Shadow Detection

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Shadow

• Occurs when an object partially or totally occludes direct.

• Types:
  – Self: Occurs in the portion of an object
  – Cast: Area projected by the object in the direction of direct light
Cast shadow segmentation using invariant color features

Elena Salvador, Andrea Cavallaro and Touradj Ebrahimi
2004
Goal

• Detection of cast shadows on video and on still images.
Constraints

• The ambient light assumed to be a proportional to direct occluded light.
• Inter-object reflection among different surfaces not taken in account.
• Video
  – The camera is not moving.
Geometrical properties of Shadows

- Generation of shadows
- Shadows Types
  - Cast shadows
  - Self shadows
Intro – Shadow detection techniques

• Shadow detection techniques classification:
  – Model based
    • prior knowledge of the geometry of the scene, the objects, and the illumination.
  – Property based
    • geometry, brightness or color
Model Based Technique

• Applications:
  – Video Surveillance
  – Areal Image Understanding

• Features (Geometric)
  – Edges, Lines, Corners

• Only applicable to the specific application they are designed for
Property Based Technique

• Uses spectral and geometric features of shadows

• Features:
  – Luminance, chrominance, and gradient density
  – Edge, Texture
Spectral Properties of Shadows
Dichromatic reflection model

• Radiance of light: \( L_r(\lambda, p) = L_a(\lambda) + L_b(\lambda, p) + L_s(\lambda, p) \)

• When object obstructing the direct light we have:

• Let \( L_{r\_shadow}(\lambda, p) = L_a(\lambda) \) to be a spectral sensitivities of R, G and B sensors of color camera.

\[ S_R(\lambda), S_G(\lambda), S_B(\lambda) \]
Dichromatic reflection model - cont

- The color components of reflected intensity that reaching the camera sensors are:

\[ C_i(x, y) = \int_{V} E(\lambda, x, y) S_{Ci}(\lambda) d\lambda \]

- Sensor measurements in direct light:

\[ C_i(x, y)_{lit} = \int_{V} \alpha \left( L_a(\lambda) + L_b(\lambda, \vec{p}) + L_s(\lambda, \vec{p}) \right) S_{Ci}(\lambda) d\lambda \]

- For a point in shadow the measurements are:

\[ C_i(x, y)_{shadow} = \int_{V} \alpha L_a(\lambda) S_{Ci}(\lambda) d\lambda \]
Dichromatic reflection model - cont

• The conclusions are:

\[ R_{\text{Shadow}} < R_{\text{Lit}} \]
\[ G_{\text{Shadow}} < G_{\text{Lit}} \]
\[ B_{\text{Shadow}} < B_{\text{Lit}} \]
Color Invariants

• Photometric color invariants
  – Definition: Let $F_1$ is the value assumed in a point in light, and $F_s$ is the value in the same point in shadow. Then, $F_1 = F_s$

– Models of photometric color invariants
  • Normalized rgb
  • Hue ($H$) and saturation ($S$)
  • $(C_1, C_2, C_3)$ and $(L_1, L_2, L_3)$
Color Invariants - cont

- $C_1C_2C_3$ color invariant features defined as:

\[
C_1 = \arctan \left( \frac{R}{\max(G, B)} \right)
\]

\[
C_2 = \arctan \left( \frac{G}{\max(R, B)} \right)
\]

\[
C_3 = \arctan \left( \frac{B}{\max(R, G)} \right)
\]

( Color Based Object Recognition
Theo Gevers and Arnold W.M. Smeulders 1999 )
Algorithm steps

• Hypothesis generation
  – Dichromatic model

• Accumulation of evidence
  – Color invariance test
  – Geometric properties test

• Decision
Hypothesis

• Makes use of the property that shadows darken the surface upon which they are cast.
• Compare $I(x,y)$ with ref pixel $I(x_r,y_r)$
• Shadow Pixels:

\[
S_c = \{(x, y) : R(x_r, y_r) > R(x, y), G(x_r, y_r) > G(x, y), B(x_r, y_r) > B(x, y)\}.
\]
Hypothesis generation

• Still images:
  – Detect Shadow Contours
    • Find edges with Sobel operator.
  – The ref pixels is the neighbor of the pixel under consideration
    • 8- connected neighbors
  – Use reference pixels to find shadow suspected areas.
  – Test by analysing the gradient:
    • Shadow → If the gradient has the same orientation in all the three components
Hypothesis generation

