Moving Cast Shadow Detection in Video Based on New Chromatic Criteria and Statistical Modeling

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***Abstract*—A novel moving cast shadow detection method is presented in this paper to detect and remove the cast shadows from the foreground. First, the foreground is detected using the global foreground modeling (GFM) method. Second, the moving cast shadow is detected and removed from the foreground using a new moving cast shadow detection method that contains four hierarchical steps. In the first step, a set of new chromatic criteria is presented to detect the candidate shadow pixels in the HSV color space. In the second step, a new shadow region detection method is proposed to cluster the candidate shadow pixels into shadow regions. In the third step, a statistical shadow model, which uses a single Gaussian distribution to model the shadow class, is presented to classify shadow pixels. In the last step, an aggregated shadow detection method is presented for final shadow detection. Experiments using the public video data 'Highway-3' and the real traffic data from the New Jersey Department of Transportation (NJDOT) show the feasibility of the proposed method.**

I. Introduction

In video analysis, shadows are often detected as part of the foreground, as they share the similar motion patterns to the foreground objects [1], [2]. These cast shadows often adversely affect the video analysis performance in various applications, such as tracking and object detection. Many algorithms have been published to detect the moving foreground objects in video [3], [4], [5]. Yet the cast shadows are usually classified into the foreground class as they have the similar motion patterns to their foreground objects, which deteriorates video analysis performance. In this paper, we present a novel moving cast shadow detection method based on color and statistical modeling to detect and remove the cast shadows from the foreground region in order to improve video analysis performance.

The new moving cast shadow detection method contains four hierarchical steps, whose contributions are summarized below. First, we present a set of new chromatic criteria to detect the candidate shadow pixels in the HSV color space. We use the HSV color space for shadow detection due to its property of separating the chromaticity from intensity [6], [7], [8], [1], [9]. Second, we present a new shadow region detection method to cluster the candidate shadow pixels into shadow regions. Third, we present a statistical shadow modeling method, which uses a single Gaussian distribution to model the shadow class, to classify shadow pixels. The shadow pixels detected by both the new chromatic criteria and the new shadow region detection method tend to be more reliable shadow pixels, we therefore use these shadow pixels to estimate the Gaussian distribution for the shadow class. Finally, we present an aggregated shadow detection method that integrates the detection results using the new chromatic criteria, the new shadow region detection method, and the new statistical shadow modeling method.

We implement experiments using the public video data 'Highway-3' and the New Jersey Department of Transportation (NJDOT) traffic video sequences to show the feasibility of the proposed method. In particular, the experimental results (both qualitative and quantitative results) show that our proposed method achieves better shadow detection performance than some popular shadow detection methods [10], [11], [12], [13], [9], [14].

II. Related Work

Many methods have been published for cast shadow detection [15], [1], [2]. As color often provides useful information for shadow detection, some methods apply color information to detect shadows [6], [8], [16], [17]. Many shadow detection methods assume that the shadow areas are darker in intensity but relatively invariant in chromaticity [6], [7], [8], [1], [9]. Statistical shadow modeling is applied for shadow detection as well [18], [12], [19]. There are also methods that utilize texture for shadow detection, such as classifying a region into the shadow region or the object region based on the texture correlation between the foreground and the background [13], [20], [21]. These methods extract the texture information in different sizes of the regions. The advantage of these methods is that they are more robust to illumination changes than the color based methods, but the disadvantage is that the computation efficiency of matching the texture features is low. Many methods based on deep neural network are proposed to solve the shadow detection problem recently [22], [23], [14]. These methods do not use any hand-craft features, but use large training samples to extract some high dimensional deep features using the deep neural networks.

