scenes. The physical method tend to be more accurate than chromacity-based methods, but fails with objects having similar chromacity to that of the background. The small-region texture based method is potentially powerful for pixels whose neighborhood is textured, but may take longer to implement and is the most computationally expensive. The large-region texture based method produces the most accurate results, but has a significant computational load due to its multiple processing steps.

In addition, Al-Najdawi et al. [8] presented another survey of shadow detection methods in



2012. The algorithms are classified under a four-layer taxonomy based on object and environment dependency and domain of implementation. A further classification into monochrome/color, for pixel domain algorithms is given (see Fig. 5). Performance of algorithms in different domain of implementations are compared quantitatively and qualitatively. Their conclusions significantly agreed with what Sanin et al. conclude but with some more additions. Their results reported that transform domain algorithms can be more robust to noise and are less complex as the number of features extracted are fewer and more precise. However, their performance is limited by the flexibility and the sharpness of shadow detected.

Fig. 5 Al-Najdawi taxonomy of shadow detection algorithms

III. PROPOSED METHOD

When studying the properties of shadow regions in terms of their features including intensity, color, and edge information, one can find that the intensity of a shadow pixel decreases when compared to the reference background [27]. In addition, the reduction rate changes smoothly between neighboring pixels. For the color feature when considering the HSV color space, both the hue component and the saturation component of shadow pixels change but within a certain limit [27]. In RGB color space, although all RGB values are lower in the shadow region than in the background region, the amount of reduction is not proportional. Shadow pixels are more saturated toward blue. As a result, shadow pixels falling on neutral surfaces, such as asphalt roads, tend to be more bluish. For the edge features, shadow regions generally do not have strong edges. Compared with the reference background, edge magnitude values of shadow pixels are lower, while shadows do not significantly modify the edge gradient at any pixel [27].

To detect shadows, most algorithms convert RGB color space to HSV (Hue, Saturation, and Value) or YCbCr color spaces. Y is the luminance component and Cb and Cr are the blue-difference and red-difference chroma components. These color spaces are characterized by its ability to separate the light intensity component from the chrominance

components. Instead, the proposed method works on RGB color space to eliminate shadows since RGB color camera system is one of the most popular color spaces.

The proposed method incorporates estimated background model information and gamma decoding to detect cast shadow. This integration has greatly increased the scope of applicability and brought significant enhancements in the shadow-free images and the time of processing. The proposed method shows a significant elimination of the shadows in the frames of image sequences.

Algorithm:	Shadow Removal Algorithm
	Inputs: BK, fr_shadow
	Output: fr_shadowless
	Steps:
	<ol style="list-style-type: none"> 1. // Compute the difference between fr_shadow and BK and convert the result to black & white image $Diff = abs(BK - fr_shadow)$ $Diff = im2bw(Diff)$ 2. // Normalize the frame $fr_shadow = fr_shadow / BK$ 3. // Apply Gamma Decoding to the normalized frame $fr_shadow = A * fr_shadow^\gamma$ 4. // Convert fr_shadow from RGB image to grayscale image $fr_shadow = RGBtoGrayscale(fr_shadow)$ 5. // Compute the suitable threshold using Otsu's method $Thresh = Otsu's\ method(fr_shadow)$ 6. // Thresholding fr_shadow For i=1 to fr_height For j=1 to fr_width If $Diff(i,j) > 0$ then If $fr_shadow(i,j) > Thresh$ then $fr_shadowless(i,j) = fr_shadow(i,j)$ else $fr_shadowless(i,j) = 0$ end if end if end for end for

Fig. 6 The proposed shadow removal algorithm.

Fig. 6 shows the steps of the proposed shadow removal method and Table I illustrates the list of symbols used in the algorithm. The inputs of the algorithm are the video frame that contains the shadow and the background image of the video sequence. The background image represents what the environment looks like without any foreground objects. In fact, it will be already estimated during the tracking process. Hence, It will not incur more

overhead to the shadow removal algorithm. It is reasonable to assume that a clear view of the background can be obtained, or that the background can be estimated even in the presence of foreground objects. The output of the algorithm is only the video frame after eliminating the shadow.

