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NOVEL APPROACH FOR DETECTION AND REMOVAL OF MOVING CAST SHADOWS BASED ON RGB, HSV AND YUV COLOR SPACES

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Abstract. Cast shadow affects computer vision tasks such as image segmentation, object detection and tracking since objects and shadows share the same visual motion characteristics. This unavoidable problem decreases video surveillance system performance. The basic idea of this paper is to exploit the evidence that shadows darken the surface which they are cast upon. For this reason, we propose a simple and accurate method for detection of moving cast shadows based on chromatic properties in RGB, HSV and YUV color spaces. The method requires no a priori assumptions regarding the scene or lighting source. Starting from a normalization step, we apply canny filter to detect the boundary between self-shadow and cast shadow. This treatment is devoted only for the first sequence. Then, we separate between background and moving objects using an improved version of Gaussian mixture model. In order to remove these unwanted shadows completely, we use three change estimators calculated according to the intensity ratio in HSV color space, chromaticity properties in RGB color space, and brightness ratio in YUV color space. Only pixels that satisfy threshold of the three estimators are labeled as shadow and will be removed. Experiments carried out on various video databases prove that the proposed system is robust and efficient and can precisely remove shadows for a wide class of environment and without any assumptions. Experimental results also show that our approach outperforms existing methods and can run in real-time systems.

Keywords: Computer vision, shadow detection, chromaticity, GMM

1 INTRODUCTION

Computer vision systems dedicated to video processing require some paramount procedures sash as detection and tracking of moving objects. When the objects of interest have a well-defined shape, the advanced classifiers can be used to segment objects directly from the image. These techniques work well for objects with well-defined contours, but are difficult to carry out for objects with flexible contour. Gaussian mixtures model (GMM) are among the most commonly used approaches for detecting moving objects in a video sequence. However, GMM generally have one major drawback, shadows tend to be classified as part of the foreground leading to confusion between the object and its shadow. Indeed, shadows share the same movement patterns and have intensity change similar to moving objects, which influences video surveillance systems performance.

In recent years, many works have been published to solve the problem of detecting and removing shadows, and the contributions reported in the literature can be organized into three types: those whose works focus on algorithms [1], others according to the relationship between object/environment and implementation domain [2], and the latest based on choice of relevant characteristics [3]. Prati et al. [1] have regrouped related works into two main classes: statistical algorithms with versions both parametric [4] and non-parametric [5], and deterministic algorithms with model-based approach [6] and non-model-based approach [7]. Another point of view is proposed by Al-Najdawi et al. [2] to categorize the contributions according to a new taxonomy based on dependence between methods and objects [8, 9, 10, 11, 12], methods and environment [13, 14, 15] or on both [16, 7]. Sanin et al. [3] observed that the choice of features has a great influence on the results compared to the choice of algorithms, and proposed a new taxonomy composed of two essential categories: spectral and spatial characteristics. Moreover, spectral characteristics are divided into intensity [14, 17], chromaticity [4, 7, 18, 19] and physical properties [20]; spatial characteristics are split into geometry [21, 22, 23] and textures [24, 25].

The importance given to this field has prompted researchers to offer a large amount of approaches to solve shadow problems in videos. However, the proposed approaches give results only in very specific and well-defined environments [1]. In addition, the conditions imposed by the authors for the proper functioning of these systems restrict their use in wide public environments. Comparative studies in the literature have shown that the results quality obtained by the spatial characteristics is higher than spectral characteristics. However, the spatial characteristics consume much computation time and need more memory space, which limits their use in real-time and on machines with low power. Conversely, the spectral characteristics offer high execution speed, but have the inconvenience to be sensitive to change in light intensity and they give bad results when objects have an intensity or color like shadow. To avoid the problems outlined above, we propose a novel method for detecting and removing shadows in video surveillance taken from a fixed camera. The approach is based on chromatic properties in RGB, HSV and YUV color spaces. We also implemented Large Region texture-based method (LR) presented by Sanin et al. [3] and in which they showed that LR method gives better results compared with proposed methods in literature. The rest of this paper is organized as follows. Section 2 presents an overview of the shadow model. Section 3 describes in detail the proposed approach. Comparative experimental results are analyzed in Section 4. Finally, conclusion and perspectives are given in Section 5.

