Accurate Moving Cast Shadow Suppression Based on Local Color Constancy Detection

IEEE Transactions on Image Processing
Vol. 20, No. 10, 2011
Ariel Amato, Mikhail G.Mozerov, Andrew D.Bagdanov, and Jordi Gonzalez

Presented by Ji-Heon Lee

School of Electrical Engineering and Computer Science
Kyungpook National Univ.
Abstract

Proposed method

- Novel framework for color constancy
  - Used in real video sequences
    - Available on video condition
  - Detecting shadow region both achromatic and chromatic
    - Considering local color constancy
  - Better performance
    - Compared with other shadow detection algorithms
Introduction

- Moving object detection
  - Pre-processing step in computer vision
  - Subtraction of each video sequence
  - Hindered by shadow cast
    - Shape distortion, object merging, failure of object detection
  - Request effective shadow detection algorithm

- Cast shadow
  - Area projected on surface by object
  - Changing illumination only as decrease brightness
  - Achromatic and chromatic shadow
    - Considering light source and color mixture
Proposed algorithm
- Generates mask of moving object
  - Using background subtraction
- Detect shadow cast area of each moving object
  - Background luminance divided by current frame of luminance value
- Segmenting object area
- Analyzing parameters of proposed algorithm

Attribution of proposed algorithm
- Region-based analysis
  - Distinguishing feature of previous
  - Low computational complexity
- Grape-based instead of Pixel by based
  - Using local gradient values instead global region analysis
Shadow handling

Related Work

- Horprasert model
  - Comparing intensity to chromaticity component at each pixel
- Cucchiara model
  - Using shadow properties in HSV color space
- McKenna model
  - Assuming shadow region with changing intensity and chromaticity
- Stauder model
  - Using physics based luminance model to describe illuminance changing
- Yang model
  - Combining shading, color, texture, neighborhoods to moving cast shadow detection
Summarizing of shadow detection algorithms

Table 1. Comparison of different shadow detection algorithms. Each row represents an algorithm from the literature, and the columns represent a range of characteristic of shadow detection methods.

<table>
<thead>
<tr>
<th>METHODS</th>
<th>Chromatic shadow</th>
<th>Texture constraint</th>
<th>Shadows camouflage</th>
<th>Umbra &amp; Penumbra</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horprasert [10]</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Cucchiara [11]</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>McKena [3]</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Stauder [16]</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Toth [17]</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Yang [18]</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Martel-Brisson [14]</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Jia-Bin Huang [15]</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Drawback of pixelwise analysis

- Assumption of shadow region
  - Linear scaling of brightness component
  - Without considering chromaticity component
- Measurement of changing appearance in surface
- Shortage of pixelwise estimation
  - Shadow camouflage
    - Failing shadow detection when no difference between foreground and background
  - Chromatic shadows
    - Failing of shadow detection when strong chromatic shadow
Example of shadow region
- Achromatic shadow case

Fig 1. (a)-(c) Background image, current image, and hand-labeled segmentation image, respectively. (d) Histogram in polar RGB space, (e) Histogram in delta chromaticity space. (f) Histogram in DHSV space. (g)-(i) Illustrate the result of the segmentation process based on an optimal threshold from different color spaces.
- Achromatic shadow case with similarity chromaticity between foreground and background

Fig 2. (a)-(c) Background image, current image, and hand-labeled segmentation, respectively. (d) Histogram in polar RGB space, (e) Histogram in delta chromaticity space. (f) Histogram in DHSV space. (g)-(i) Illustrate the result of the segmentation process based on an optimal threshold from different color spaces.
- Achromatic shadow case with similarity chromaticity between foreground and background

Fig 3. (a)-(c) Background image, current, image, and hand-labeled segmentation, respectively. (d) Histogram in polar RGB space, (e) Histogram in delta chromaticity space. (f) Histogram in DHSV space. (g)-(i) Illustrate the result of the segmentation process based on an optimal threshold from different color spaces.
– Difference in angle and magnitude of color in RGB color space

\[
\bar{X} = |I^{bg}(x) - I^{im}(x)| \cos \left( \cos^{-1} \left( \frac{I^{bg}(x) \cdot I^{im}(x)}{|I^{bg}(x)| \cdot |I^{im}(x)|} \right) \right)
\]

\[
\bar{Y} = |I^{bg}(x) - I^{im}(x)| \sin \left( \cos^{-1} \left( \frac{I^{bg}(x) \cdot I^{im}(x)}{|I^{bg}(x)| \cdot |I^{im}(x)|} \right) \right)
\]

– Difference in chromaticity space

\[
X = \left| \frac{R^{bg}}{R^{bg} + G^{bg} + B^{bg}} - \frac{R^{im}}{R^{im} + G^{im} + B^{im}} \right|
\]

\[
Y = \left| \frac{G^{bg}}{R^{bg} + G^{bg} + B^{bg}} - \frac{G^{im}}{R^{im} + G^{im} + B^{im}} \right|
\]
Moving Shadow Detection

- Motion Region Mask Formation
  - Using differencing current image and background
  - Using threshold to make binary mask

Fig 4. Background image (a), current frame(b) binary motion pixel mask(c) and object mask (d)
Shadow Model and Reflectance Suppression

- Assuming simple luminance model

\[ L(x) = E(x) \rho(x) \]

where \( L(x) \) is luminance vector of RGB color space, 
\( \rho(x) \) is reflectance vector of object surface, reflected at pixel \( x \).