TABLE IV
THE LIST OF SYMBOLS USED IN THE PROPOSED ALGORITHM

Symbol	Meaning
BK	Estimated background
fr_shadow	Video frame that contains the shadow
fr_shadowless	Video frame after removing the shadow
fr_height	Frame height
fr_width	Frame width
A	Positive constant controls the range values
γ	Gamma value

First, the difference between the video frame and the background image is computed in a pixel-by-pixel manner and the absolute value is taken. Large values in the resultant difference image indicate the existence of foreground objects. However, small values are usually noise due to environmental factors such as illumination and background clutter. Hence, these values can be further ignored. The resultant image is then converted to black and white image to facilitate its manipulation. This difference image will be used later in the thresholding process (step no. 6). In the next step, the video frame is normalized by dividing each pixel value by its corresponding value of the background image. This is a pre-processing step to apply Gamma decoding.

To focus the shadow areas, Gamma decoding is applied on the normalized frame. It is a nonlinear operation to improve the fidelity of the brightness value magnitudes. Using the equation showed in the third step in Fig. 6, Gamma values (γ) larger than one make the image darker, while values smaller than one make dark regions lighter. In the proposed algorithm, a value larger than one is used to make shadow more apparent. By this process, the shadow pixels are getting darker and hence it can be easily separated. It compresses the low value pixels and stretches high value pixels. The input and output values of the Gamma equation are non-negative real

values. The value of the constant A in the same equation controls pixel value range. In our proposed algorithm, the typical value one is used for A. In this case, inputs and outputs are typically in the range from 0 to 1. If a value greater than 1 is used for A, the range will be expanded to be from zero to A.

It should be mentioned that in order to stress the shadow areas, using Gamma decoding is more effective than adjusting image brightness. Applying Gamma decoding does not change the level of detail in the image. It adjusts the RGB value of each pixel in an image but not by the same amount. However, using brightness in the same case can make details wash out or fade to white or black. Since brightness just adds or subtracts the same value to/from each pixel, the image may lose information at the extremes.

After Gamma decoding, the resultant video frame is converted from RGB to grayscale image. The resultant grayscale image has a range from zero to 255. To make the thresholding process more robust, the threshold value should be automatically selected with each frame. The manual threshold setting method and offline learning based method cannot adapt to the variation of the environment in real-time. So in the proposed algorithm, a dynamic threshold is calculated using Otsu's method [28]. It involves iterating through all the possible threshold values and calculating a measure of spread (intra-class variance) for the pixel levels each side of the threshold, i.e. the pixels that either fall in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum. It does not depend on modelling the probability density functions; however, it assumes a bimodal (i.e., two classes) distribution of gray-level values.

Then thresholding process is performed over the obtained grayscale image. The new image frame (shadow free image) will have all pixels with values greater than the dynamic threshold. This process ensures the removing of cast shadows because the value of shadow pixels will be less than the threshold value. However, it keeps the pixels of both foreground image and background image. In object tracking, foreground objects are more

important. Hence, the difference image obtained in step one is used as a filter during the thresholding process. That is, the thresholding is performed only on the pixels whose corresponding pixels on the difference image are white. By this way, thresholding is restricted to the foreground pixels only instead of the whole image pixels.

Fig. 7 illustrates how the proposed algorithm works. The inputs of the proposed algorithm are shown in Fig. 7.a and 7.b. A video frame taken from an outdoor surveillance camera is shown in Fig. 7.a. The frame image contains a number of vehicles with their cast shadows. Note how shadows represent a change in both intensity and color of the prevailing illumination. Fig. 7.b is the estimated background model obtained from the tracking process. The difference between the video frame and the estimated background is shown in Fig. 7.c. The image shows the vehicles mask with their cast shadows (foreground objects). Also, some trees leaves appear on both sides of the road. This is because the motion of the leaves usually cause mismatch between the leaves positions of the estimated background model and leaves positions of the video frame. Then, the result of frame normalization is shown in Fig. 7.d. Since the normalization process is performed by dividing the video frame pixel values by its corresponding pixel values in the estimated background, the white

pixels indicate the matching positions between the video frame and the background model (their division result equals to approximately one). Fig. 7.e shows the normalized video frame after applying Gamma decoding. Note how the shadow areas are getting darker. Focusing the shadow areas is the main role that Gamma decoding play in the proposed algorithm.