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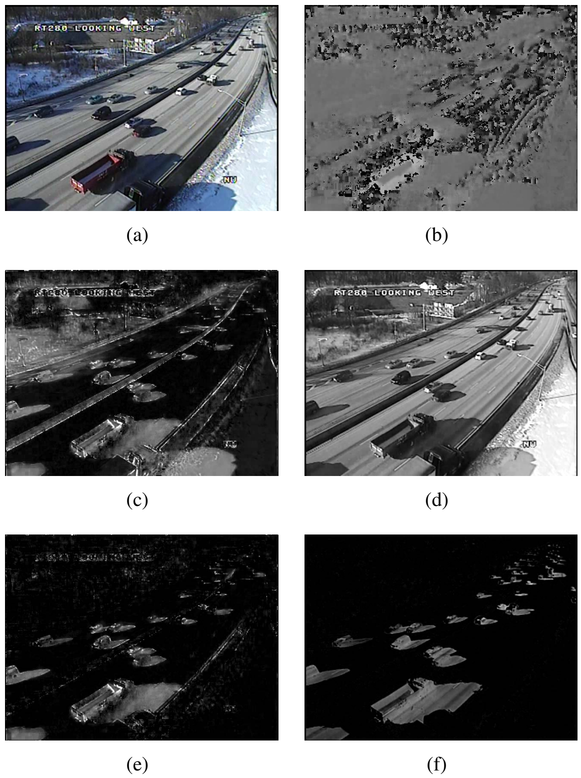

Fig. 1. (a) A video frame from an NJDOT traffic video. (b) The H (hue) component of a video frame. (c) The S (saturation) component of the video frame. (d) The V (value) component of the video frame. (e) The difference of the S component between the frame and the background. (f) The difference of the V component between the background and the frame.

III. A Novel Moving Cast Shadow Detection Method

In video analysis, shadows are often detected as part of the foreground, which deteriorates the performance of many video analysis tasks. We therefore present in this section a novel moving cast shadow detection method that is able to detect and remove the cast shadows from the foreground.

A. New Chromatic Criteria for Shadow Pixel Detection

As color provides useful information for shadow detection, we present in this section a new method based on a set of new chromatic criteria for shadow pixel detection. After foreground detection, we need to detect the cast shadow pixels in the foreground region. Our new method will apply the new chromatic criteria to detect candidate shadow pixels. As the HSV color space is widely used in shadow detection due to its property of separating the chromaticity from intensity, we choose this color space for shadow detection. Let H, S, and V be the H (hue), S (saturation), and V (value) components in the HSV color space. Let S_f and V_f be the S and V components of a pixel in the foreground region, respectively, and S_b and V_b be

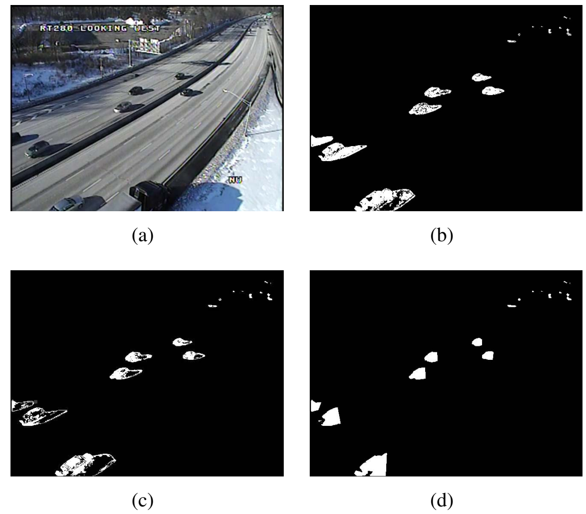

Fig. 2. (a) A video frame from an NJDOT traffic video. (b) The shadow detection results using Huang and Chen's method [12]. (c) The shadow detection results using our new chromatic criteria. (d) The shadow detection results using our shadow region detection method.

the S and V components of the same pixel in the background, respectively. Our new chromatic criteria are defined as follows:

$$\begin{cases} \tau_{sl} < S_f - S_b < \tau_{sh} \\ \tau_{vl} < V_b - V_f < \tau_{vh} \end{cases} \tag{1}$$

where τ_{sl}, τ_{sh}, τ_{vl}, and τ_{vh} represent the thresholds. If a pixel in the foreground region satisfies these chromatic criteria, it is classified as a candidate shadow pixel.

To illustrate the rationale of our new chromatic criteria, we show the difference of the S component between the foreground and the background, and the difference of the V component between the background and the foreground, respectively. In particular, Fig. 1 (a) shows a color video frame, Fig. 1 (b)-(d) display the H (hue), S (saturation), and V (value) components in the HSV color space, Fig. 1 (e) shows the difference of the S component between the foreground and the background, and Fig. 1 (f) shows the difference of the V component between the background and the frame. From Fig. 1 (e) we can see that for the shadow pixels the difference values of the S component between the frame and the background are within a range that can be bounded by two threshold values τ_{sl} and τ_{sh} as shown in Eq. 1. From Fig. 1 (f) we can see that for the shadow pixels the difference values of the V component between the background and the frame also fall into a range that can be bounded by two threshold values τ_{vl} and τ_{vh} as shown in Eq. 1.