2 SHADOW

When light strikes an opaque object it is scattered, absorbed or reflected, but at the back of the object light does not pass, it is a shadow area. So we can say that shadow is a dark area created by the interposition of an opaque object between a light source and the surface on which the light is reflected. This shadow takes a shape of a silhouette without thickness which depends on the source intensity and its location relative to the object. There are four types of shadows (Figure 1, [26]):

- The attached shadow is a region of the object that receives no light. It is located behind the object, in the area where the light from the source does not arrive.
- The umbra is a region of space where the light rays from the source do not pass because they are stopped by the object.
- The cast shadow is a region of a screen placed behind an object relative to the light source and not receiving radius. The size and shape of the cast shadow depend on the shape, size and position of the object relative to the source, but also depend on the location and angle of the screen.
- The penumbra is a border area that appears between the illuminated part and the shade part.

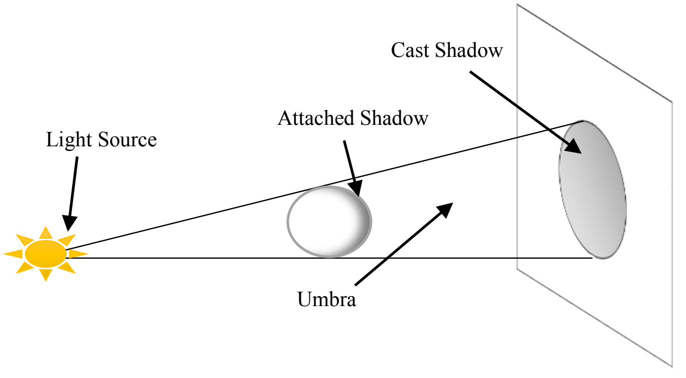

Figure 1. Shadow type representation

3 PROPOSITION

The ability to extract moving objects from a video sequence is a crucial issue in many video surveillance systems. The primary role of image processing operations in such system is not the correct detection of the object details, but the robust detection of shapes in motion. Unfortunately, these shapes are generally deformed by their own shadow. In addition, in dynamic scenes, all pixels of moving objects or shadows are detected at the same time, shadows and objects share the same visual motion characteristics. Taking into account of all the considerations mentioned before, we propose a simple and reliable method able to detect and remove shadows generated by one or more light sources. Figure 2 shows the overall architecture of our system.

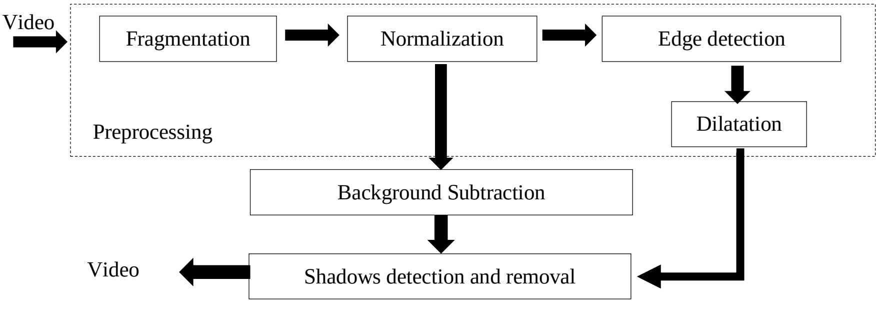

Figure 2. Architecture of the proposed system

3.1 Preprocessing

Preprocessing involves four steps: First thing to do is segment the video stream into frames, where each frame represents an image of the video. Then all frames are normalized to avoid disparities in size among the images taken by different cameras. In the next step, canny filter is used to detect edges that will serve to segment the image into a set of connected components and to separate between the attached shadow and cast shadow. Finally, the size of edges is increased using morphological to remove any discontinuities.