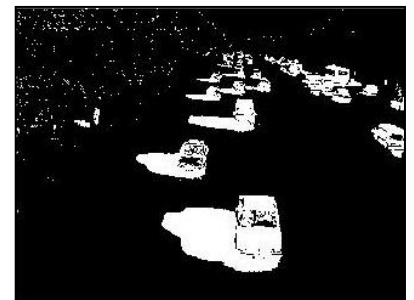
Before thresholding can be performed, the resultant video frame should be converted to a grayscale image as shown in Fig. 7.f. Moreover, Fig. 7.g shows the result of applying the dynamic threshold obtained from Otsu's method to the grayscale image. The white pixels represent those pixels with values greater than the dynamic threshold while the black pixels represent the shadow areas. This process alone is not enough. Referring to the difference image obtained in step one (Fig. 7.c), the result can be filtered to obtain the foreground only without the background (Fig. 7.h). Also, Fig. 7.i shows the final frame after removing shadows. One can detect how the proposed algorithm eliminates the cast shadows efficiently. Although the shadow removal may not be perfect, the effect of shadows is so greatly neutralized so that many tracking algorithms can easily benefit from it.



(a) Video frame that contains the cast shadow



(b) Estimated background model



(c) Difference between the video frame and the background image

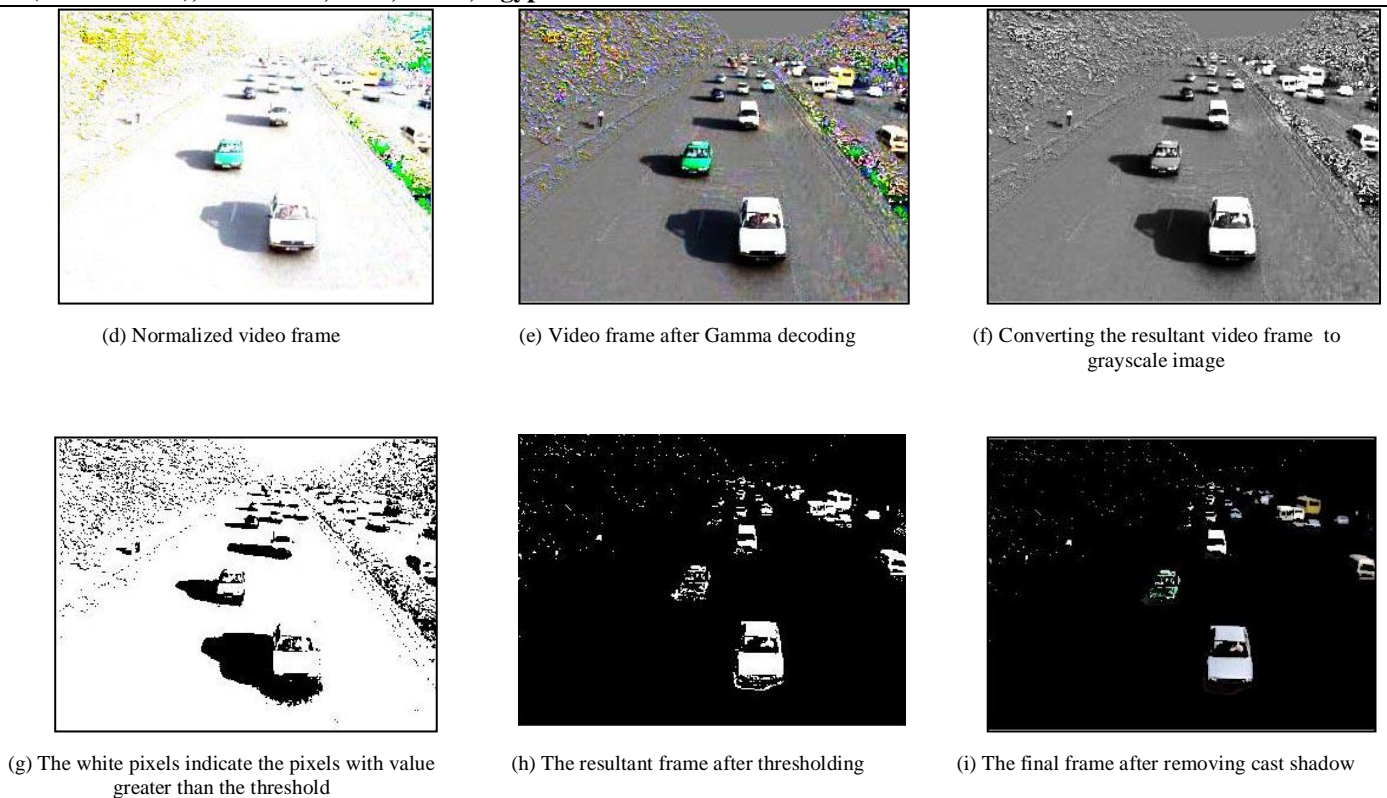


Fig. 7 The proposed shadow removal algorithm.

IV. EXPERIMENTAL RESULTS

In order to measure the performance of the proposed algorithm, several experiments were conducted on different datasets that contains different color vehicle, different background and different light source direction. The experiments were implemented on a 2.27GHz Intel Core i5 PC with 4GB memory, running under Windows 8 Enterprise. The algorithm is coded using MATLAB 8.1.0.604 (R2013a).

