Color Models of Shadow Detection in Video Scenes

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Foreground detection for video surveillance

- **Static camera:** static
- **Long** video sequence is available
- **Goal:** <u>*accurate*</u> *retrieval* of the object *shapes;* <u>cast shadow removal</u>
- **Adaptive model**
  - <u>Sharpness of shadow may change in time</u>

Color modeling problem of cast shadows

- Model framework for comparing color spaces
- Experiments for appropriate color space selection
  - Grayscale vs color images
  - RGB space vs CIE uncorrelated spaces
  - Chrominance, luminance or “mixed” spaces

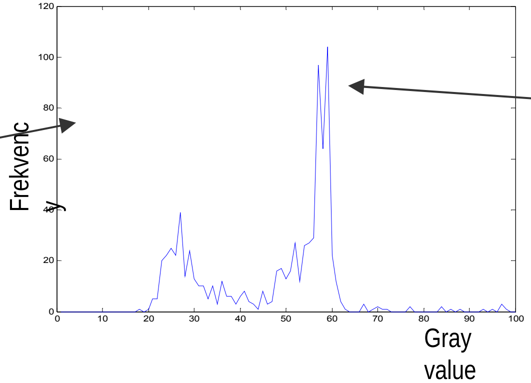
Outline

- Background modeling
- Overview on the state-of-the art shadow detectors
- Feature selection
- Study on the shadow domain in the feature space
- Evaluation

Background calculus

Stauffer-Grimson algorithm

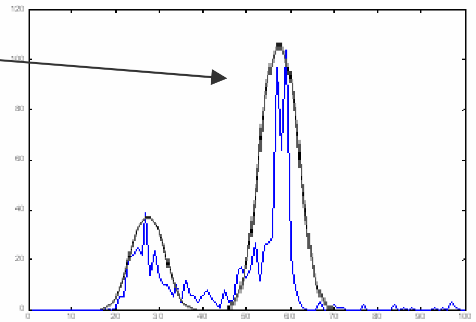
Time histogram for the selected pixel ‘s’



Greatest peak: background

Approximation with mixture of Gaussians, using real time on-line k-means algorithm

<u>Background component</u>: Gaussian with the greatest weight



Probability of ‘s’ in the background has value x(s):

$$p_{bg}(s) = \eta(x(s), \mu_{bg}(s), \Sigma_{bg}(s))$$

$$\Sigma_{bg}(s) = \sigma_{bg}^2(s) I$$

Background image synthesis

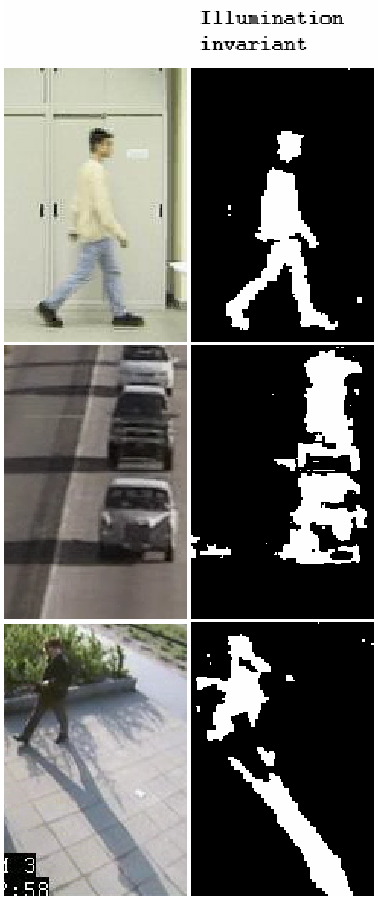
Result of background subtraction

Approaches on shadow detection/1

- Deterministic
  - ON/OFF decision processes at each pixel
- Statistical
  - Probability density functions describe the *confidence* of the shadow membership (MRF models)