3.2 Background Subtraction

Tracking moving objects is hard task to realize in automated video surveillance systems. In literature, there are two distinct contributions: Influence of discriminative power of the features on system performance and the separation algorithm between foreground and background with better variations management. Generally, a good separation algorithm simplifies the further treatments, reduces run time and consumes less memory space. Among the research conducted in this field, works done in [27] showed that GMM offers a good compromise between extraction quality and runtime compared to other background subtraction methods. Despite their widespread use in various applications, they still suffer from some problems such as local variations, the instantaneous variations in brightness as well as the background complexity [27]. For background subtraction, we use an improved GMM approach proposed in [28]. The following algorithm illustrates the process used for background subtraction.
Algorithm:

Initialization:
- Split the first image into several equal size areas
- Assign a thread for each area
- Convert all the image pixels from RGB to HSV
- Calculate and store the color histogram of each zone
- Initialize the GMM parameters

Iteration
- FOR each new frame
  - Convert all image pixels from RGB to HSV
  - FOR each area
    - Calculate the color histogram
    - Measure the similarity degree between the calculated histogram and the stored one
    - If the difference is greater than a threshold T
      - Memorize the new histogram
      - Updating the GMM parameters

```
            END IF
        END FOR
    END FOR
```

3.3 Shadows Detection and Removal

In the literature several color spaces have been used to model separately the brightness and chromaticity. Usually, the systems using chromaticity as a criterion for detecting and removing shadows choose an adequate color space that allows a natural separation between intensity and chromaticity. In the current process, we use RGB, HSV and YUV color spaces reported as the most robust among others to detect the shadow [2, 3]. Each color space is presented to better understand its effect on the shadow.

- RGB color space is the vector space generated by the three primary components Red, Green and Blue. It is the basic color space. It easily allows switching from one space to another, but it does not explain the influence of brightness and saturation on color because their change affects all basic components.
- HSV color space characterizes the colors with more intuitive way, in accordance with natural color perception. The hue (H) is the name used to describe the color conveniently associated with a wavelength. Saturation (S) is the color purity level, which should be between the maximum purity (bright color) and achromatic (gray level). The value (V) is the color light-intensity measure, which should be between the absolute black and white.
- YUV color space represents colors by using a luminance component Y, and two chrominance components U and V. The luminance component Y is a weighted average of relative human sensitivity to primary colors. The chrominance components (U and V) are the contrast blue/yellow and the contrast red/cyan. YUV color space provides a natural separation between the chromaticity and brightness.

We conducted several studies and experiments to understand the shadow impact on colors. The obtained results led to the following remarks:

- Shadows density is the most relevant and the most difficult characteristic for modeling the shade.
- The shadow depends on the amount of light reflected by the surface on which the shadow is projected.
- In HSV color space, shadow does not change the hue of the color, but tends to decrease the value (V) and the saturation (S) components; for example, if a red object is covered by shadow it becomes dark-red which is darker than red but remains red.
- The shadow effect on the values of the three components R, G and B in RGB space disturbs indirectly the values of H and S components in HSV space sup-

posed invariant to light intensity change. The changeover from RGB to HSV color space makes modeling the shadow effect on colors more difficult.

- Using one color space is not enough to express all changes made by adding shadow on color.
- The value of Y component in YUV color space is the best light-intensity direct measurement to model the shadow effect.
- The shadows effect on objects causes the same change degree to the three components of RGB color space. This condition is necessary but not sufficient to deduce that there is a shadow.

Proposed solutions:
To detect and remove moving shadows, using a background model as reference is required. For each new frame we extract moving objects, and then we calculate the change degree of pixels values for all components in RGB, HSV and YUV color spaces. This process is guaranteed by calculating the ratio change between pixels values in the background model (BG) and the pixels values of current frame (F) using the following empirical equations. The ratio change of R, G and B components in RGB color space are described by Equations (1), (2) and (3):

$$RC_R = \frac{R_{BG} - R_F}{R_{BG}}, \tag{1}$$

$$RC_G = \frac{G_{BG} - G_F}{G_{BG}}, \tag{2}$$

$$RC_B = \frac{B_{BG} - B_F}{B_{BG}} \tag{3}$$

where (R_{BG}, G_{BG}, B_{BG}) and (R_F, G_F, B_F) are the pixels values for red, green and blue components in RGB color space. The ratio change of hue and saturation in HVS color space are described by Equations (4) and (5):

$$RC_H = H_F - H_{BG}, \tag{4}$$

$$RC_S = S_F - S_{BG} \tag{5}$$

where (H_{BG}, S_{BG}) and (H_F, S_F) are the pixels values for hue and saturation components in HSV color space. The ratio change of luminance component in YUV color space is given by Equation (6):