- Irradiance component of one lighting source in shadow area

\[ E(x) = C_a + C_b \cos(\theta(x)) \zeta(x) \]  

(1)

where \( C_a \) is intensity of ambient light, 
\( C_b \) is intensity of light source, 
\( \theta(x) \) is angle between light direction and surface 
\( \zeta \) is shadow parameter.
- Luminance ratio of pixel

\[ D(x) = \frac{L^{bg}(x)}{L^{im}(x)} = \frac{E^{bg}(x)\rho^{bm}(x)}{E^{im}(x)\rho^{im}(x)} \]  

(2)

where \( D \) is illuminance ratio,

\( L^{im}(x) \) is pixels belonging to cast shadow,

\( L^{bg}(x) \) is pixels belonging to background.

- Result of luminance ratio

\[ D(x) = \frac{E^{bg}(x)}{E^{im}(x)} \quad \forall x \in R^{sh} \]  

(3)

where \( D \) is illuminance ratio.
- After substituting (1) in (3)

\[ D(x) = \frac{C_a^{bg} + C_b^{bg} \cos(\theta(x))}{C_a^{im} + C_b^{im} \cos(\theta(x))\zeta(x)} \]  

(4)

- Representing \( \Delta x \) distance between two neighboring pixels

\[ D(x) - D(x + \Delta x) = \frac{C_a^{bg} + C_b^{bg} \cos(\theta(x))}{C_a^{im} + C_b^{im} \cos(\theta(x))\zeta(x)} \]

\[ - \frac{C_a^{bg} + C_b^{bg} \cos(\theta(x + \Delta x))}{C_a^{im} + C_b^{im} \cos(\theta(x + \Delta x))\zeta(x + \Delta x)} \]

(5)

- Assuming scale factor and angle are slowly varying function

\[ D(x) - D(x + \Delta x) \approx 0 \]

(6)
- Meaning of Eq.(6)
  - Local color constancy exist for any pair of pixel belonging to shadow
  - Derived using single light source model

- Meaning of shadow region
  - Including color constancy information

 Regions with local color constancy

- Luminance ratio for single pixel

\[
D(x) = \frac{L^b(x) + \nu}{L^m(x) + \nu}
\]  \hspace{1cm} (7)

where $\nu$ is quantization constant.
Example of luminance ratio image in RGB space

Fig 5. (a) Background image, (b) current image, and (c) luminance ratio image in the RGB color space.
Using GSCN segmentation

- Definition of GSCN
  - Gradient connected pixels as set of pixel
- Illustrate path between pixels

Fig 6. (a) Illustration of the GSCN concept, (b) Formed gradient-space-connected neighborhoods.
Standard graph-based technique

\[ w(e(x_i, x_j)) = \prod_{c \in \{R, G, B\}} H(\partial - |D_c(x_i) - D_c(x_j)|) \]  

(8)

where \( H \) is Heaviside step function

\[
H = \begin{cases} 
0, & \text{if } y < 0 \\
1, & \text{otherwise.}
\end{cases}
\]

All pixels of tree form subsegment inside considered object

\[
\bigcup_{l=1}^{L_k} s^k_l = o_k \\
\bigcap_{l=1}^{L_k} s^k_l = \phi \\
\bigcup_{k=1}^{K} o_k = \phi
\]

(9)

where \( L_k \) is number of trees,
\( s^k_l \) is subsegment,
\( o_k \) is subdivision of object.
• Example of shadow splitting

Fig 7. (a) Illustration of the GSCN concept, (b) Formed gradient-space-connected neighborhoods.
Classification process

- Exploit local feature of region
  - Definition of value

\[
\mu_l^k = \left| s_l^k \right|^{-1} \sum_{x \in s_l^k} D(x) \quad , \quad \left| s_l^k \right| = \sum_{x \in \partial_k} M_{x \in s_l^k}(x) \quad , \quad \tau_l^k = \frac{\hat{t}_l^k (s_l^k)}{t_l^k (s_l^k)}
\]

where \( \mu_l^k \) is Mean value in region \( s_l^k \),
\( \left| s_l^k \right| \) is Number of pixels belong to segment \( s_l^k \),
\( \tau_l^k \) is Terminal pixel weight,
\( \hat{t}_l^k (s_l^k) \) is number of external terminal pixels of subsegment \( s_l^k \),
\( t_l^k (s_l^k) \) is number of all terminal pixels of subsegment \( s_l^k \),
– Classified by combination of three decision rule
  
  • Luminance difference criterion

  \[ Sh_{\mu}(\mu_l^k) = \prod_{c \in \{R,G,B\}} H(\mu_c(s_l^k) - 1) \]  

  where \( Sh(s_l^k) = 1 \) when \( s_l^k \) belong to shadow class,
  
  \( Sh(s_l^k) = 0 \) when \( s_l^k \) belong to foreground.

