Moving Shadow Detection by Nonlinear Tone-Mapping

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Presentation's Outline

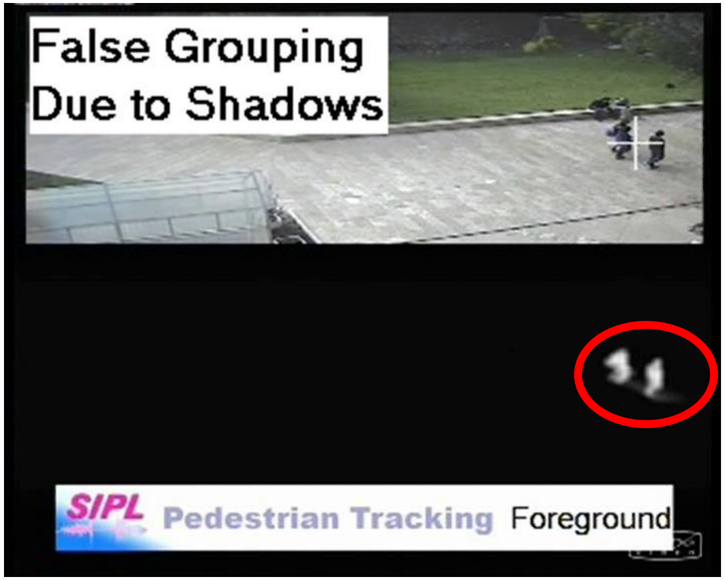
- Introducing the problem
- Existing Solutions
- Proposed Solution
- Metric Approximation
- Results
- Conclusion

Introducing the Problem

- Surveillance systems perform object segmentation & tracking
- Moving shadows may cause identification failure

No Detection

Object Merging



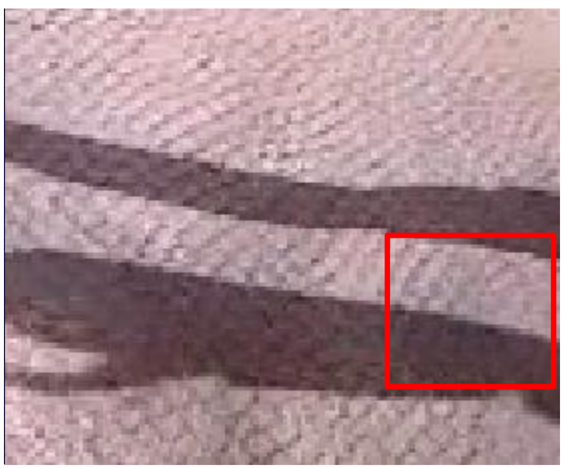
Existing Solutions

- Most solutions are not suitable for shadow detection using a low-cost outdoor surveillance camera
  - Solutions are designed for specific conditions
  - May require pre-calibration of camera and scene parameters
  - May use assumptions that are not met in a surveillance scenario
  - Difficult to generalize

Proposed Solution

- Assumption: Structural content (textures and edges) is preserved from the original non-shadowed scene in shadowed regions

Shadowed



Background

Proposed Solution

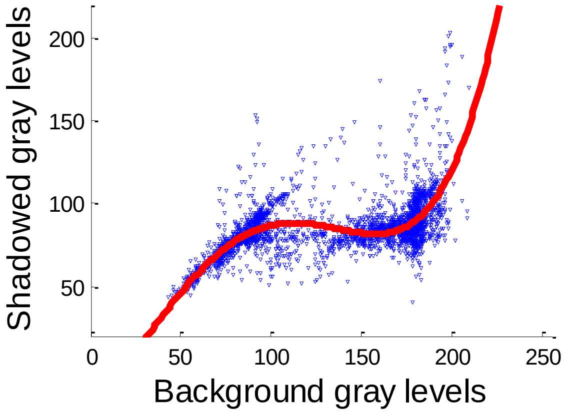
- Observation: Non-linear tone mapping between background and shadow

(a)

Background

(b)

Shadowed



(c)

Tone mapping

Shadow Detection Scheme

- Use a non-linear tone-mapping-invariant metric termed Matching by Tone Mapping (MTM)
  - Recently proposed by (Hel-Or et al., ICCV 2011)
- Measure MTM between suspected foreground p and background w pixels:

$$D(p,w) = \min_{\mathcal{M}} \left\{ \frac{\|\mathcal{M}(p) - w\|^2}{m \cdot \mathrm{var}(w)} \right\}$$