B. A New Shadow Region Detection Method

One inherent problem in shadow detection is that the outlines of the shadow region are often classified to the foreground class. As a result, after removing the shadow pixels from the foreground, the shadow regions are only partially removed, and the shadow outlines are often classified to the

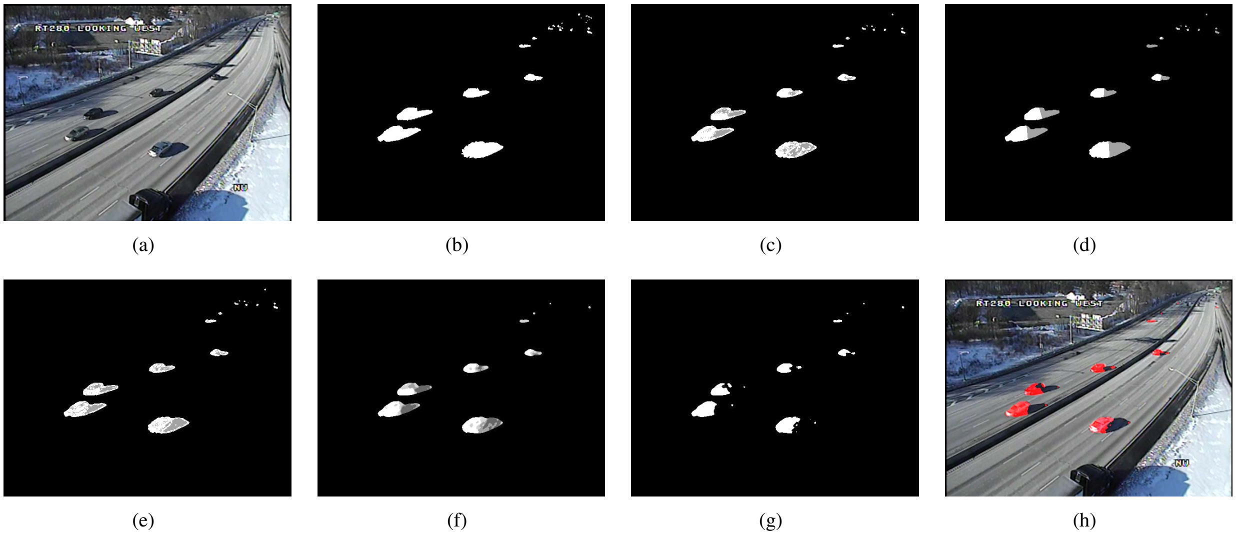

Fig. 3. (a) A video frame from the NJDOT traffic video. (b) The detected foreground (with shadow) using the new foreground detection method. (c) The detected shadow pixels using the new chromatic criteria. (d) The detected shadow regions using the shadow region detection method. (e) The detected shadow pixels using statistical shadow modeling and classification. (f) The detected shadow pixels using the aggregated shadow detection method. (g) The shadow free foreground. (h) The video frame with the foreground in red color.

foreground. Fig. 2 (b) and (c) show the partially removed shadow regions and the shadow outlines that are not removed. These unremoved shadow regions and outlines often deteriorate the performance of video analysis tasks, such as video tracking and incident detection.

To solve this problem, we present a new shadow region detection method based on the prior knowledge that both the foreground objects and their cast shadows should define continuous regions. The idea of our new shadow region detection method is to cluster the shadow pixels and the foreground object pixels into two classes using the centroids of the two classes. Specifically, in each foreground region B, we first find the centroid of the candidate shadow pixels $Cent_S(B)$ and the centroid of the foreground pixels $Cent_O(B)$. We then compute the Euclidean distances between each pixel and the two centroids. We finally classify the pixel into a foreground object class or a shadow class based on the Euclidean distances: if the distance to the foreground object class is smaller, the pixel is assigned to the foreground object class, and vice versa. In particular, for the pixel $\mathbf{x}$ at location (i, j) in each foreground region B, we calculate the distance between the pixel and the shadow centroid $Dist(\mathbf{x}_{ij}, Cent_S(B))$ and the distance between the pixel and the foreground object centroid $Dist(\mathbf{x}_{ij}, Cent_O(B))$, respectively. If $Dist(\mathbf{x}_{ij}, Cent_S(B))$ is smaller, than we classify $\mathbf{x}_{ij}$ into the shadow class. Otherwise, we classify it into the foreground object class. The new shadow region detection method thus detects the candidate shadow regions.