The first set of experiments aims to directly test the performance of the proposed method algorithm qualitatively. This is achieved by running the proposed algorithm on different video sequences and see its efficiency in removing cast shadows. The video sequences are selected so that it contains vehicles of different dimensions, different colors, and different lighting conditions.

Fig. 8 and Fig. 9 show the results of running the proposed algorithm on two video sequences (bungalows, highway) provided by “Changedetection.net” (a change detection benchmark dataset available at [\[jodoin.dmi.usherb.ca/dataset/\]\(http://jodoin.dmi.usherb.ca/dataset/\)\) \[29\]. The two testing inputs are uncompressed AVI video files. The resolution of each video frame of “bungalows” and “highway” is \$360 \times 240\$ and \$320 \times 240\$ respectively. The moving objects for both video sequences are vehicles. The first column of the two figures shows the original frames. The second column shows the frame after applying Gamma decoding. The third column shows the foreground objects found in the frame after removing cast shadows. As it can be seen from the two figures, the shadows are removed quite effectively. However, there are a number of artifacts introduced into the images but it does not affect the tracking process at all. Actually, in tracking, we do not need a 100% shadow free object. We just need to prune the shadow effect in a way that prevents presenting two objects as one object as a result of a shadow merge.](http://wordpress-</p>
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Fig 8. The results of applying the proposed shadow removal algorithm on “bungalows” video sequence.

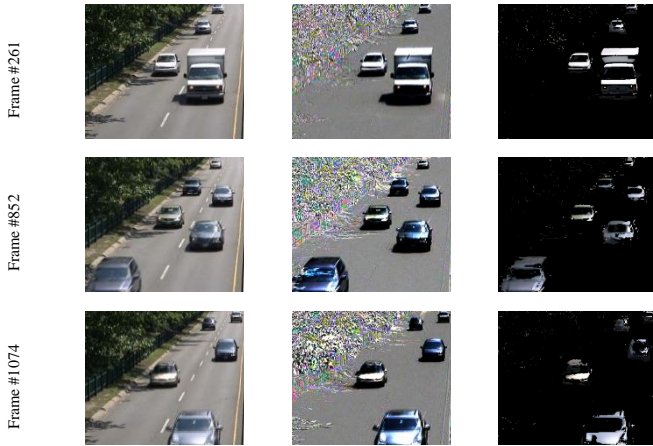


Fig 9. The results of applying the proposed shadow removal algorithm on “highway” video sequence.