• Video
  – The reference image represents the background of the scene (typically a frame).
  – Analysis performed only in areas that identified by motion detector
    • Analyse only the difference image
      $$ D(x,y) = I(x_r, y_r) - I(x, y) $$
    
  • For noisy case:
    – $$ R(x_r, y_r) - R(x, y) > b \quad \text{instead of} \quad R(x_r, y_r) - R(x, y) > 0 $$
    – Should satisfy for all $R$, $G$ and $B$ channels
Hypothesis generation

• To obtain more robustness the analysis performed on window surrounding each pixel

\[ D_w(x,y) = \frac{1}{(2N + 1)(2M + 1)} \sum_{i=-N}^{N} \sum_{j=-M}^{M} D(x+i, y+j) \]

• Shadow Pixel: If each component of \( D_w(x,y) \) is larger than the corresponding component of \( b \).
Hypothesis generation - cont

• Result of the first level:
The candidate shadow points belonging to the edge map:
Accumulation of evidence – overview

• Color invariance property used to strength or cancel the hypothesized shadow areas.

\[ S_e = \{ (x, y) : \text{Inv}(x_r, y_r) = \text{Inv}(x, y) \} \]

Where,

\[ \text{Inv}(x, y) = (c_1(x, y), c_2(x, y), c_3(x, y)) \]

– Pixels with RGB values below 30 are not considered.

• Checking the existence of shadow line and hidden line.
Accumulation of evidence – Still Images

• Color edge detection performed in the invariant space.

• **Morphological dilation** applied on the edge map.

• Isolated pixels removed.
Accumulation of evidence – in video

• Compute invariant feature values by:

\[ d(x, y) = (|c_1(x_r, y_r) - c_1(x, y)|, |c_2(x_r, y_r) - c_2(x, y)|, |c_3(x_r, y_r) - c_3(x, y)|) \]

• Geometric property test

  – Position of shadow with respect to the object is tested.
Fig. 2. First row: (A) original image; (B) candidate shadow points belonging to the color edge map of the RGB image and verifying property in Eq. (11). Second row: (C) color edge map of the invariant features containing material boundaries for which the shadow hypothesis is weakened; (D) integration of the shadow evidence from the spectral analyses of (B) and (C). Third row: Refinement by means of geometric analysis providing the shadow line and hidden shadow line (E), and complete shadow contours (F).
Information integration
(Results of integrating all stages).

- Color edge map of the invariant features
- Integration of shadow evidence from (B) and (C)
- (E) And (F) contains refinement by means of geometric analysis providing the shadow line and hidden shadow line.
Results
References

• Shadow identification and classification using invariant color models. Elena Salvador, Andrea Cavallaro, Touradj Ebrahimi 2001

• Cast shadow segmentation using invariant color features. Elena Salvador, Andrea Cavallaro and, Touradj Ebrahimi 2004

Image difference threshold strategies and shadow detection

Rosin & Ellis, BMVC 95.
Approach

• Shadow is modeled as a constant contrast change between the reference or background image and the current image.

• **Detection**: locate areas of constant photometric gain in the difference image using region growing.

• Heuristic rules are then used to cue possible shadow regions.
Region Growing

• Calculate Gain=$R(x,y)/I(x,y)$ for each pixel in the BG subtracted blob.
• Region growing
• Merge Similar neighboring regions.
Shadow Identification

• Apply heuristics
  – Region statistics should vary smoothly
  – homogeneous intensity ratio regions
  – Gain > 1
  – regions’ boundary which is shared with other regions
  – boundary shared with the background, against the total boundary length
Result

Figure 4: SHADOW (a) Grey-level composite (5 frames), (b) frame differenced and thresholded, (c) first region boundaries, (d) second stage regions, after merging, (e) composite of shadow classified regions
Learning Moving Cast Shadows for Foreground Detection

Jia-Bin Huang, and Chu-Song Chen

VS2008
Overview
Modeling the Background

- BG color info is modeled by GMM.
- Top B states model the BG

\[
B = \arg \min_b \sum_{k=1}^{b} \omega_{BG,k} > T_{BG},
\]

- Likelihood of pixel \( p \) belonging to BG

\[
p(z(p) \mid l_p = BG) = \frac{1}{W_{BG}} \sum_{k=1}^{B} \omega_{BG,k} G(z(p), \mu_{BG,k}, \Sigma_{BG,k})
\]
Learning Moving Cast Shadow

• Observation
  – Shadow cast by different objects are similar and independent of FG objects.
  – The ratio of shadowed and illuminated value of a given surface point is considered to be nearly constant.

