Estimating Natural Illumination from a Single Outdoor Image

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(Slide from Lalonde)
In this section, we present and discuss each of the aforementioned results.

The first experiment was designed to test the hypothesis about the relative performance of the considered algorithms described in Section 2. We compared the algorithms using an image database constructed by Hallinan at the Harvard Robotics Laboratory in which lighting has been systematically varied. Secondly, we have constructed a database at Yale that includes variation in both facial expression and lighting. From this database, we used 330 images of five people (66 images for each person) for testing.

We extracted five subsets to quantify the effects of varying lighting. Sample images from each subset are shown in Fig. 4. The space of light angles, was then sampled in 15 directions, including a dominant light source. The space of light orientation varied between a minimum of 0° and a maximum of 90° from the camera axis.

For all experiments, classification was performed using a nearest neighbor classifier. All training images of an individual were used to train the classifier, and the corresponding image in the database was used for testing. For Subset 1, which contains 30 images for which both the longitudinal and latitudinal angles of light source direction are 75° from the camera axis, the classifier achieved 100% accuracy. For Subset 2, which contains 85 images for which the greater of the longitudinal and latitudinal angles of light source direction is 45° from the camera axis, the classifier achieved 98% accuracy. For Subset 3, which contains 85 images for which the greater of the longitudinal and latitudinal angles of light source direction is 30° from the camera axis, the classifier achieved 95% accuracy. For Subset 4, which contains 45 images for which the greater of the longitudinal and latitudinal angles of light source direction is 15° from the camera axis, the classifier achieved 90% accuracy. For Subset 5, which contains 105 images for which the greater of the longitudinal and latitudinal angles of light source direction is less than 15° from the camera axis, the classifier achieved 85% accuracy.

In summary, the algorithms performed better when they exploited the fact that images with variable illumination were facing the camera. This is consistent with previous findings that illumination caused by the recording flash was a major source of variation in the database.
Lighting in the wild

Kemelmacher-Shlizerman and Seitz
ICCV 2011

Jung et al. CVPR 2015

[Lalonde, Narasimhan & Efros, ECCV ’08 + IJCV ’09]
Figure 1: Geometric context from a single image: ground (green), sky (blue), vertical regions (red) subdivided into planar orientations (arrows) and non-planar solid (’x’) and porous (’o’).

[Hoiem et al., IJCV ’07]
Perez Sky Model

\[ l_p = f(\theta_p, \gamma_p) = [1 + a \exp(b/ \cos \theta_p)] \times [1 + c \exp(d\gamma_p) + e \cos^2 \gamma_p] \]
Perez Sky Model

\[ \theta_p \approx \theta_c - \arctan \left( \frac{v_p}{f} \right) \]

Camera Zenith Angle  Focal length  Sun location

\[ l_p = f(\theta_p, \gamma_p) = g(u_p, v_p, \theta_c, \phi_c, f_c, \theta_s, \phi_s) \]

Pixel Coord.
Bottom-up projection
Sky
Sky

Given camera zenith angle and focal length

Predicted sky at current sun position

Original sky
Sky probabilities

$P(\text{sun position} \mid \text{sky pixels})$

$\exp - \left( - \left( \mu^2 - \sigma^2 \right) \right)$
Sky

Predicted sky at current sun position

Original sky
Camera Zenith Angle Approximation

And, focal length via EXIF tag
What if the sky is not clear?
Clear vs overcast vs patchy

Clear

Overcast

Patchy clouds

Show image where clouds are subtracted?

Show the one on 23.
Sun position given sky
Limitations of the sky cue

Sun behind camera

Sky not visible
Cast shadows
Shadow detection

[L channel]

[a channel]

[Khan & Reinhard, ICIP '05]

[Kosecka & Wang, ECCV '02]
Shadow detection

Extracted edges
Shadow detection

Extracted edges
Shadows
$P(\text{sun azimuth } \mid \text{ ground})$
Sun position given shadows
Limitations of shadows cue

Shadow detection

Non-vertical objects
Surfaces
Vertical surfaces

[Hoiem et al., IJCV '07]
Surfaces
Sun position given surfaces
Limitations of surfaces cue

No flat surfaces
Sun prior

\[ P(\theta_s, \Delta \phi_s) = P(f(L, D, T, \phi_c)) \]

Sun position
Latitude, Date, Time, Azimuth

Uniform sampling
Sun prior

Uniform

Probability vs. Sun elevation and Horizon

- Probability decreases as Sun elevation increases.
- Sun elevation ranges from 0 (Horizon) to 90 (Straight up).
- Horizon ranges from 0 to 90.

The graph shows a smooth curve that indicates a lower probability for higher Sun elevations.
Sun prior

\[ P(\theta_s, \Delta \phi_s) = P(f(L, D, T, \phi_c)) \]

Sun position \hspace{1cm} Latitude, Date, Time, Azimuth

Data-driven sampling (6 million images)

[Sun plots and data from Hays and Efros, CVPR '08]
Sun prior

Uniform

Data-driven

Probability

Sun elevation

Horizon

Straight up
Cue combination

\[ P(\text{sun position} | \text{sky}) \]
\[ P(\text{sun position} | \text{shadows}) \]
\[ P(\text{sun position} | \text{surfaces}) \]
\[ P(\text{sun position}) \]
\[ P(\text{sun position} | \text{image}) \]
Quantitative evaluation
Quantitative evaluation

Scenes cues + uniform
Data-driven prior
Scenes cues + data

% of images (984 images total)

Error (deg)
Conclusion

- sky, shadows, surfaces
- single, outdoor image
- “illumination aware” scene interpretation
Reviewer Rating

Pros:
1. A novel approach to tackle a very hard problem.
2. Convincing results.

Cons:
1. Heavy use of heuristics.
2. Exposition is poor.

Overall rating: 2/5