In the second set of experiments, to compare the performance of the proposed shadow removal algorithm with existing methods quantitatively, we calculate the shadow detection rate η (Eta) and shadow discrimination rate ζ (Zeta), which are the performance metrics presented in the benchmark paper [11] by Prati et al. Since that time, these two metrics are used widely as a standard metrics for testing the performance of shadow detection algorithms [30-33]. They are defined as follows:

$$\text{Shadow detection rate } (\eta) = \frac{TP_s}{(TP_s + FN_s)}$$

$$\text{Shadow discrimination rate } (\zeta) = \frac{TP_f}{(TP_f + FN_f)}$$

where TP and FN stand for true positive and false negative pixels with respect to either shadows (S) or foreground objects (F). This means TP_s is the number of pixels which are determined correctly as shadow pixels; TP_f is the number of pixels which are determined correctly as foreground object pixels. FN_s is the number of errors in which a shadow pixel is defined as an object pixel, and FN_f

is the number of false detection which identified an object pixel as a shadow pixel. The shadow detection rate is concerned with labelling the maximum number of cast shadow pixels as shadows. The shadow discrimination rate is concerned with maintaining the pixels that belong to the moving object as foreground. In general, η is reduced with increasing ζ , and ζ is reduced with increasing η ; thus, η and ζ are a reciprocal relationship.

The proposed approach has been tested on two real data sequences “highway I” and “highway III” (see Table II for a detailed description of the two videos). The data set is provided by the Computer Vision and Robotics Research Laboratory of UCSD (<http://cvrr.ucsd.edu/aton/shadow>). Fig. 10 and Fig. 11 show the results of applying the proposed algorithm on “highway I” and “highway III” respectively. In each Fig., the first column shows the original frame. The second column shows the shadow detection result after applying the proposed algorithm (red pixels indicates the foreground object while black pixels indicates the shadow pixels). Finally, the third column shows the ground truth images used to evaluate the proposed algorithm performance (white pixels indicates the foreground object while black pixels indicates the shadow pixels). The ground truth masks is obtained from <http://arma.sourceforge.net/shadows/>. Note that the size of vehicles in the video sequence shown in Fig. 11 is much smaller compared with vehicles size in Fig. 10. However, moving cast shadows of the objects in both figures have been identified effectively.

TABLE II
DESCRIPTIONS OF TESTING VIDEOS

	highway I	highway III
Frames Number	440	2227
Frame Resolution	320 × 240	320 × 240
Frame Rate	14 fps	10 fps
Scene Type	Outdoor	Outdoor
Scene Surface	Asphalt	Asphalt
Objects Type	Vehicles	Vehicles
Objects Size	Large	Small

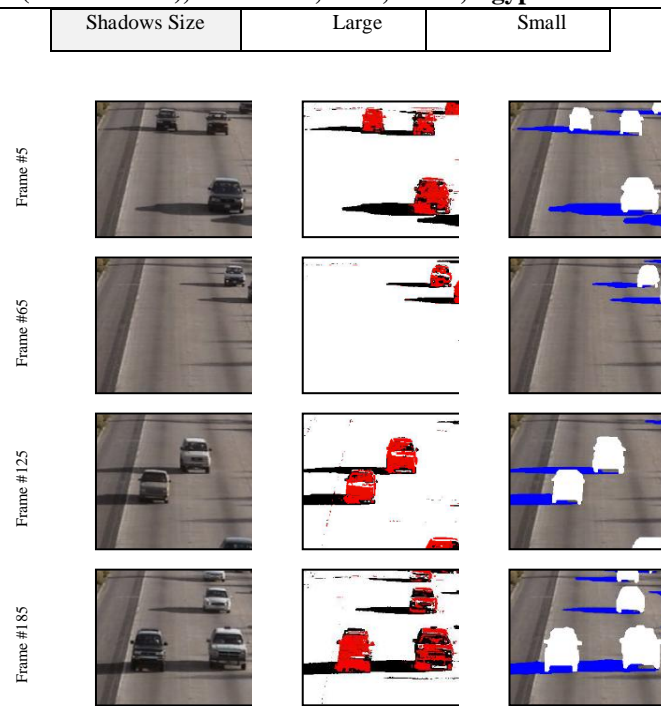


Fig. 10 The results of applying the proposed algorithm on “highway I” video sequence: original frame, shadow detection result, ground truth image from left to right, respectively