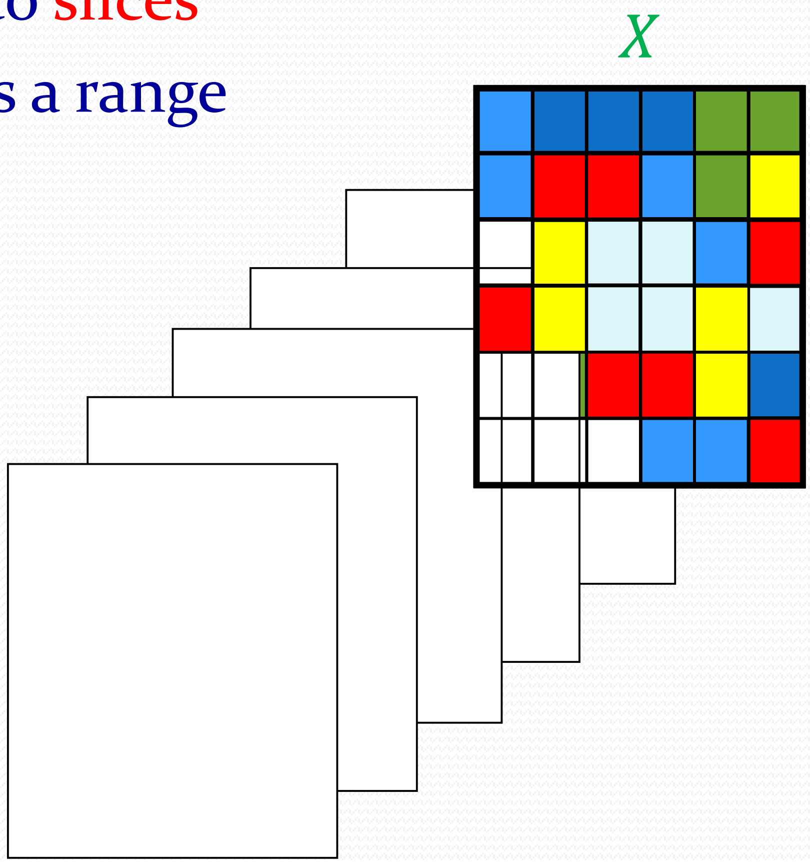
Non-linear mapping

Denominator enforcing scale invariance

- Can be approximated very efficiently
- Compensates for non-linear mapping
  - Small value $\Rightarrow$ shadow
  - Large value $\Rightarrow$ foreground

