A Method for Shadow and Highlight Removal in Nonparametric Moving Object Detection Strategies

Virginia Pascual, Carlos Cuevas, and Narciso García
Grupo de Tratamiento de Imágenes, Universidad Politécnica de Madrid, Spain

***Abstract*—An efficient algorithm for shadow and highlight removal in nonparametric moving object detection strategies is proposed. By the nonparametric modeling of the variations of the brightness and the chromaticity along the sequences, shadows and highlights are identified. In this way, the quality of the detections is significantly improved.**

I. Introduction

The demand for new applications for computer vision tools (e.g. video-surveillance, military, traffic monitoring, etc.) is rapidly increasing [1]. Moving object detection is a very important stage in these applications, since it is used for tasks such as classification, tracking, or event detection.

Along the last decades several strategies to efficiently detect moving objects have been proposed [2]. Among the wide range of proposed detection methods, three of them have been extensively used by several authors in the literature: The Running Gaussian Average (RGA) algorithm, the Gaussian Mixture Models (GMMs), and the nonparametric modeling (NPM) methods. On the one hand, RGA-based strategies are very fast and provide satisfactory results in short sequences recorded in simple and indoor scenarios [3]. On the other hand, GMM-based and NPM-based algorithms are able to model correctly the variations of dynamic backgrounds. So, they provide high-quality detections in a larger variety of scenarios [4]. While GMM-based methods have probably been the most used, NPM methods are those that have drawn more attention from the researches along the last years, since they provide the best quality detections even in sequences with very complex and dynamic background.

The presence of shadows and highlights in the video sequences usually results in a drastic decrease of the quality of the detections provided by all these strategies, since many shadows and highlights are erroneously detected as moving objects [5]. To avoid this important drawback, some strategies to remove shadows and highlights from the detections have been proposed [6]. Among these strategies, it must be highlighted that proposed in [7], since it has been applied repeatedly both on RGA-based and GMM-based algorithms. However, although the NPM methods are those which seem to provide the highest quality detections, to our knowledge, there are no methods specifically adapted for the suppression of shadows and highlights resulting from their use.

We propose a novel and high-quality shadow and highlight removal algorithm particularly adapted to NPM-based detection strategies. This method, taking as starting point the strategy in [7], constructs a nonparametric model of the brightness and chromaticity distortions along the sequences, improving significantly the quality of the results provided by not only previous nonparametric methods but also GMM-based and RGA-based strategies. Additionally, it reduces the influence on the results of the values of the parameters that must be manually selected by the users. Therefore, our strategy also improves the usability of previous approaches.

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II. Proposed strategy

Let us consider an image I^n, at time n, whose pixels are defined by its RGB color components (R^n, G^n, B^n) and by its coordinates (h^n, w^n). Let $\{\mathbf{x}_i(R_i, G_i, B_i, h_i, w_i)\}_{i=1}^{N}$ denote a set of N reference samples corresponding to one of these pixels, which have been extracted from previous images into a spatial neighborhood around the spatial position of such pixel.

In a first stage, applying the spatio-temporal nonparametric background-foreground modeling in [8] in conjunction with the algorithms proposed in [4] to improve the spatio-temporal nonparametric background modeling, we obtain a set of M pixels, $\{\mathbf{z}_j(R_j, G_j, B_j, h_j, w_j)\}_{j=1}^{M}$ not belonging to the background (foreground pixels) of the sequence. This set is composed not only by pixels belonging to moving objects but also by pixels corresponding to shadows and highlights cast by these moving objects.

In a second stage, to identify and separate shadows and highlights from the moving objects, the probability of each foreground pixel, $\mathbf{z}_j$, to be a shadow, Sh, or a highlight, Hl, is obtained non-parametrically using weighted Gaussian kernels as,

$$\Pr(Sh, Hl \mid \mathbf{z}_j) = \frac{1}{\sum_{i=1}^{N} w_i} \sum_{i=1}^{N} w_i \exp\left(\frac{(\alpha_{i,j}-1)^2}{\sigma_\alpha^2}\right) \exp\left(\frac{CD_{i,j}^2}{\sigma_{CD}^2}\right), \quad (1)$$

where w_i is the weight factor associated to the i-th reference sample (proportional to the probability of the reference sample to belong to the background [4]), σ_α and σ_{CD} are the standard deviations of the Gaussian kernels, and $\alpha_{i,j}$ and $CD_{i,j}$ are, respectively, the brightness and chromaticity distortions resulting from comparing the foreground pixel $\mathbf{z}_j$ and the

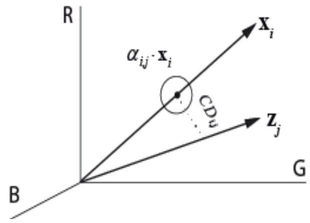

Fig. 1. Brightness and chromaticity distortions resulting from comparing a current foreground pixel, $\mathbf{z}_j$, and a reference sample $\mathbf{x}_i$.

i-th reference sample, $\mathbf{x}_i$.