Fig. 2 (a) displays a video frame from an NJDOT traffic video, Fig. 2 (b) shows the shadow detection results using Huang and Chen's method [12], Fig. 2 (c) shows the shadow detection results using the new chromatic criteria introduced in section. III-A, and Fig. 2 (d) shows the shadow detection results using the new shadow region detection method. Fig. 2 (b) and (c) reveal that the outlines of the shadow region are often classified to the foreground class leading to the incorrect shadow detection. In contrast, Fig. 2 (d) shows that our proposed new shadow region detection method is able to detect the whole shadow regions including their outlines.

C. A New Statistical Shadow Modeling and Classification Method

We present in this section a new statistical shadow modeling and classification method. For statistical modeling, we use a single Gaussian distribution to model the shadow class. In the previous two sections, our proposed method using the new chromatic criteria detects candidate shadow pixels and our new shadow region detection method detects the candidate shadow regions. As the shadow pixels detected in both methods tend to be more reliable shadow pixels, we apply these shadow pixels to estimate the Gaussian distribution for the shadow class.

Specifically, let $\mathbb{S}_c$ and $\mathbb{S}_r$ be the candidate shadow pixel sets detected by our proposed method using the new chromatic criteria and our new shadow region detection method, respectively. For each pixel $\mathbf{x}$ in the foreground, if $\mathbf{x} \in \mathbb{S}_c$ and $\mathbf{x} \in \mathbb{S}_r$, we will use $\mathbf{x}$ to update the Gaussian distribution $N_s(\mathbf{M}, \Sigma)$ as follows:

$$\mathbf{M}' = \mathbf{M} - \alpha(\mathbf{M} - \mathbf{x}) \tag{2}$$

$$\Sigma' = \Sigma + \alpha((\mathbf{M} - \mathbf{x})(\mathbf{M} - \mathbf{x})^t - \Sigma) \tag{3}$$

where $\mathbf{M}$ and Σ are the mean vector and the covariance matrix of the shadow Gaussian distribution, respectively. α is a small number which influences the model updating speed.

For shadow pixel classification, we apply the following discriminant function for each pixel $\mathbf{x} \in \mathbb{R}^d$ in the foreground:

$$s(v_i) = (\mu_i - v_i)^2 - p\,\sigma_i \qquad i \in \{1, 2, \ldots, d\} \tag{4}$$

where v_i is the i-th element of the inpute vector $\mathbf{x}$, μ_i is the i-th element of the mean vector $\mathbf{M}$, σ_i is the i-th diagonal element of the covariance matrix Σ, and p is the parameter which determines the threshold. If $s(v_i)$ is greater than zero for any $i \in \{1, 2, \ldots, d\}$, we classify $\mathbf{x}$ into the foreground object class. Otherwise we classify it as a shadow pixel. Our new statistical shadow modeling and classification method thus detects the candidate shadow pixels.

D. Aggregated Shadow Detection

The final step for cast shadow detection is the aggregated shadow detection that integrates the detection results using the new chromatic criteria, the new shadow region detection method, and the new statistical shadow modeling and classification method discussed in the previous three sections. Specifically, we first assign all the pixels in the shadow class a gray scale value of 128, and the pixels in the foreground object class a gray scale value of 255. We then define three weights for the three methods to indicate their significance for the final cast shadow detection: w_c for the new chromatic criteria, w_r for the shadow region detection, and w_s for the statistical modeling. The weights are normalized so that their summation equals one:

$$w_c + w_r + w_s = 1 \tag{5}$$

Note that the larger a weight is, the greater impact the corresponding method exerts to the final shadow detection results. These weights may be trained from some training data, but without any prior information, they may be set to equal values.