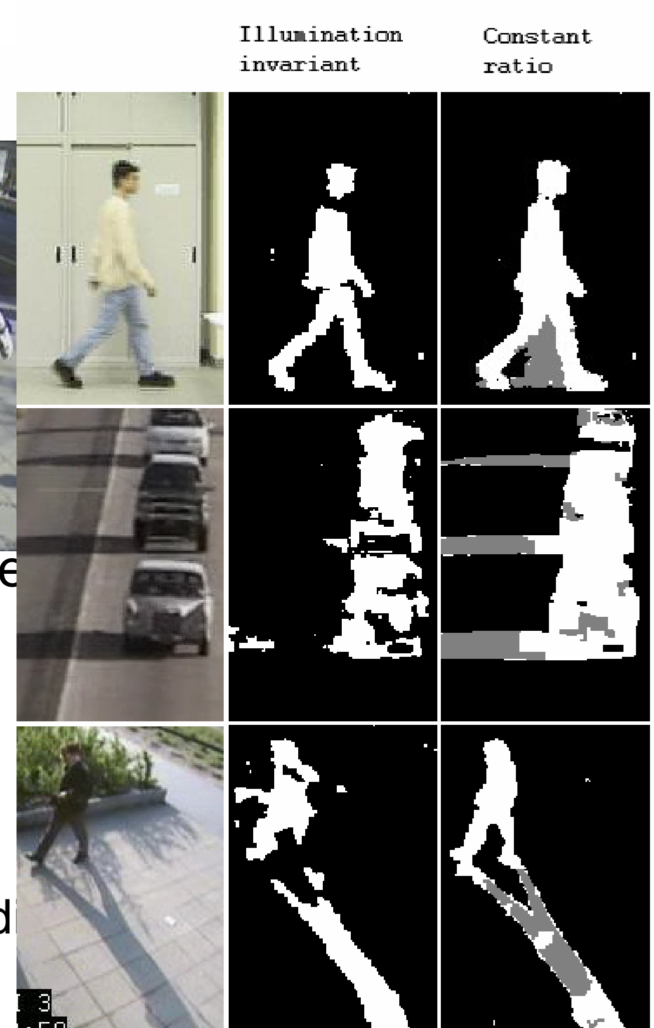
Approaches on shadow detection/2

- Non-parametric models
  - illuminant-invariant approaches (e.g. normalized rgb or $C_1C_2C_3$ spaces)
  - Limited validity
- Parametric models
  - Feature extraction using the actual and background values of the pixels
  - Color space selection
  - Shape of the shadow domain in the feature space



Physical approach on shadow detection

- Lambertian illumi
  - g(s): camera sens
  - e: illumination fun
  - ρ: reflection functi
  - v: sensor sensitivi



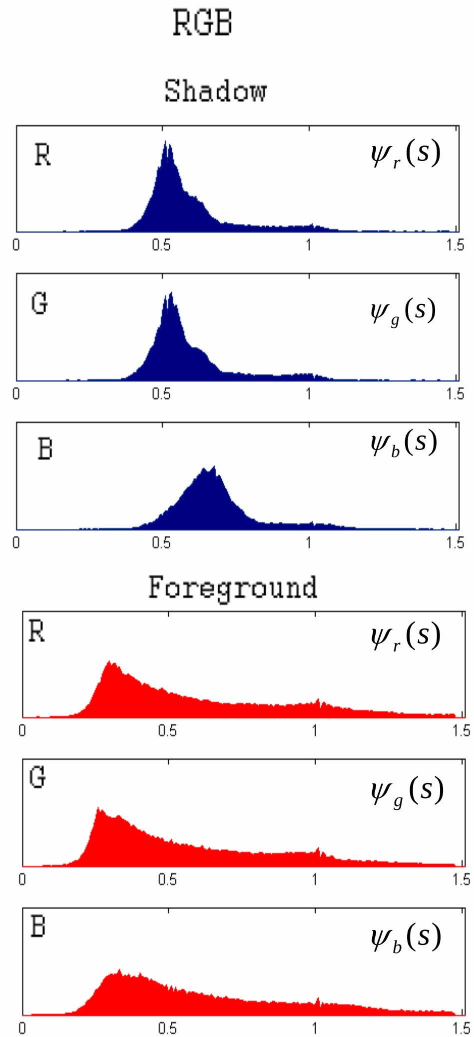
- Constant ratio model (simplification of the e(.,.) independent of *s*)
  - $g_{shadow}(s) \approx A \cdot g_{background}(s)$
  - Corrupted by illumination artifacts
- Proposed statistical model:
  - $\Psi(s)=g(s)/g_{background}(s)$ follows statistical d