• This regularity of shadows is used to describe the color ratio of a pixel under shadow and normal illumination.
Algorithm

• Detect FG pixels using BG model (object + shadow pixels included)
• Employ weak shadow detector to extract possible shadow points
• Train LSM and GSM using these samples
Weak Shadow Detector

- Cast shadows on a surface reduce luminance values and change the saturation
- Potential shadow values fall into the conic volume around the corresponding background color

\[
    r_l(p) = \frac{\|b_t(p)\|}{\|z_t(p)\| \cos(\theta(p))},
\]

\[
    \theta(p) = \arccos\left(\frac{\langle z_t(p), b_t(p) \rangle}{\|z_t(p)\| \|b_t(p)\|}\right)
\]

A pixel \( p \) is considered as potential cast shadow point if:

\[
    r_{min} < r_l(p) < r_{max}, \theta(p) < \theta_{max}
\]
Weak Shadow Detector
Local Shadow Model

• The color ratio between shadowed and illuminated intensity values of a given pixel $p$

$$r_t(p) = \left( \frac{z_t^r(p)}{b_t^r(p)}, \frac{z_t^g(p)}{b_t^g(p)}, \frac{z_t^b(p)}{b_t^b(p)} \right)$$

  - Where, $b_t^i(p); i = r; g; b$ are the means of the most probable Gaussian distributions (with the highest $w/\Sigma$ value)

• LSM is modeled by GMM from the candidate shadow points obtained from weak shadow detector with the following parameters ($CR \rightarrow$ Color Ratio).

$$\{\omega_{CR,k}, \mu_{CR,k}, \Sigma_{CR,k} \}$$
LSM

• Likelihood if pixel p shadowed:

\[ p(z(p) | l_p = SD) = \frac{1}{W_{SD}} \sum_{k=1}^{S} \omega_{SD,k} G(z(p), \mu_{SD,k}, \Sigma_{SD,k}) \]

Where,

\[ \omega_{SD,k} = \omega_{CR,k} \]
\[ \mu_{SD,k} = \mu_{BG,1} \mu_{CR,k} \]
\[ \Sigma_{SD,k} = \mu_{BG,1}^2 \Sigma_{CR,k} + \mu_{CR,k}^2 \Sigma_{BG,1} + \Sigma_{CR,k} \Sigma_{BG,1} \]

\( \{\mu_{BG,1}, \Sigma_{BG,1}\} \rightarrow \text{Most probable BG Gaussian} \)
\( \{\omega_{CR,k}, \mu_{CR,k}, \Sigma_{CR,k}\} \rightarrow \text{LSM parameter} \)

Requires several sample for convergence
GSM

• To increase convergence rate
• Use all candidate shadow points to model the GMM
• Here, Gaussian states with higher prior probabilities and smaller variances would be considered as shadows.
• For each candidate shadow pixel, evaluate the confidence value predicted by the GSM and then update the LSM through confidence-rated learning
Foreground Model and Segmentation

• No GMM due to estimation of $K$ (states)
• Build KDE based model for FG from impossible shadow points ($G$).
• Likelihood

$$p(z_p | l_p = FG) = \frac{1}{M} \sum_{i=1}^{M} K_H(z_p - g_i)$$
Results

(a) Frame in the sequence. (b) Detection result by the weak shadow detector. (c) The confidence map by GSM. (d) Foreground and Segmentation result.
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(a) Frame in the sequence. (b) Detection result by the weak shadow detector. (c) The confidence map by GSM. (d) Foreground and Segmentation result
Tracking And Object Classification For Automated Surveillance

Omar Javed and Mubarak Shah
Shadow Properties used

- Pixels in the shadow regions are darker than those in the reference background
- Shadows retain some texture and color information of the underlying surface
Method

• Extract FG regions darker than reference BG
• Perform color segmentation on these regions (contains self, cast shadow and dark objects)
  – K-means based color segmentation
• Perform connected component analysis and region merging
  – Now each segment belongs to cast shadow or self shadow or dark object
• Examine the texture of each region using gradient information.
  – Gradient direction used \( \theta = \arctan(fy/fx) \) [ratio \( fy/fx \) not sensitive to illumination change]
• Check correlation with BG, if corr > 0.75 \( \rightarrow \) cast shadow
Fig. 1. Results of shadow removal. (a) and (d) show the calculated bounding box with shadow removal. (b) and (e) show the background subtraction results (zoomed). (c) and (f) show the silhouette after the segments belonging to the cast shadows have been removed.