For each location (i, j) in the foreground, the gray level $G(i, j)$ is calculated as follows:

$$G(i, j) = w_c C(i, j) + w_r R(i, j) + w_s S(i, j) \tag{6}$$

where $C(i, j)$, $R(i, j)$ and $S(i, j)$ are the values at location (i, j) derived by using the new chromatic criteria, the shadow region detection, and the statistical modeling method, respectively.

In the gray-scale image, the smaller value a pixel has, the more likely it is a shadow pixel. We use a threshold T_s to generate a shadow free binary foreground mask. The binary value B(i,j) at location (i, j) is calculated as follows:

$$B(i, j) = \begin{cases} 0, & if\ G(i, j) < T_s \\ 255, & otherwise \end{cases} \tag{7}$$

Fig. 3 shows the results of our novel cast shadow detection method step by step. Fig. 3 (a) is a video frame from an NJDOT traffic video. Fig. 3 (b) shows the foreground detected using our new foreground detection method. Fig. 3 (c)-(e) show the shadow detection results using the chromatic criteria detection, the shadow regions detection, and the statistical modeling detection. Note that the shadow pixels are indicated using the gray scale value of 128. Fig. 3 (f) shows the gray-scale image generated by the aggregated shadow detection method. Fig. 3 (g) shows the foreground after removing the shadows. Fig. 3 (h) displays the video frame with the foreground in red color.

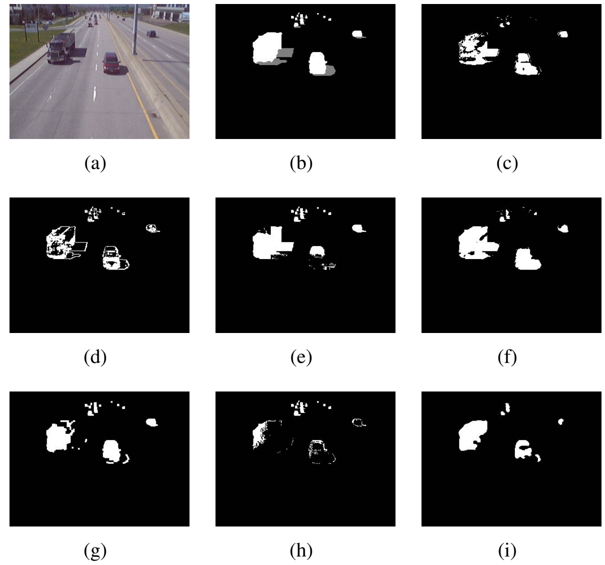

Fig. 4. The foreground masks obtained by different methods. (a). One video frame of 'Highway-3' video. [1] (b). The ground truth of foreground mask. The white parts are the foreground objects. The gray parts are the cast shadows. (c) The shadow free foreground mask of Cucchiara et al.'s method. [6] (d)The shadow free foreground mask of Huang and Chen's method. [12] (e)The shadow free foreground mask of Hsieh et al.'s method. [10] (f)The shadow free foreground mask of Leone and Distante's method. [11] (g)The shadow free foreground mask of Sanin et al.'s method. [13] (h)The shadow free foreground mask of Zhu et al.'s method. [14] (i)The shadow free foreground mask of our proposed method.

IV. Experiments

We first show the quantitative evaluation results using a challenging video, the 'Highway-3' video [1]. This video, which is publicly available and broadly used, facilitates the comparative evaluation of our proposed method with other representative shadow detection methods published in the literature. We then use the New Jersey Department of Transportation (NJDOT) traffic video sequences to evaluate our proposed method qualitatively. Specifically, we apply four NJDOT traffic videos, each of which is 15 minutes with a frame rate of 15 frames per second or fps. The computer we use is a DELL XPS 8900 PC with a 3.4 GHz processor and 16 GB RAM. The 'Highway-3' video has the spatial resolution of 320×240, and it takes 9ms to process each frame using our method. The NJDOT videos have the spatial resolution of 640×482, and it takes 39ms to process each frame using our method. As a result, our proposed shadow detection method is able to perform real time analysis of these videos.

