Bayesian Foreground and Shadow Detection in Uncertain Frame Rate Surveillance Videos

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Abstract

In this paper we propose a new model regarding foreground and shadow detection in video sequences. The model works without detailed a-priori object-shape information, and it is also appropriate for low and unstable frame rate video sources. Contribution is presented in three key issues: (1) we propose a novel adaptive shadow model, and show the improvements versus previous approaches in scenes with difficult lighting and coloring effects. (2) We give a novel description for the foreground based on spatial statistics of the neighboring pixel values, which enhances the detection of background or shadow-colored object parts. (3) We show how microstructure analysis can be used in the proposed framework as additional feature components improving the results. Finally, a Markov Random Field model is used to enhance the accuracy of the separation. We validate our method on outdoor and indoor sequences including real surveillance videos and well-known benchmark test sets.

Index Terms

Foreground, Shadow, Texture, MRF.

DOCUMENT AVAILABILITY

Full paper available: `http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4457811`
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TABLE I

COMPARISON OF DIFFERENT CORRESPONDING METHODS AND THE PROPOSED MODEL. NOTES: * TEMPORAL FOREGROUND DESCRIPTION, ** PIXEL STATE TRANSITIONS

Method	High frame rate requirement	Shadow detection	Shadow parameter update	Foreground estimation from current frame	indoor / outdoor	texture	Dynamic background
Mikic 2000 [21]	No	global, constant ratio	No	No	outdoor	No	No
Paragious 2001 [28]	No	illumination invariant	No	No	indoor	No	No
Salvador 2004 [29]	No	illumination invariant	No	No	both	No	No
Martel-Brisson 2005 [31]	No	local process	Yes	No	indoor	No	No
Sheikh 2005 [3]	Yes: tfd *	No	-	No	both	No	Yes
Wang 2006 [12]	Yes: pst **	global, constant ratio	No	No	indoor	first ordered edges	No
Proposed method	No	global, probabilistic	Yes	Yes	both	different microstructures	No

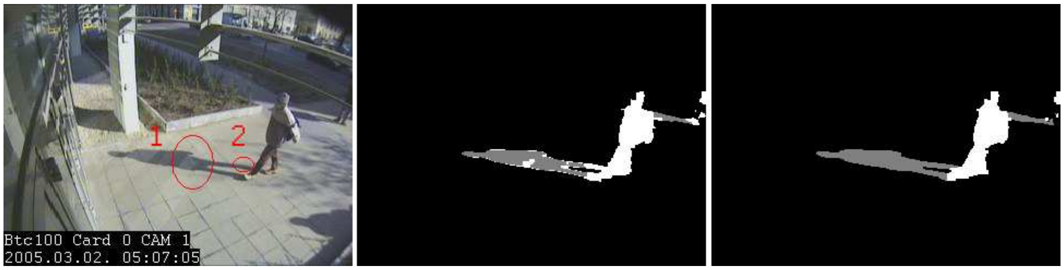

Fig. 1. Illustration of two illumination artifacts (the frame in the *left* image has been chosen from the ‘Entrance pm’ test sequence). 1: light band caused by a non-Lambertian reflecting surface (a glass door) 2: dark shadow part between the legs (more object parts change the reflected light). The constant ratio model (see image in the *middle*) causes errors, while the proposed model (*right* image) is more robust.