  • Segment size criterion

  \[ Sh_{|s|}(|s_l^k|) = \begin{cases} 1, & \text{if } |s_l^k| > |o_k| \lambda \\ 0, & \text{otherwise} \end{cases} \]

  where \( \lambda \) is relative size of smallest subsegment on \( o_k \)
Fig 8. Pointwise border representation: white borderlines represent end points of the segment spatially connected with another object’s segments, and black borderlines represent extrinsic terminal points.
• Extrinsic terminal point weight criterion

\[ Sh_\tau (\tau^k_l) = \begin{cases} 1, & \text{if} (\tau^k_l > \tau_0) \\ 0, & \text{otherwise} \end{cases} \]  

(12)

where \( \tau_0 \) is an experimentally determined threshold.

• Final shadow classification rule

\[ s^k_l = \begin{cases} \text{Shadow}, & \text{if} (Sh_\mu (\mu^k_l) \cap Sh_{|s|} (|S^k_l|) \cap Sh_\tau (\tau^k_l)) \\ \text{Foreground}, & \text{otherwise} \end{cases} \]  

(13)

– Edge noise correction
  • Edge effect result from compression technique
  • Using erosion mask to overcome
Experimental Result

Parameter analysis

- Minimum gradient threshold

\[
\hat{\partial}_k = \alpha \left| o_k \right|^2 \left( \sum_{x \in o_k} |\mu_{bg}^{x}(x)| \right) \left( \sum_{x \in o_k} |\sigma_{bg}^{x}(x)| \right)
\]

(14)

where \( \mu_{bg}^{x}(x) \) is mean value,
\( \sigma_{bg}^{x}(x) \) is standard value,

- Relative size threshold
  - Calculated on two criteria
    - True positive foreground(TPf)
    - False positive foreground(FPf)
Extrinsic terminal point weight threshold
- Calculated using same process as relative size threshold
- Calculated for each scene

Performance Evaluation
- Parameter of Shadow detection rate and discrimination rate

\[
\eta = \frac{TP_S}{TP_S + FN_S} \quad \zeta = \frac{TP_F}{TP_F + FN_F} \tag{15}
\]

where subscript S stands for shadow, F for foreground,
\( TP_F \) is number of foreground pixel TPf minus number of points detected as shadows.
Performance Result
- Result of proposed method

Fig 9. Result of different steps of our method (red color means foreground and green color means shadow): (a) image being segmented, (b) motion detection mask, (c) object mask, (d) image difference plane, (e) result of GSCN segmentation, (f) edge noise correction, (g) classification based on the luminance difference and segment size criteria, (h) classification based on the terminal point weight criterion, and (i) final segmentation. The sequence used are: (I) grass field #184, (II) highway #157, and (III) highway II #801
– Result of proposed method

(d)

(e)

(f)
- Result of proposed method
Result of proposed method

Fig 10. Result of implementation of our method in different scenarios: (I) hallway #163, (II) auto #1143, (III) highway II #253, (IV) highway I #353, and (V) CVC outdoor #509. The meaning of each column here is: (a) current image, (b) motion object mask, (c) final classification.
– Result of proposed method
- Result of proposed method

**Table 2.** Quantitative results for different sequences.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Highway I</td>
<td>η: 0.81</td>
<td>0.70</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>ξ: 0.85</td>
<td>0.82</td>
<td>0.84</td>
</tr>
<tr>
<td>Highway II</td>
<td>η: 0.72</td>
<td>0.76</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>ξ: 0.75</td>
<td>0.74</td>
<td>0.71</td>
</tr>
<tr>
<td>Hallway</td>
<td>η: 0.84</td>
<td>0.82</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td>ξ: 0.91</td>
<td>0.90</td>
<td>0.86</td>
</tr>
<tr>
<td>Pets2009 V7</td>
<td>η: 0.96</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ξ: 0.95</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CVC Outdoor</td>
<td>η: 0.91</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ξ: 0.96</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Football Match</td>
<td>η: 0.80</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ξ: 0.95</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
Conclusion

- Proposed method
  - Novel approach for distinguishing moving object from shadow
  - Exploiting of local color constancy for shadow region
  - High recognition rates achieved of sequences
  - Fast algorithm