The shadow detection rate η and the F-measure are popular metrics used to evaluate shadow detection performance quan-

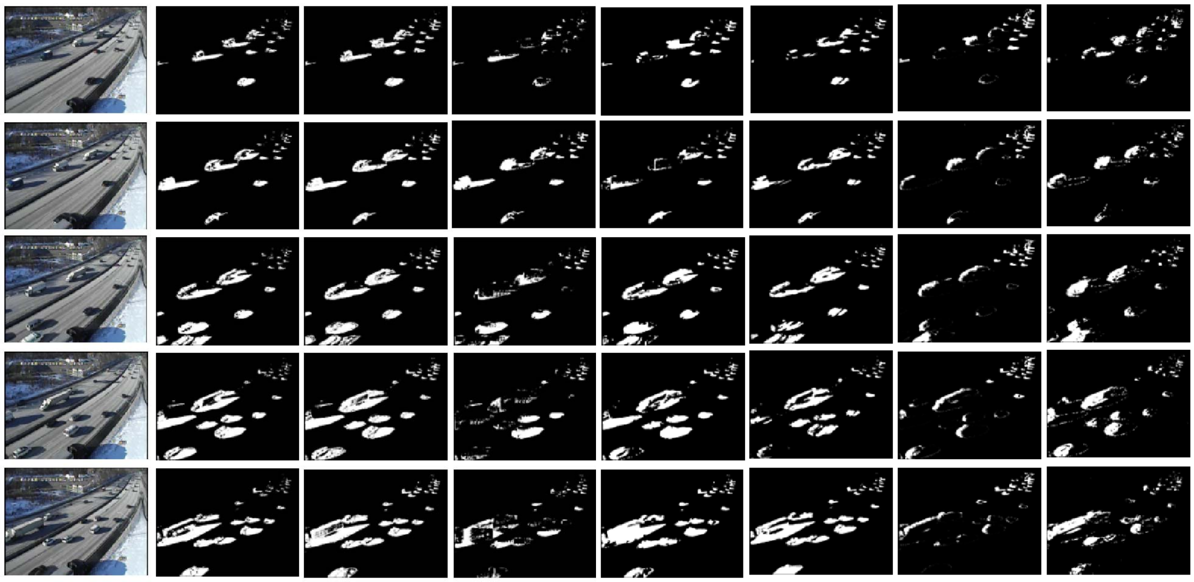

Fig. 5. The comparison of shadow detection performance of different methods. From left to right are the original video frames, the shadow free foreground masks of Cucchiara et al.'s method [6], the shadow free foreground masks of Huang and Chen's method [12], the shadow free foreground masks of Hsieh et al.'s method [10], the shadow free foreground masks of Leone and Distante's method [11], the shadow free foreground masks of Sanin et al.'s method [13], the shadow free foreground masks of Zhu et al.'s method [14], and the shadow free foreground masks of our proposed method, respectively.

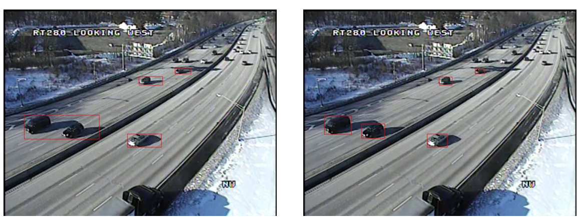

Fig. 6. The comparison of vehicle tracking performance between the tracking result without shadow detection(left) and the result with shadow detection(right).

TABLE I
THE QUANTITATIVE SHADOW DETECTION RESULT OF SOME POPULAR METHODS AND OUR PROPOSED METHOD

Methods	η	ξ	F-measure
Sanin et al. [13]	62%	**91%**	74%
Lalonde et al. [27]	39%	86%	54%
Bullkich et al. [28]	80%	61%	69%
Guo et al. [20]	42%	82%	55%
Gomes et al. [9]	65%	90%	75%
Zhu et al. [14]	88%	32%	46%
proposed	**90%**	76%	**83%**

titatively [26], which are defined as follows: $\eta = \frac{TP_s}{TP_s+FN_s}$, $\xi = \frac{TP_o}{TP_o+FN_o}$, and $F-measue = \frac{2\eta\xi}{\eta+\xi}$, where TP_s and FN_s represent the number of true positive and false negative shadow pixels, respectively, and TP_o and FN_o stand for the number of true positive and false negative foreground object pixels, respectively.