$$RC_Y = \frac{Y_{BG} - Y_F}{Y_{BG}} \tag{6}$$

where (Y_{BG}, Y_F) are the pixels values for luminance component in YUV color space. Based on the remarks mentioned above, a pixel is considered part of the shadow if it satisfies simultaneously the following three rules:

$$|RC_R - RC_G| < 3 \quad \text{and} \quad |RC_B - RC_G| < 3 \quad \text{and} \quad |RC_R - RC_B| < 3, \tag{7}$$

$$RC_H < P1 \quad \text{and} \quad RC_S < P2, \tag{8}$$

$$0 < RC_Y < RC_H - RC_S \tag{9}$$

where $P1$, $P2$ represent thresholds optimized empirically.

4 EXPERIMENTS

4.1 Settings

The algorithms presented in this paper are implemented in Java on a computer with an Intel Core i5 2.67 GHz and a 4 GB memory capacity. This section seeks to highlight the results obtained from tests performed on videos. The used videos are different with respect to the contexts, light intensity, fluctuations in objects, number and kind of objects, movements caused by nature elements (clouds, dust and noise), and camera movements. To rate system performance we used four databases in which three are public.

The first one (DBA) has six videos taken in four environments representing: a campus, a highway (I, I2 and II), an intelligent room and a laboratory [1]. The second (DBB) is constituted of nine videos representing: a bootstrap, a campus, a curtain, an escalator, a fountain, a hall, a lobby, a shopping mall and a water surface [29]. The third (DBC) has two videos representing: a highway and a hallway [30]. Our own database (DBD) is constituted of four environments representing a campus, a hallway, a highway and a public park where each environment is taken with three videos. Each sequence gives a new challenge to our method for detecting shadows and for testing robustness. Table 1 shows some details about the used videos in the test.

4.2 Performance Evaluation

In-depth comparative works done by Sanin et al. [3] showed that the method based on large region texture (LR) gives better results compared to other methods. *In all cases, the large region texture-based method performs considerably better than all the others, obtaining high values for both the detection and discrimination rates in all sequences.* For this reason and to better situate our approach over what exists in the state of the art, we implemented the LR method which will be used as a reference method.

4.2.1 Qualitative Results

In this section we present some qualitative results performed on video databases mentioned above. For a good visual comparison, the blue color areas show the

Data Base	Environment	Number of Frame	Resolution	Length (mn)	Frame Rate (frame/s)
DBA	Campus	1178	352 × 288	01:57	10
	Highway I	439	320 × 240	00:29	10
	Highway I2	439	320 × 240	00:29	14
	Highway II	499	320 × 240	00:33	14
	Intelligent room	299	320 × 240	00:30	10
	Laboratory	886	320 × 240	01:28	10
DBB	Bootstrap	3054	160 × 120	/	/
	Campus	2438	160 × 120	/	/
	Curtain	23963	160 × 120	/	/
	Escalator	4814	160 × 130	/	/
	Fountain	1522	160 × 128	/	/
	Hall	4583	176 × 144	/	/
	Lobby	2545	160 × 128	/	/
	Shopping Mall	2285	320 × 256	/	/
	Water surface	1632	160 × 128	/	/
DBC	Hallway	1799	320 × 240	03:00	10
	Highway III	2055	320 × 240	03:42	10
DBD	Campus	526 896 896	320 × 240	00:17 01:30 02:38	30
	Hallway	616 893 382	640 × 480	00:20 00:29 00:12	29
	Highway	1210 420 896	640 × 480	00:40 00:14 00:29	29
	Public Park	559 585 555	640 × 480	00:18 00:19 00:18	29

Table 1. Description of used databases

detected shadow on the target image and the shadow mask in the neighbor frame. The sequences of images below show the shadow detection in indoor/outdoor videos taken under different constraints, noise and light intensity variations.

It is clear to see (Figure 3) that our approach can detect shadows for all moving objects without any prior assumptions about the nature of the environment or on the moving objects and produces better results compared to LR method. In frame 275, one can notice that textures have failed to distinguish between the object and its shadow. The frame 135 shows that our system can differentiate between cast shadow and attached shadow, which is not the case in systems based on LR.