Shadow descriptor in the RGB space

- Definition of the shadow descriptors for each color channel (r,g,b)
  - Current pixel value: $[x_r(s), x_g(s), x_b(s)]$
  - Mean background value: $[\mu_r^{bg}(s), \mu_g^{bg}(s), \mu_b^{bg}(s)]$
  - Shadow descriptor:

$$\psi_r(s) = \frac{x_r(s)}{\mu_r^{bg}(s)} \qquad \psi_b(s) = \frac{x_b(s)}{\mu_b^{bg}(s)} \qquad \psi_g(s) = \frac{x_g(s)}{\mu_g^{bg}(s)}$$

- Gaussian distribution for the color components regarding the shadow



Shadow ψ-statistics in different color spaces

- HSV, CIE L*a*b*, CIE L*u*v* spaces:
  - ‘L’ color components: depends on the brightness of the pixel (V and L)
  - ‘C’ components: ‘illumination independent’ (H,S,a,b,u,v)
- rg, $C_1C_2C_3$
  - Only ‘C’ components
- ‘grayscale’, RGB
  - Only ‘L’ components

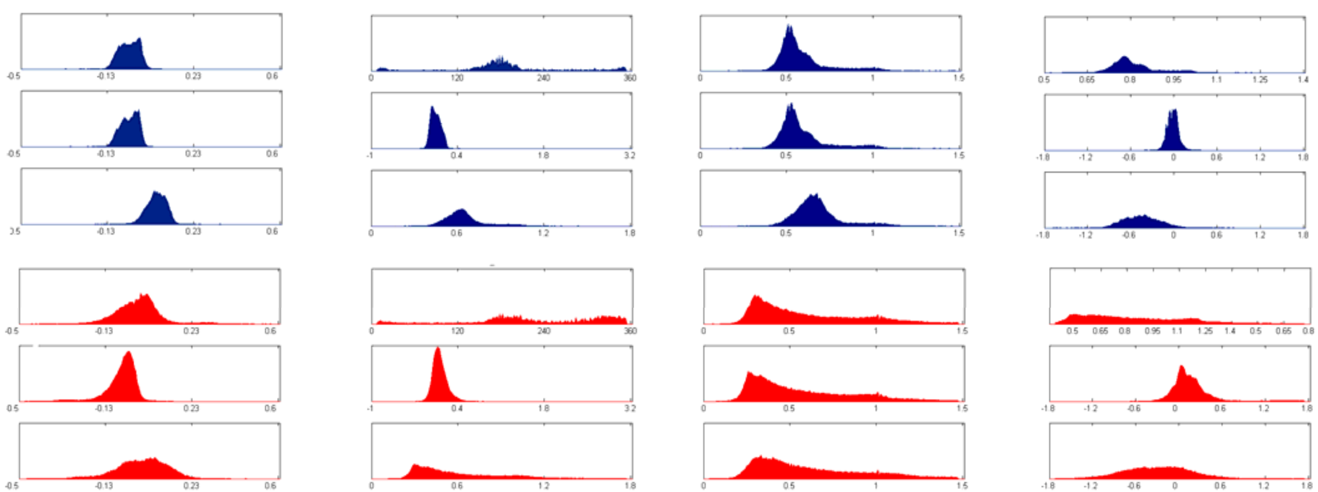
Shadow ψ-statistics in different color spaces

- Shadow descriptor in a given color space
  - Current pixel value: $[x_0(s), x_1(s), x_2(s)]$
  - Mean background value: $[\mu_0^{bg}(s), \mu_1^{bg}(s), \mu_2^{bg}(s)]$
  - Shadow descriptor:

For 'L' channels: $\psi_i(s) = \dfrac{x_i(s)}{\mu_i^{bg}(s)}$

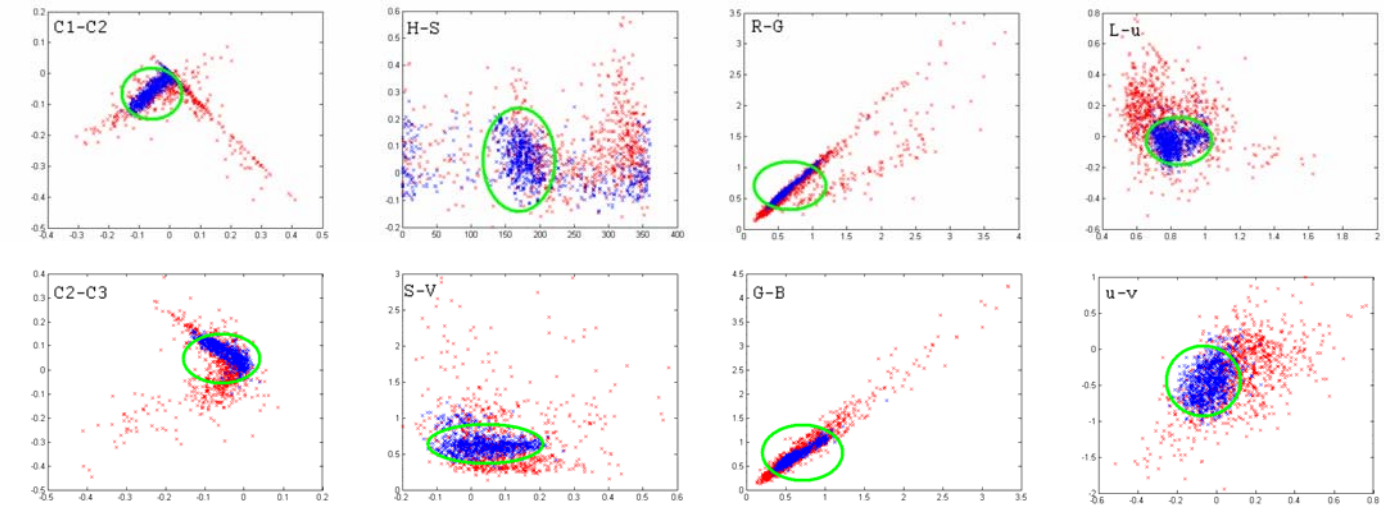
For 'C' channels: $\psi_i(s) = x_i(s) - \mu_i^{bg}(s)$

$C_1C_2C_3$ HSV RGB CIE L*u*v



Shape of the shadow domain

$C_1C_2C_3$ HSV RGB CIE L*u*v



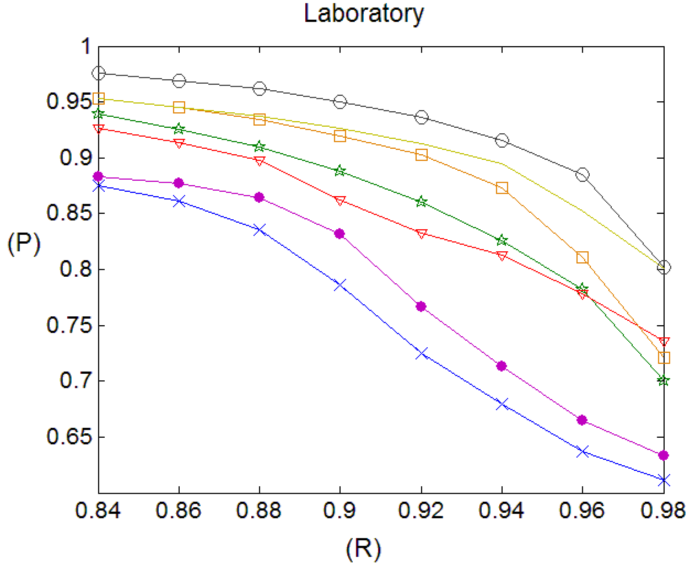
CIE L*u*v: uncorrelated features –less free parameters