These distortions, which are illustrated in Fig.1, are obtained as:

$$\alpha_{i,j} = \operatorname{argmin}(\mathbf{z}_j - \alpha_{i,j}\mathbf{x}_i) \quad (2)$$

$$\mathrm{CD}_{i,j} = \left\| \mathbf{z}_j - \alpha_{i,j}\, \mathbf{x}_i \right\| \quad (3)$$

III. RESULTS

The proposed strategy has been evaluated on eight sequences from LASIESTA database [9]. These sequences contain several shadows and highlights, making difficult to obtain high-quality detections. We have compared our results with those obtained with the strategy in [8] (which is the spatio-temporal NPM reference work) improved with the algorithms in [4] (Str. 1), and with the results provided by the same strategy but using the appearance component vector proposed in [10] (Str. 2), which to our knowledge is the only one proposal to reduce the influence of shadows and highlights in NPM-based methods.

Table I shows the Recall (R), Precision (P), and F percentages [4] obtained from the performed analysis. Fig.2 illustrates some significant results comparing the detections obtained with the three compared algorithms. These results show that the detections obtained with the proposed strategy are the best, improving not only those resulting from Str.1 but also those provided by Str. 2.

IV. CONCLUSION

An efficient strategy to remove shadows and highlights from the detections provided by nonparametric moving object detection algorithms has been proposed. To separate the data that actually belong to the moving objects from false detections due to shadows and highlights cast by such moving objects, we model the variations of the brightness and the chromaticity distortions of each pixel by applying a novel nonparametric modeling using Gaussian kernels.

The obtained results have shown that the proposed algorithm is able to achieve very high quality detections, improving significantly the quality of the results provided by previous nonparametric approaches. Therefore, our proposal is perfectly suited to the new computer vision applications demanded by consumer electronic users, since these users require efficient moving object detection strategies that must be robust to false detections due to shadows and highlights cast by moving objects.

TABLE I
RECALL (R), PRECISION (P) AND F PERCENTAGES OBTAINED WITH DIFFERENT MOVING OBJECT DETECTION STRATEGIES

Sequence	Str. 1			Str. 2			Proposed strategy		
	R	*P*	*F*	*R*	*P*	*F*	*R*	*P*	*F*
I_IL_01	99	12	22	99	55	70	95	51	67
I_OC_01	99	50	67	99	52	68	94	93	94
I_OC_02	97	57	72	99	76	86	92	95	93
I_CA_01	92	70	80	93	74	82	89	87	88
O_CL_01	99	84	91	99	87	93	96	97	97
O_CL_02	98,	66	79	99	71	83	81	96	88
O_SU_01	96	68	80	98	35	52	69	92	79
O_SU_02	97	72	83	99	59	74	87	89	88
Total	96	43	60	97	77	80	90	83	86

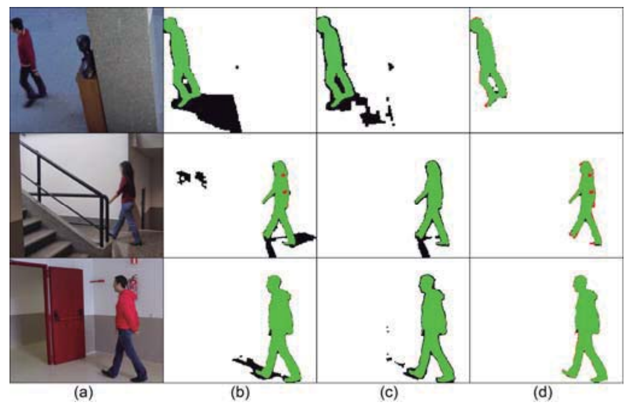

Fig. 2. (a) Original images. (b) Detections obtained with Str. 1. (c) Detections provided by Str. 2, (d) Detections obtained with the proposed algorithm. Color notation: correct detections (green), misdetections (red), and false detections (black).

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