In Figure 4, the first video was taken into Guelma University campus in a sunny day with frequent cloud passage. This phenomenon creates an instant brightness

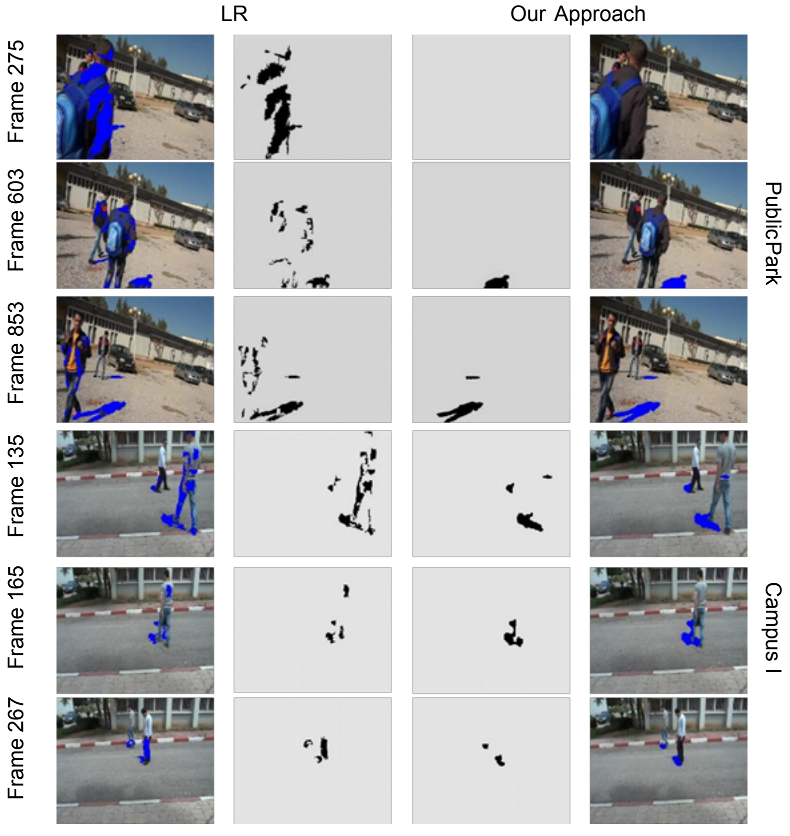

Figure 3. Shadow detection of multiple moving objects in an outdoor environment with multiple variations

change affecting all background colors. Once again, results show the effectiveness of this approach and its adaptability to multiple color changes in the background. The second video was taken into a highway with the same conditions as the first video. The frames 339 and 347 show that LR method cannot distinct between cast shadow and attached shadow, and also has completely distorted the moving object when removing shadows, while our system has perfectly separated the shadow from object in both frames.

Even in partially dark environments with light reflection effects on the wall and floor, our method is effective as shown in three frames (Figure 5). Frame 23 shows that our method differentiates between attached shadow and cast shadow. Therefore it possesses a superior performance than LR method.

These frames (Figure 6) highlight the ability of our system to detect shadows in public video databases. The frame 248 shows that the proposed method is able to