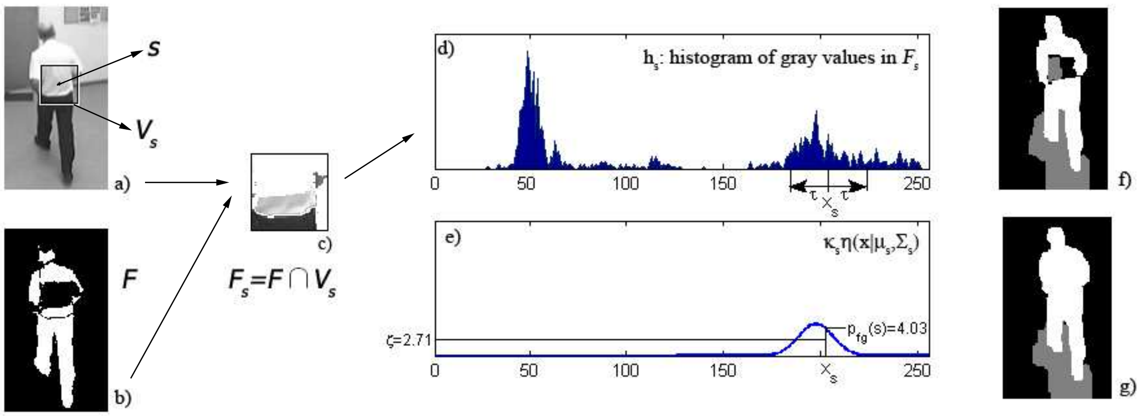

Fig. 2. Determination of the foreground conditional probability term for a given pixel s (demonstrated in grayscale). a) video image, with marking s and its neighborhood V_s (with window side $m = 45$). b) noisy preliminary foreground mask c) Set F_s: preliminary detected foreground pixels in V_s. (Pixels of $V_s \backslash F_s$ are marked with white.) d) Histogram of F_s, marking x_s, and its τ neighborhood e) Result of fitting a weighted Gaussian term for the $[x_s - \tau, x_s + \tau]$ part of the histogram. Here, $\zeta = 2.71$ is used (it would be the foreground probability value for each pixel according to the ‘uniform’ model), but the procedure increases the foreground probability to 4.03. f) Segmentation result of the model optimization with the uniform foreground calculus g) Segmentation result by the proposed model

Fig. 3. Different periods of the day in the ‘Entrance’ sequence, segmentation results. Above left: in the morning (‘am’), right: at noon, below left: in the afternoon (‘pm’), right: wet weather.

TABLE II

VALIDATION OF THE MODEL ELEMENTS. RESULTS WITH (#1) ‘CONSTANT RATIO’ SHADOW MODEL WITH THE ‘UNIFORM’ FOREGROUND MODEL (#2) ‘CONSTANT RATIO’ SHADOW MODEL WITH THE PROPOSED FOREGROUND MODEL (#3) ‘UNIFORM’ FOREGROUND MODEL WITH THE PROPOSED SHADOW MODEL, (#4) RESULTS WITH OUR PROPOSED SHADOW AND FOREGROUND MODEL

Video	Recall				Precision			
	#1	#2	#3	**#4**	#1	#2	#3	**#4**
Entrance pm	0.89	0.97	0.85	**0.96**	0.66	0.62	0.85	**0.83**
Entrance am	0.85	0.92	0.86	**0.93**	0.62	0.63	0.82	**0.81**
Highway	0.82	0.84	0.86	**0.90**	0.73	0.72	0.80	**0.80**

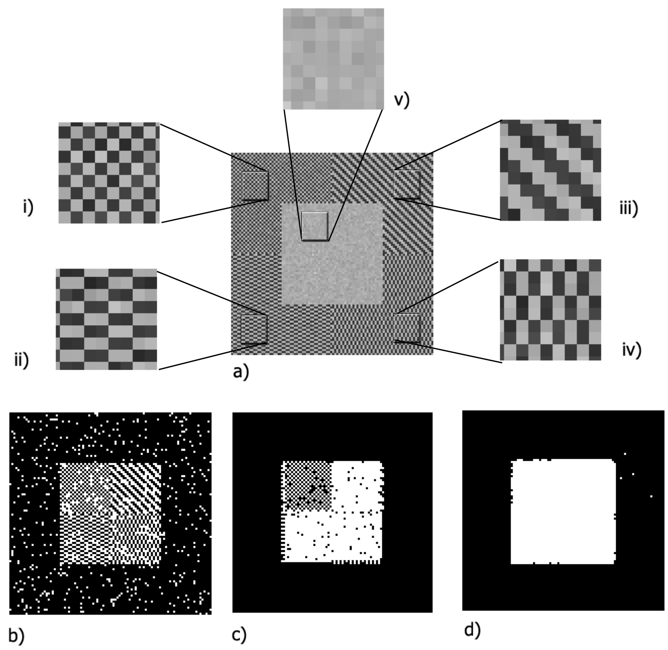

Fig. 4. Synthetic example to demonstrate the benefits of the microstructural features. a) input frame, i-v) enlarged parts of the input, b-d) result of foreground detection based on: (b) gray levels (c) gray levels with vertical and horizontal edge features (d) proposed model with adaptive kernel