Table. I shows the comparative shadow detection performance of our proposed method and some popular shadow detection methods using the publicly available challenging 'Highway-3' video. In particular, our proposed method achieves the highest shadow detection rate of 90%, and the best F-measure score of 83% compared with the other methods.

Figure. 4 shows the experimental results using a frame from the 'Highway-3' video. We can see from Figure. 4 that our proposed shadow detection method achieves better shadow detection and removal results than the other popular shadow dtection methods.

Another dataset we apply in our experiments is the NJDOT real traffic video sequences. The first column in Fig. 5 shows several frames in the NJDOT traffic video, and each column shows the shadow free foreground mask by using one method. From left to right are the Cucchiara et al.'s method [6], Huang and Chen's method [12], Hsieh et al.'s method [10], Leone and Distante's method [11], Sanin et al.'s method [13], Zhu et al.'s method [14], and our proposed method, respectively. The significance of shadow detection in these videos is to improve the performance of video analysis tasks such as tracking and object detection. In particular, Fig. 6 shows comparatively the vehicle tracking performance using the NJDOT traffic videos: the vehicle tracking results without shadow detection and the vehicle tracking results with shadow detection using our proposed shadow detection method. We can see in the left figure that two vehicles are connected together by their cast shadows and fall into one tracking block when no shadow detection algorithm is applied. After applying our shadow detection algorithm, these two vehicles are separated into two tracking blocks. As a result, the tracking performance is more accurate.

V. Conclusion

We have presented in this paper a novel moving cast shadow detection method in video using new chromatic criteria and statistical modeling. Specifically, we first used a global foreground modeling method (GFM) to detect the foreground, which includes both the foreground object and the shadow. We then presented a new moving cast shadow detection method in video that contains four hierarchical steps. First, a set of new chromatic criteria is proposed for candidate shadow pixel detection. Second, a new shadow region detection method is presented to detect continuous candidate shadow regions. Third, a statistical shadow model is built using a single Gaussian distribution for shadow pixel classification. Fourth, an aggregated shadow detection method is presented to generate the foreground without shadows. The experimental results using the 'Highway-3' video and the NJDOT videos have shown that our proposed method achieves better shadow detection performance than other popular shadow detection methods.

VI. Acknowledgments

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References

[1] A. Sanin, C. Sanderson, and B. C. Lovell, "Shadow detection: A survey and comparative evaluation of recent methods," *Pattern recognition*, vol. 45, no. 4, pp. 1684–1695, 2012.

[2] R. Mahajan and A. Bajpayee, "A survey on shadow detection and removal based on single light source," in *2015 IEEE 9th International Conference on Intelligent Systems and Control (ISCO)*, Jan 2015, pp. 1–5.

[3] T. Bouwmans, A. Sobral, S. Javed, S. K. Jung, and E. Zahzah, "Decomposition into low-rank plus additive matrices for background/foreground separation: A review for a comparative evaluation with a large-scale dataset," *Computer Science Review*, vol. 23, pp. 1–71, 2017.

[4] T. Bouwmans, C. Silva, C. Marghes, M. S. Zitouni, H. Bhaskar, and C. Frelicot, "On the role and the importance of features for background modeling and foreground detection," *Computer Science Review*, vol. 28, p. 2691, 05 2018.

[5] A. Boulmerka and M. S. Allili, "Foreground segmentation in videos combining general gaussian mixture modeling and spatial information," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 28, no. 6, pp. 1330–1345, June 2018.

[6] R. Cucchiara, C. Grana, M. Piccardi, and A. Prati, "Detecting moving objects, ghosts, and shadows in video streams," *IEEE transactions on pattern analysis and machine intelligence*, 2003.

[7] E. Salvador, A. Cavallaro, and T. Ebrahimi, "Cast shadow segmentation using invariant color features," *Computer vision and image understanding*, vol. 95, no. 2, pp. 238–259, 2004.

[8] C.-T. Chen, C.-Y. Su, and W.-C. Kao, "An enhanced segmentation on vision-based shadow removal for vehicle detection," in *2010 International Conference on Green Circuits and Systems (ICGCS)*. IEEE, 2010, pp. 679–682.

[9] V. Gomes, P. Barcellos, and J. Scharcanski, "Stochastic shadow detection using a hypergraph partitioning approach," *Pattern Recognition*, vol. 63, [illegible] 2017.