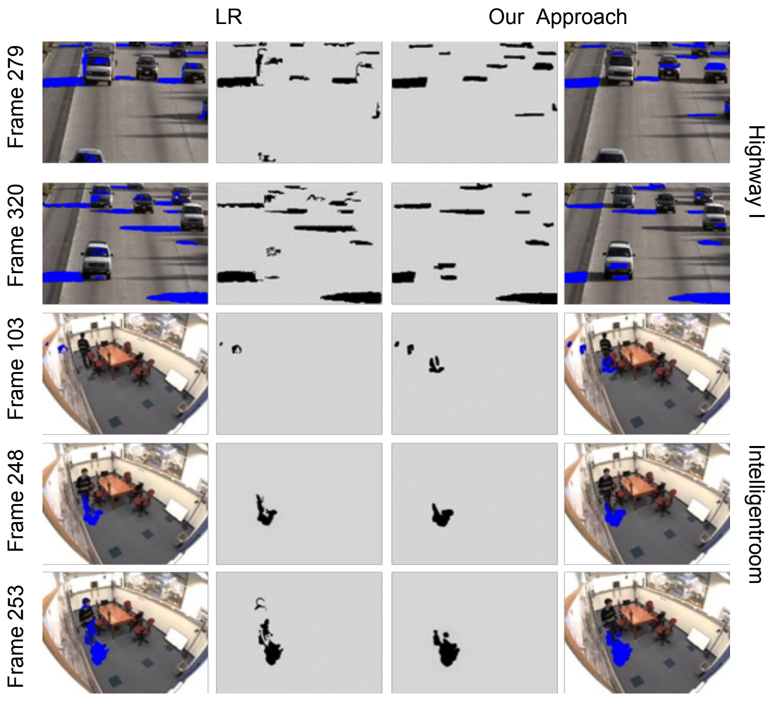

Figure 4. Shadow detection of a single moving object with brightness variations in environment

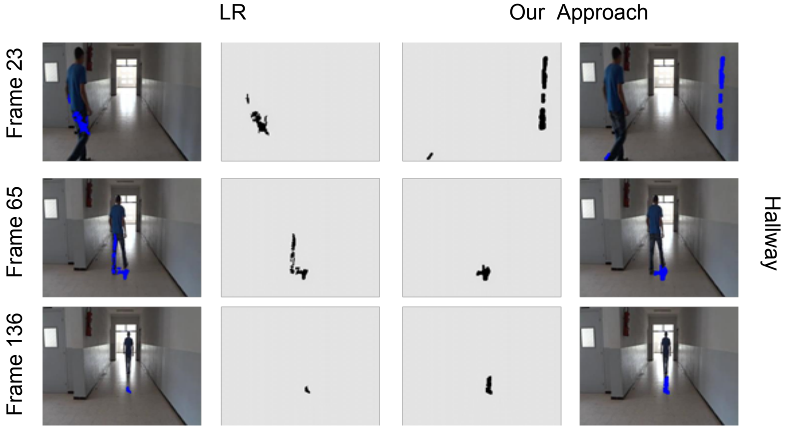

Figure 5. Shadow detection in a dark indoor environment with reflection effects

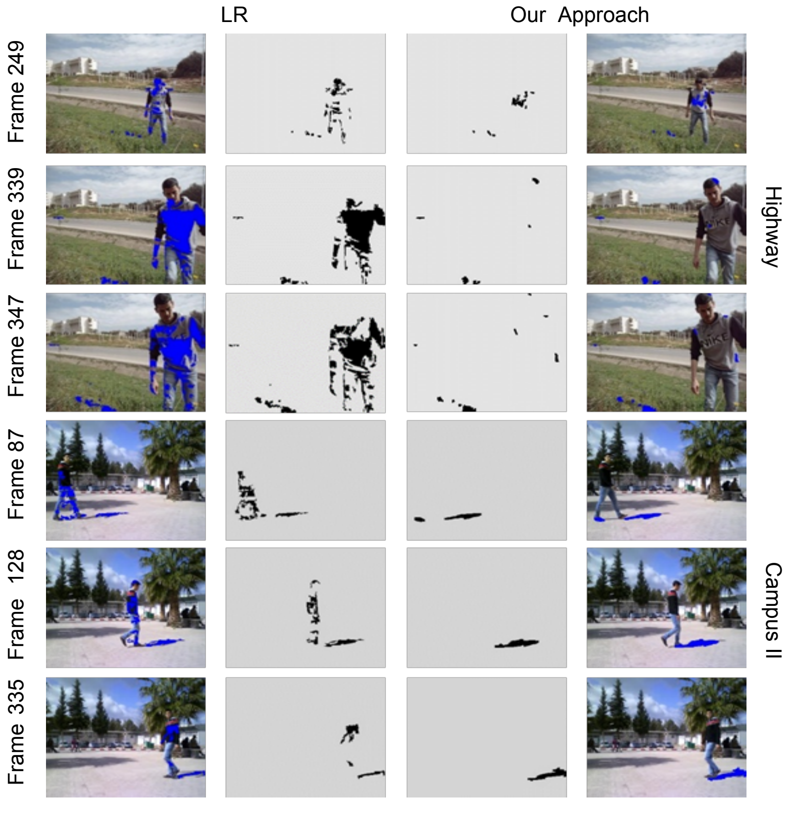

Figure 6. Shadow detection in DBA database

detect completely shadow in the case where the floor color is substantially similar to shadow color. This scenario is one of the most difficult cases to treat in chromaticity-based method.