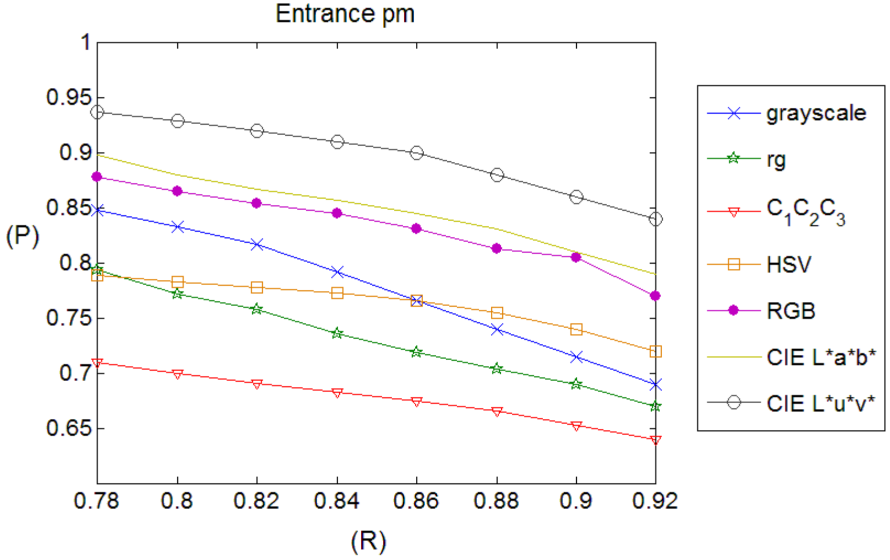
Pixel ‘s’ is shadowed $\Leftrightarrow \sum_{i=0}^{2}\left(\frac{\psi_i(s)-a_i}{b_i}\right)\leq 1$

Evaluation

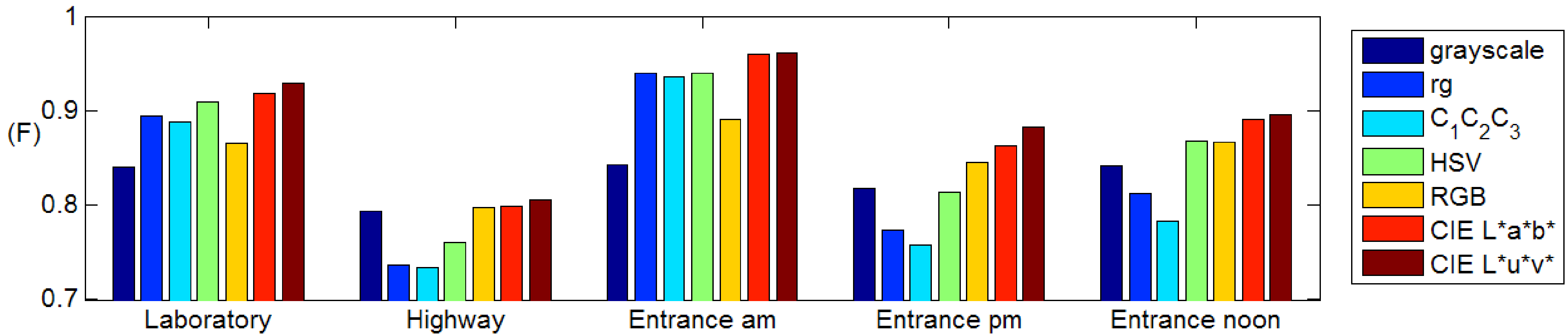
- Measuring the tentative limits of the elliptical shadow domain
  - Discriminating foreground and shadowed pixels purely based on the shadow descriptors
  - Manual parameter settings
- Measuring the performance in real surveillance environment
  - Spatial smoothing the segmented image
  - Automated parameter adaption

Comparison with the ellipse model: Precision/Recall plots





Comparison with the ellipse model: F-measure (harmonic mean of P and R)