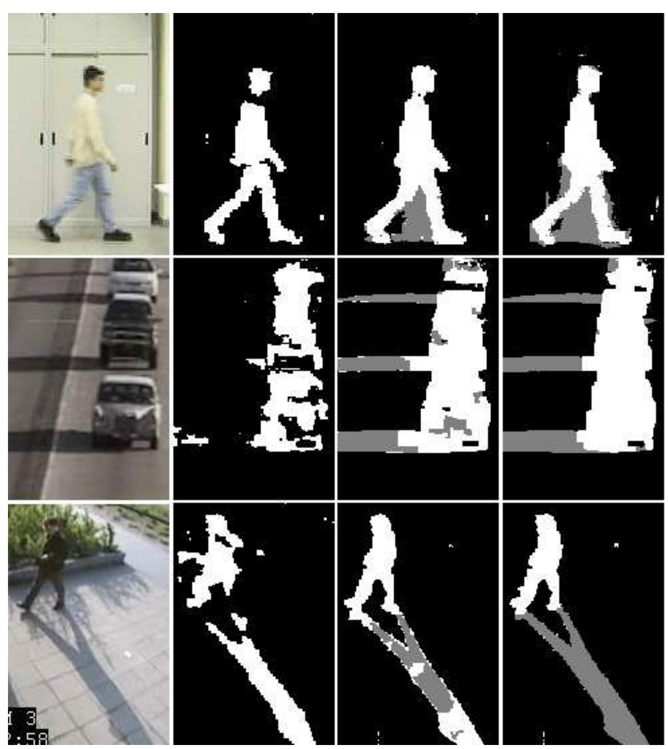

Fig. 5. *Shadow model validation:* Comparison of different shadow models in 3 video sequences (From above: ‘Laboratory’,‘Highway’,‘Entrance am’) . Col. 1: video image, Col. 2: $C_1C_2C_3$ space based illumination invariants. Col. 3: ‘constant ratio model’ (without object-based postprocessing) Col 4: Proposed model