In summary, the qualitative results presented through these experiments show that our approach is effective without any assumptions on the nature of the environment, image quality, and light variations or color. Further, it outperforms LR method almost in all considered videos.

4.2.2 Quantitative Results

In order to evaluate quantitatively shadow detection, we used two metrics [1]. The shadow detection rate η, which indicates how well the algorithm detects shadows. The shadow discrimination rate ξ, which describes how the system can differentiate between shadows and foreground pixels. They are evaluated by Equations (10) and (11), respectively. For further evaluation, we also calculated the processing time per sequence for each method.

$$\eta = \frac{TP_S}{TP_S + FN_S}, \tag{10}$$

$$\xi = \frac{\overline{TP_F}}{TP_F + FN_F} \tag{11}$$

where TP is the true positive pixels representing the number of pixels correctly detected and the FN is the false negative pixels representing the number of pixels incorrectly detected. Subscripts S and F denote shadow and foreground, respectively. $\overline{TP_F}$ is the correct number of points on foreground objects minus the number of points on foreground objects marked as shadow. TPS and FNS are calculated according to ground-truth shadows pixels; TP_F and FN_F are calculated using ground-truth objects pixels.

To test and evaluate the performances of the proposed approach in our video data base (DBD), a ground truth data set is also necessary. Objects ground truth and cast shadows ground truth are obtained by manually labeling objects and cast shadows after extracting backgrounds with GMM. During producing ground truth data set for the captured videos, we noticed that labeling shadows is a hard task to accomplish accurately especially in the scene where floor or objects color is similar to shadow. For giving more credibility to tests, all frames are taken randomly to produce ground truth data set. Public video ground truth for DBA, DBB and DBC are available respectively in [1, 29, 30].

A selection of well-known methods is compared to our method in terms of quantitative measures. Seventeen selected methods were evaluated quantitatively based on η and ξ.

Table 2 compares the result obtained by our method with results achieved by the other methods. The experimental results show that our method provides both a good detection and discrimination rate relative to other methods. However, we cannot draw deep conclusions because improving shadow detection performance is proportional to improvement in background subtraction performance.

For rational comparison, we also implemented the LR method using the same background subtraction method as proposed in our approach. The comparison results are shown in Table 3. Quantitative results clearly show that the proposed system allows both good detection with an average of 91.37 % and better discrimination with an average of 95.98 %, which means that our method obtained a gain of 3.44 % in detection and 7.98 % in discrimination relative to the LR method [3].

We note that there is a drop in performance especially in Highway I and Highway III videos due to a poor contours detection. The qualitative results also showed this decreased performance because our system has badly detected edges between the object and its shadow. In return, the LR method gives good shadow detection with a stable performance in all cases. However, discrimination is a little weak due to non-availability of discriminative texture in the treated cases.

	Highway I		Intel-Room		Laboratory		Campus	
	$\eta\%$	$\xi\%$	$\eta\%$	$\xi\%$	$\eta\%$	$\xi\%$	$\eta\%$	$\xi\%$
Mikic[31]	59.59	84.70	76.27	90.74	64.85	95.39	72.43	74.08
Haritaoglu[32]	81.59	63.76	72.82	88.90	84.03	92.35	82.87	86.65
Cucchiara[33]	69.72	76.93	78.61	90.29	76.26	89.87	82.87	86.65
Stauder[34]	75.49	62.38	62.00	93.89	60.34	81.57	69.10	62.96
Salvador[35]	71.82	79.29	73.45	86.52	88.24	93.57	72.4	72.4
Martel.Brisson[36]	75.43	74.67	73.60	79.10	76.62	75.14	66.2	72.3
Al-Najdawi[37]	N/A	N/A	87.24	95.85	90.22	92.83	90.67	93.34
Horprasert[38]	N/A	N/A	72.82	88.90	84.03	92.35	80.58	69.37
Joshi[39]	88.21	97.00	91.02	97.66	N/A	N/A	N/A	N/A
Jung[40]	N/A	N/A	97.67	86.21	85.84	95.1	87.69	92.18
Zhang[41]	67.17	90.19	88.63	88.97	86.28	92.64	87.95	97.74
Siala[42]	83.30	68.92	N/A	N/A	N/A	N/A	N/A	N/A
Song[43]	76.86	80.52	N/A	N/A	N/A	N/A	N/A	N/A
Martel.Brisson[44]	72.10	79.70	N/A	N/A	N/A	N/A	N/A	N/A
Celik[45]	79.74	90.07	86.24	98.96	67.18	96.52	N/A	N/A
Choi[46]	84.98	88.97	95.01	91.39	90.63	94.00	N/A	N/A
Proposed method	79.29	98,78	93,15	96,39	95,39	98,92	95,55	96,68