Dark shadows: ‘C’ spaces are poor

Measuring the performance in real surveillance environment

- Representative ground truth foreground-shadow points are not available, the optimal ellipse parameters should be estimated somehow
- The classification of a given pixel is usually done considering other effects than color, like neighborhood connection.
- Markov Random Field Framework (Potts model)

Probabilistic model description

- A likelihood classification model for pixel 's'

Pixel value: x_s →

→ P(x_s | s is in foreground) = $p_{fg}(s)$

→ P(x_s | s is in background) = $p_{bg}(s)$

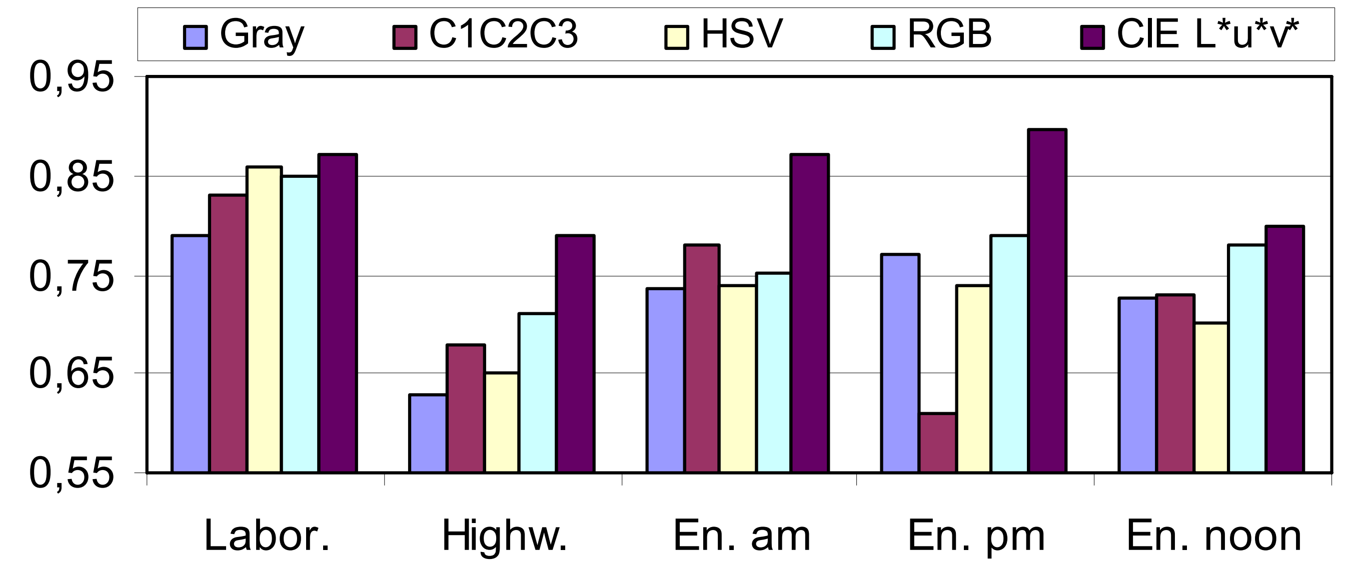
→ P(x_s | s is shadowed) = $p_{sh}(s)$
$=N(\underline{\Psi}(s),\underline{\mu},\Sigma)$

- Field energy
  - Potts model:

$$E = -\sum_{s} \log P(x_s \mid w_s) + \sum_{\substack{\{s,r\} \\ neigbours}} V_{s,r}(w_s, w_r)$$