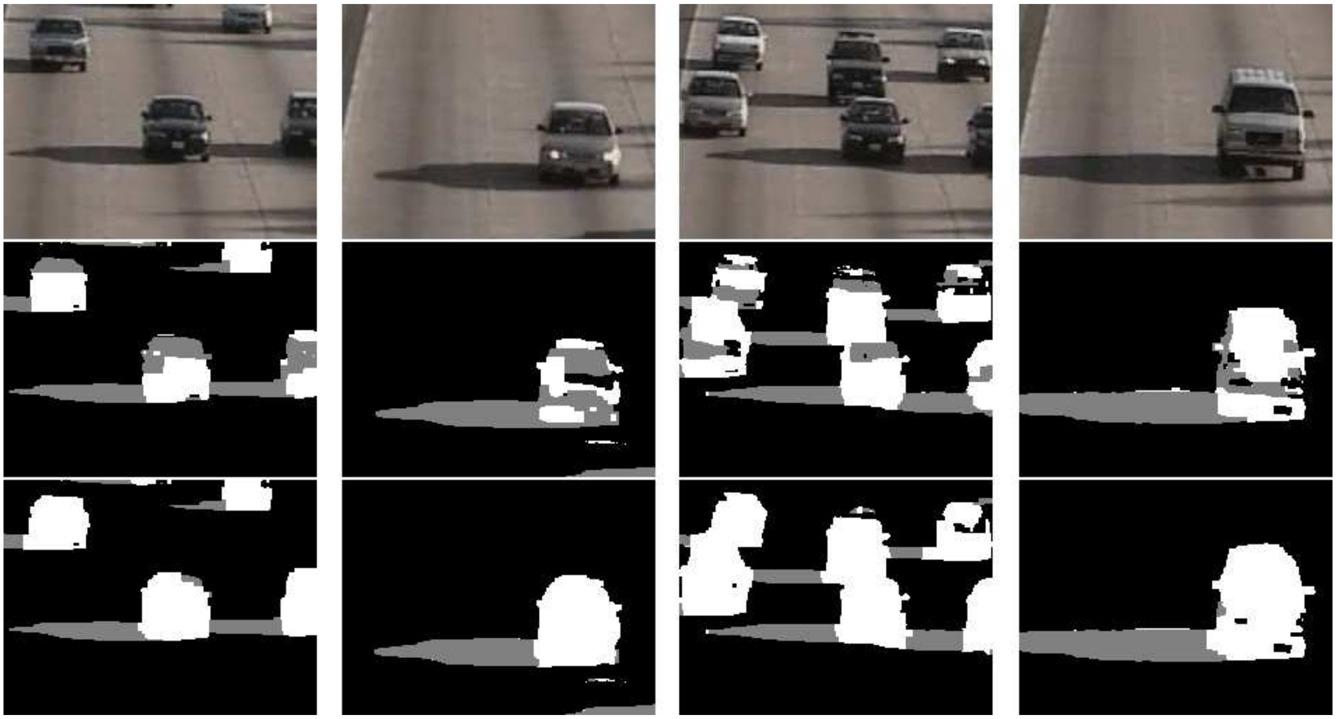

Fig. 6. *Foreground model validation:* Segmentation results on the 'Highway' sequence. Row 1: video image; Row 2: results by uniform foreground model; Row 3: Results by the proposed model

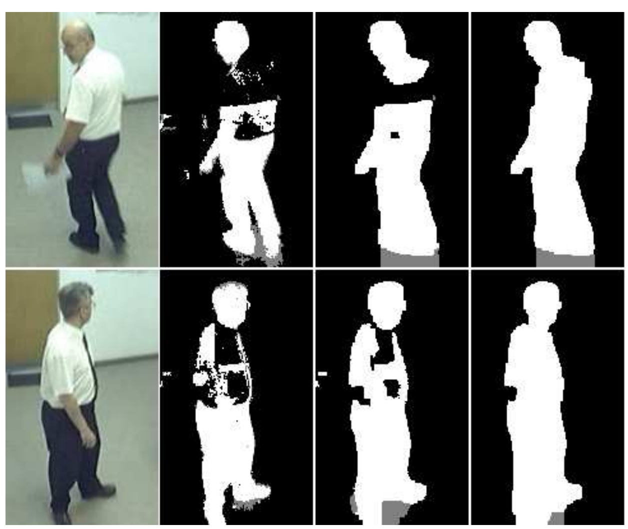

Fig. 7. *Foreground model validation* regarding the 'Corridor' sequence. Col. 1: video image, Col. 2: Result of the preliminary detector. Col. 3: Result with uniform foreground calculus Col 4: Proposed foreground model