Table 2. Comparison of the proposed method with quantitative evaluation

Data Base	Videos	Shadow Detection Rate ($\eta\%$)		Shadow Discrimination Rate ($\xi\%$)	
		LR	Our Method	LR	Our Method
DBA	Campus	89.63	95.55	92.93	96.68
	HighwayI	87.93	79.29	93.25	98.78
	Intelligentroom	90.19	93.15	88.14	96.39
	Laboratory	87.13	95.39	92.67	98.92
DBB	Bootstrap	77.86	84.06	91.89	96.73
	Campus	88.63	88.93	91.95	96.99
	Fountain	88.91	90.73	89.94	97.46
	Hall	86.27	89.66	82.91	95.07
DBC	Hallway	91.75	91.39	90.92	93.01
	HighwayIII	66.60	79.08	89.94	94.68
DBD	Campus	88.2	96.77	77.88	97.98
	Hallway	86.8	91.47	95.80	96.57
	Highway	86.52	94.28	68.95	89.52
	PublicPark	89.17	97.44	84.96	95.05
Average		87.93	91.37	88.00	95.98

Table 3. Comparison of the proposed method with LR method in both public and personal video data base

Table 4 shows that our method consumes less time compared to the LR method although both algorithms have the same operations complexity.
This is due to the extra steps required by the LR method to produce the candidate shadow regions and to calculate the gradients for each pixel. For further comparison, we computed the processing time.

	LR (ms/frame)	Our Method (ms/frame)
Campus	10.76	4.72
HighwayI	27.71	7.73
Intelligentroom	6.25	4.14
Laboratory	12.73	4.95
Bootstrap	7.35	2.56
Campus	8.69	2.76
Fountain	8.27	2.23
Hall	4.8	1.98
Hallway	13.59	4.13
HighwayIII	4.75	2.82
Campus	23.79	7.2
Hallway	22.07	5.67
Highway	22.66	7.01
PublicPark	22.43	6.44
Average	13.99	4.6

Table 4. Processing time calculated in milliseconds per frame for all used video databases

5 CONCLUSIONS

The paper proposes an effective method based on RGB, HSV and YUV color models to detect and remove shadows of moving objects in both indoor and outdoor environment and without any prior assumptions on illumination conditions.

In our method, we first applied canny algorithm to detect the boundaries for objects and shadows. This information is used later as a criterion to separate between attached and cast shadows. After extracting moving objects with an improved Gaussian mixture model, we used three criteria calculated in RGB, HSV and YUV color space to decide if a pixel belongs to shadow or to an object and to remove cast shadows.

Through the experiments and analysis, our results show an enhancement in detecting shadows compared to the existing methods. They also show the algorithm ability to deal with textured surfaces and complex environments which fall beyond the scope of numerous shadow detection methods.

The low complexity of the proposed algorithms can also save significant processing time for probable use in real time applications. Unfortunately, our method may fail to detect shadows since the latter is miss classed and considered as attached shadows if the boundaries cannot be well defined. However, the performance can be improved with a sophisticate edge detection method. Our conclusions are supported by both quantitative and qualitative experiments on shadow detection carried out on various video databases.

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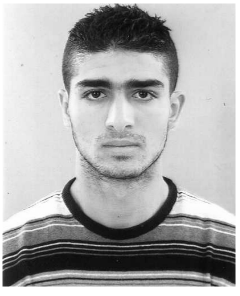

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