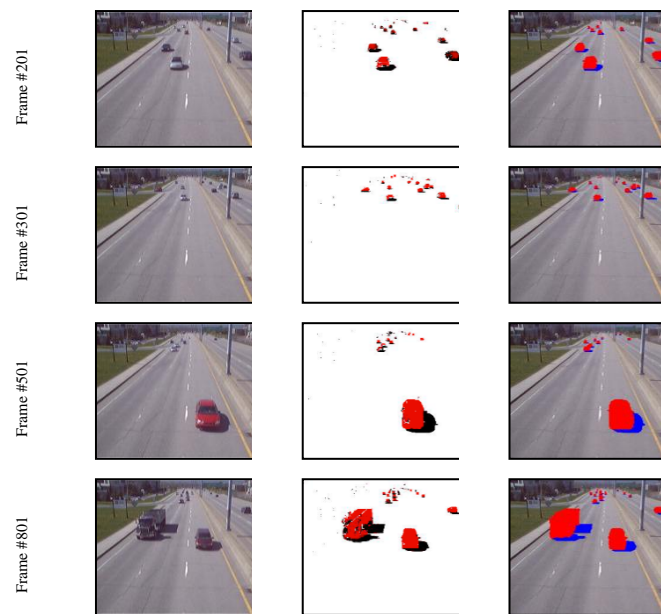


Fig. 11 The results of applying the proposed algorithm on “highway III” video sequence: original frame, shadow detection result, ground truth image from left to right, respectively

Table III lists comparative results of the proposed algorithm with some state-of-the-art methods. As the results indicates, the proposed algorithm outperforms the other algorithms. It achieves a shadow detection rate (η) equal to 93% for the two

video sequences and a shadow discrimination rate equal to 88% and 87% for highway I and highway III respectively. In addition, the average of the two rates is often used as a single performance measure. The combined score for the two video sequences is about 90%, which seems so promising results comparing to the existing methods.

In all previous experiments, the time taken to process each frame of the video images is calculated. The average processing time is 54.23 milliseconds for each frame. This means that it will be feasible for real time tracking applications. Moreover, using a faster programming language like C++, and some optimization of the code we hope to further improve the processing times of the algorithm.

TABLE III
COMPARISON OF THE PROPOSED ALGORITHM WITH EXISTING METHODS

Algor ithm	highway I			highway III		
	η	ζ	m ea n	η	ζ	m ea n
Ref [30] (2009)	6 8 %	9 1 %	79 .5 %	7 5 %	7 5 %	75 .5 %
Ref [31] (2010)	8 2 %	9 4 %	88 % %	6 5 %	9 2 %	78 .5 %
Ref [32] (2010)	8 6 %	8 9 %	87 .5 %	8 4 %	9 1 %	87 .5 %
Ref [33] (2013)	8 7 %	8 5 %	86 % %	8 5 %	8 1 %	83 % %
Propo sed	9 3 %	8 8 %	90 .5 %	9 3 %	8 7 %	90 % %

V. CONCLUSION

The problem of moving shadow removal has a great interest in computer vision because of its relevance to visual tracking, object recognition, and many other important applications. The existence of cast-shadows would change the shape and size of the moving objects. Separate objects can be connected through shadows, which can confuse object recognition. Hence, it is relevant to note that

shadow removal can in fact lead to considerably better tracking performance than not using shadow removal, regardless of the tracking algorithm. In this paper, a method for removing cast shadow from vehicles is proposed. The method works by applying a gamma decoding followed by a thresholding operation and employing an estimated background model of the video sequence.

The proposed method is tested with several real data sequences that contains different color vehicle, different background and different light source direction. Also, several experiments have been designed to measure the algorithm performance. The results obtained from the implementation of the proposed algorithm have illustrated effective shadow removal and applicability of the proposed technique. In some cases, even though the shadow removal may not be perfect, the effect of shadows is so greatly reduced that many existing algorithms can easily benefit from it. Also, a comparison with some existing methods has been conducted in terms of measuring shadow detection rate η and shadow discrimination rate ζ and the results shows that the proposed algorithm outperforms the other algorithms.

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