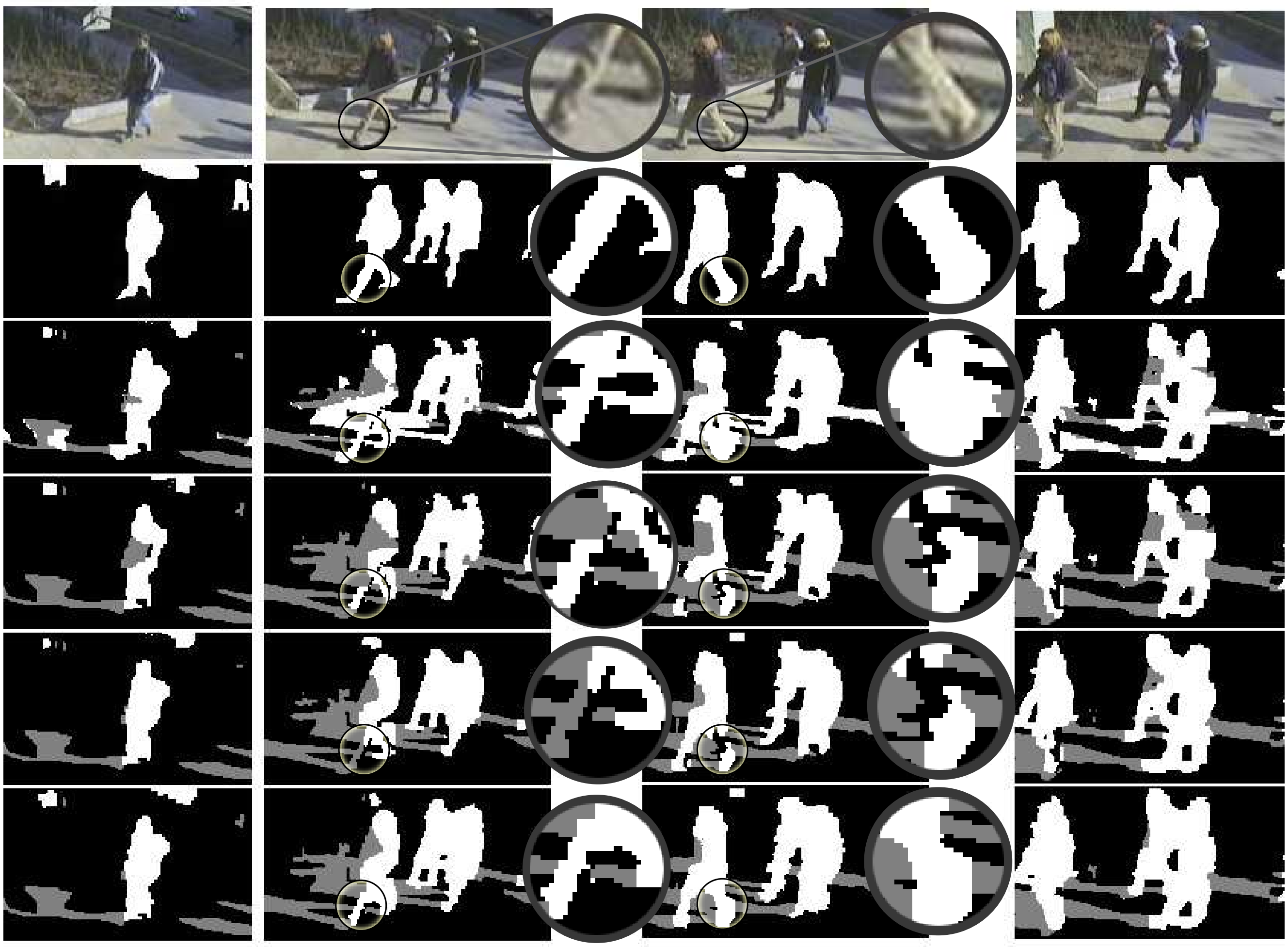

Fig. 8. *Validation of all improvements* in the segmentation regarding 'Entrance pm' video sequence Row 1. Video frames, Row 2. Ground truth Row 3. Segmentation with the 'constant ratio' shadow model, Row 4. Our shadow model with 'uniform foreground' calculus Row 5. The proposed model without microstructural features Row 6. Segmentation results with our final model.

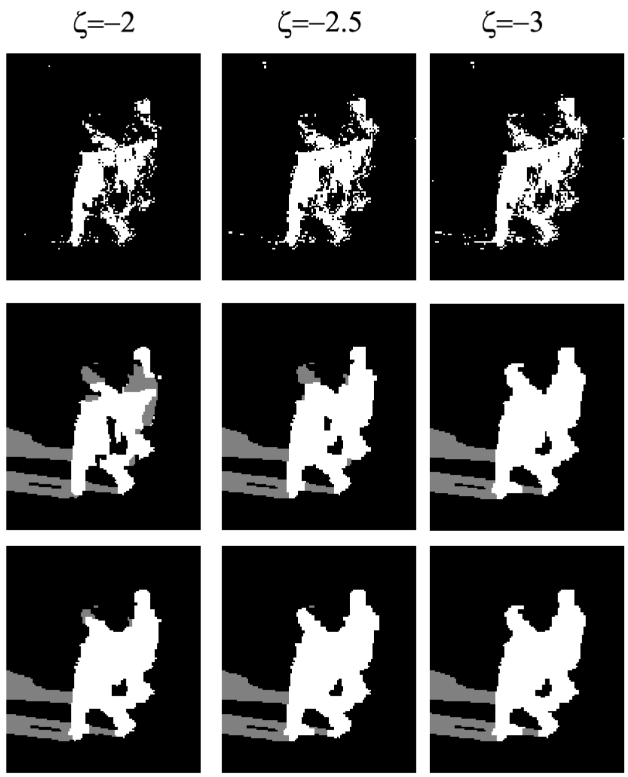

Fig. 9. *Effect of changing the ζ foreground threshold parameter*. Row 1: preliminary masks (F), Row 2: results with uniform foreground calculus using $\epsilon_{\mathrm{fg}}(s) = \zeta$, Row 3. results with the proposed model. Note: for the uniform model, $\zeta = -2.5$ is the optimal value with respect to the whole video sequence.