[10] J.-W. Hsieh, W.-F. Hu, C.-J. Chang, and Y.-S. Chen, "Shadow elimination for effective moving object detection by gaussian shadow modeling," *Image and Vision Computing*, vol. 21, no. 6, pp. 505–516, 2003.

[11] A. Leone and C. Distante, "Shadow detection for moving objects based on texture analysis," *Pattern Recognition*, vol. 40, no. 4, pp. 1222–1233, 2007.

[12] J.-B. Huang and C.-S. Chen, "Moving cast shadow detection using physics-based features," in *IEEE Conference on Computer Vision and Pattern Recognition, 2009. CVPR 2009.* IEEE, 2009, pp. 2310–2317.

[13] A. Sanin, C. Sanderson, and B. C. Lovell, "Improved shadow removal for robust person tracking in surveillance scenarios," in *2010 20th International Conference on Pattern Recognition (ICPR).* IEEE, 2010, pp. 141–144.

[14] L. Zhu, Z. Deng, X. Hu, C.-W. Fu, X. Xu, J. Qin, and P.-A. Heng, "Bidirectional feature pyramid network with recurrent attention residual modules for shadow detection," in *ECCV*, 2018.

[15] A. Prati, I. Mikic, M. M. Trivedi, and R. Cucchiara, "Detecting moving shadows: algorithms and evaluation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 7, pp. 918–923, July 2003.

[16] B. Sun and S. Li, "Moving cast shadow detection of vehicle using combined color models," in *2010 Chinese Conference on Pattern Recognition (CCPR).* IEEE, 2010, pp. 1–5.

[17] A. Amato, M. G. Mozerov, A. D. Bagdanov, and J. Gonzalez, "Accurate moving cast shadow suppression based on local color constancy detection," *IEEE Transactions on Image Processing*, vol. 20, no. 10, pp. 2954–2966, Oct 2011.

[18] S. Nadimi and B. Bhanu, "Physical models for moving shadow and object detection in video," *IEEE Transactions on Pattern Analysis & Machine Intelligence*, vol. 26, no. 8, pp. 1079–1087, 2004.

[19] Y. Wang, "Real-time moving vehicle detection with cast shadow removal in video based on conditional random field," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 19, no. 3, pp. 437–441, March 2009.

[20] R. Guo, Q. Dai, and D. Hoiem, "Paired regions for shadow detection and removal," *IEEE Transactions on Pattern Analysis & Machine Intelligence*, vol. 35, no. 12, pp. 2956–2967, 2013.

[21] T. F. Y. Vicente, M. Hoai, and D. Samaras, "Leave-one-out kernel optimization for shadow detection and removal," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 3, pp. 682–695, March 2018.

[22] Y. Wang, X. Zhao, Y. Li, X. Hu, K. Huang, and N. CRIPAC, "Densely cascaded shadow detection network via deeply supervised parallel fusion." in *IJCAI*, 2018, pp. 1007–1013.

[23] H. Le, Y. Vicente, F. Tomas, V. Nguyen, M. Hoai, and D. Samaras, "A+ d net: Training a shadow detector with adversarial shadow attenuation," in *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 662–678.

[24] H. Shi and C. Liu, "A new foreground segmentation method for video analysis in different color spaces," in *24th International Conference on Pattern Recognition*. IEEE, 2018.

[25] ——, "A new global foreground modeling and local background modeling method for video analysis," in *International Conference on Machine Learning and Data Mining in Pattern Recognition*. Springer, 2018, pp. 49–63.

[26] W. Ji and Y. Zhao, "Moving cast shadow detection using joint color and texture features based on direction and distance," in *2016 2nd IEEE International Conference on Computer and Communications (ICCC).* IEEE, 2016, pp. 439–444.

[27] J.-F. Lalonde, A. A. Efros, and S. G. Narasimhan, "Detecting ground shadows in outdoor consumer photographs," in *European Conference on Computer Vision (ECCV).* Springer, 2010, pp. 322–335.

[28] E. Bullkich, I. Ilan, Y. Moshe, Y. Hel-Or, and H. Hel-Or, "Moving shadow detection by nonlinear tone-mapping," in *2012 19th International Conference on Systems, Signals and Image Processing (IWSSIP).* IEEE, 2012, pp. 146–149.