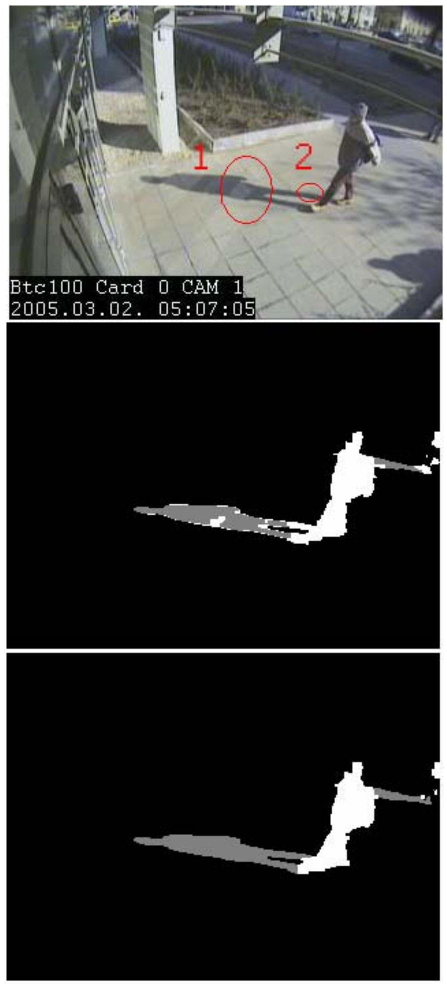
$$V_{s,r}(w_s, w_r) = \begin{cases} -\beta & w_s = w_r \\ +\beta & w_s \neq w_r \end{cases}$$

Segmentation results – comparison of different color spaces



F-rates for Foreground-shadow discrimination (compared to manually generated ground truth)

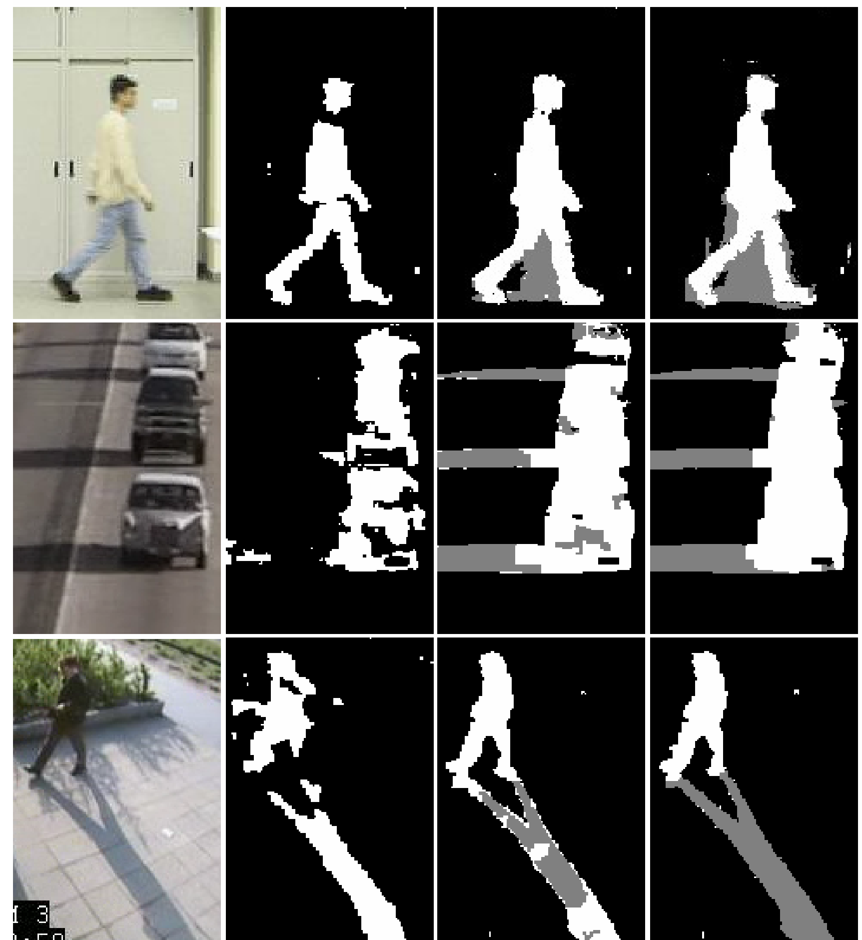
Segmentation results – comparison of different approaches



Constant ratio

Proposed

Illumination invariant | Constant ratio | Proposed



Conclusion

- Model framwork
  - Parametric, but has a few free parameters
  - Appropriate with different color spaces
- Results
  - CIE L*u*v* space is the most efficient

Thank you for your attention!

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