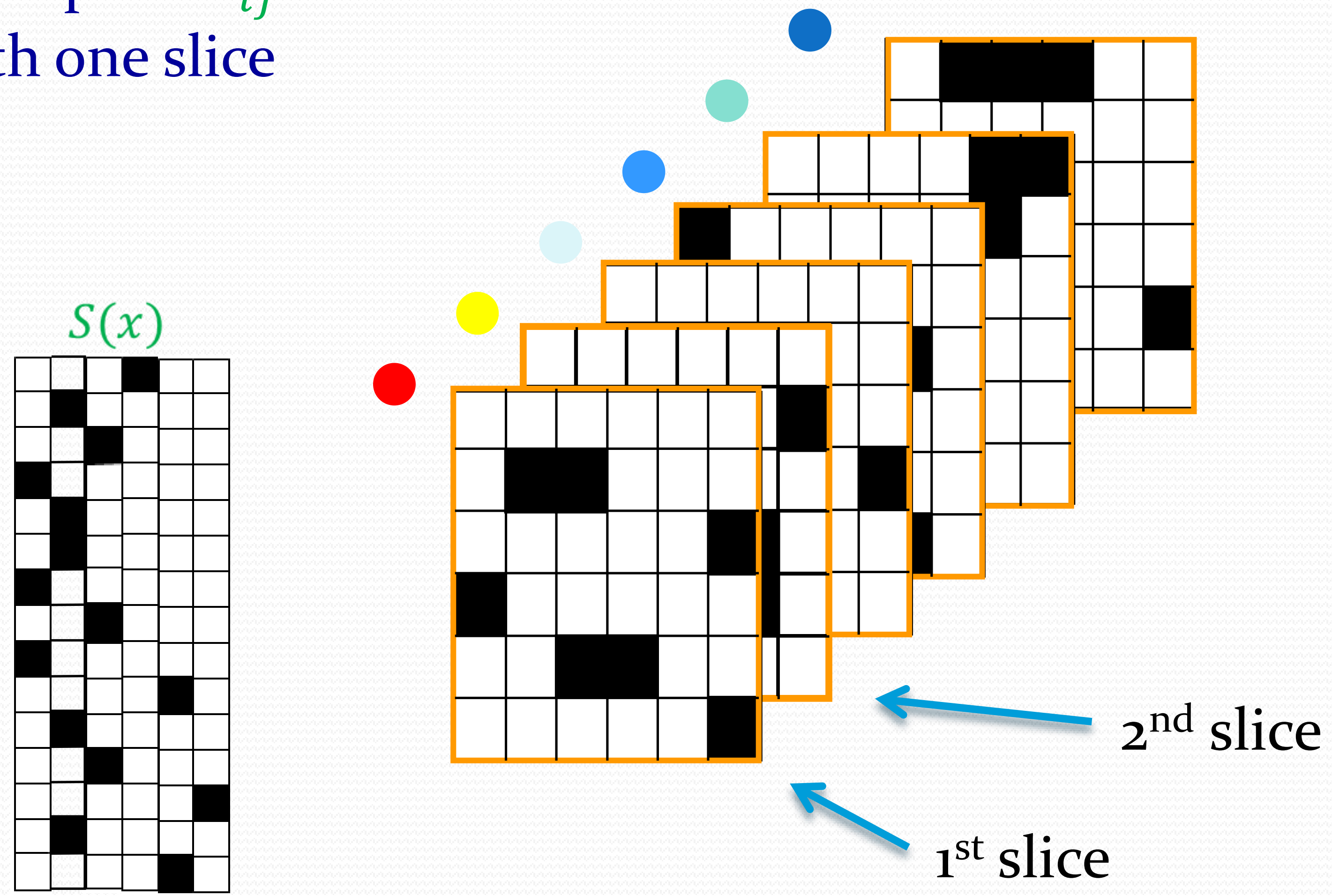
Metric Approximation

- Divide the image into slices
- Each slice represents a range of gray levels



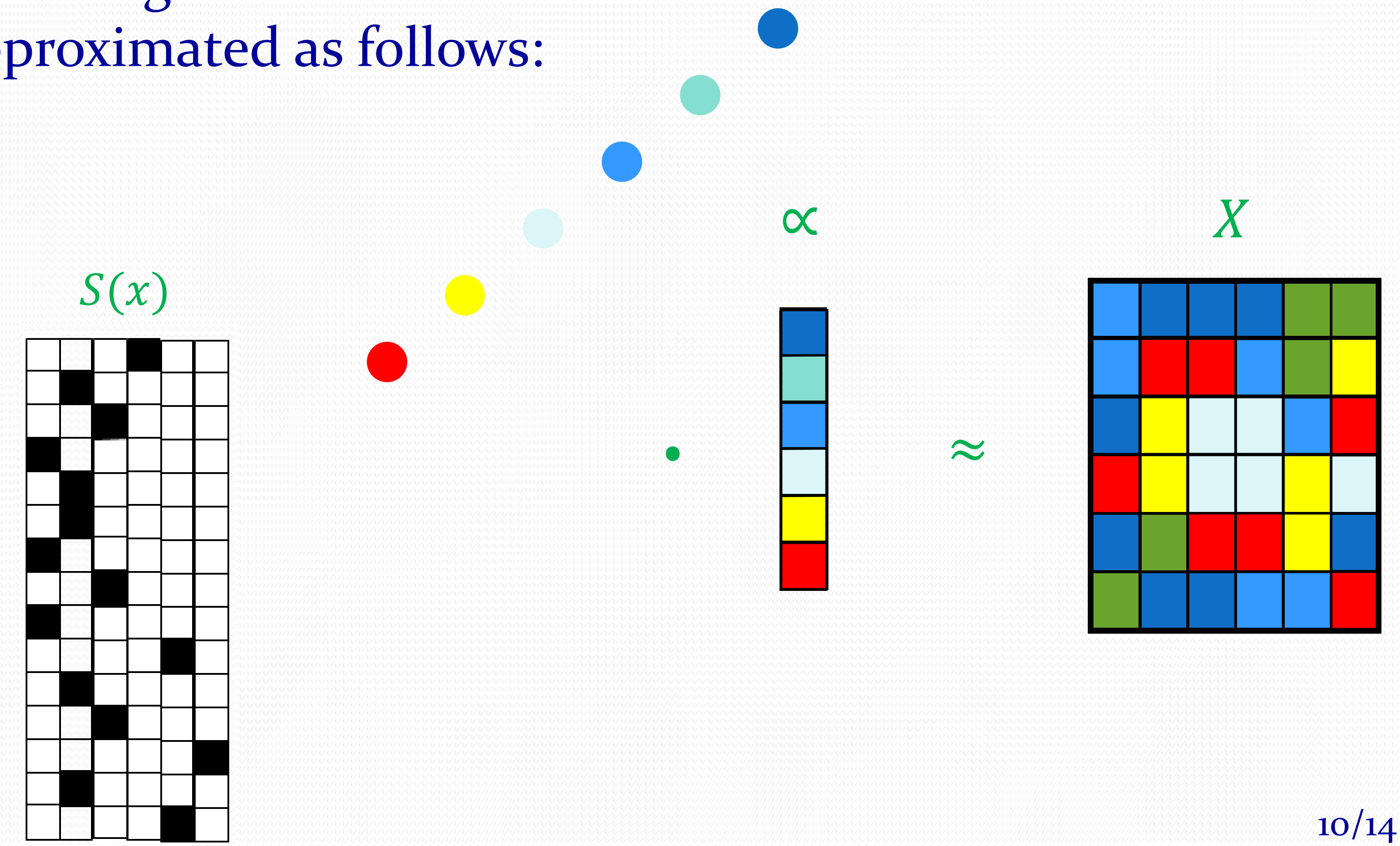
Metric Approximation

- Each pixel X_{ij} is associated with one slice



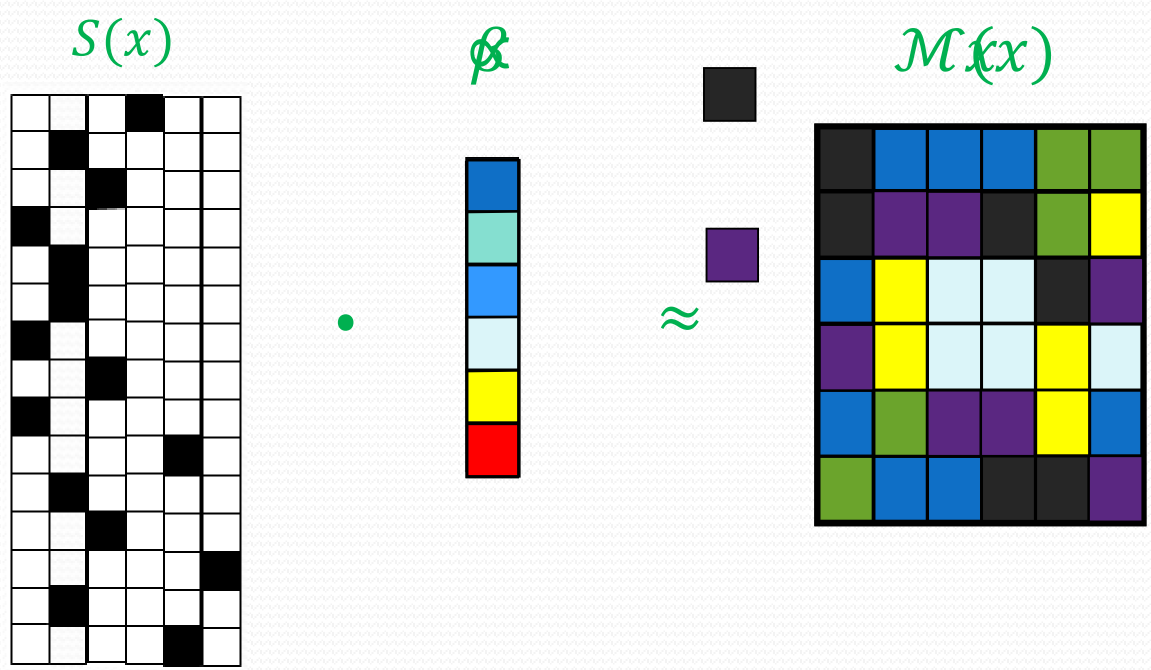
Metric Approximation

- The image X can be approximated as follows:



Metric Approximation

- And in the same way we can represent any piece-wise constant mapping of the image



Metric Approximation

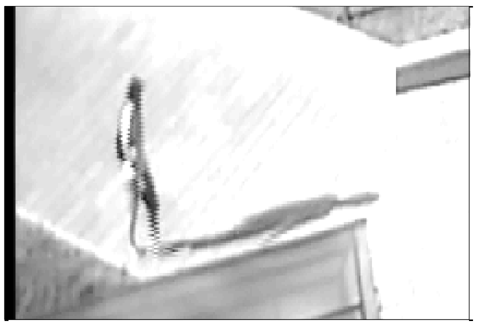
- "Raw" MTM metric: $D(p,w) = \min_{\beta}\left\{\frac{\|\mathrm{M}(p)-w\|^2}{m\cdot \mathrm{var}(w)}\right\}$

- Giving $\mathrm{M}(p) \approx S(p)\beta$, the solution for this minimization problem is: $\hat{\beta} = arg\min_{\beta}\|S\beta - w\|^2 = (S^T S)^{-1} S^T w$

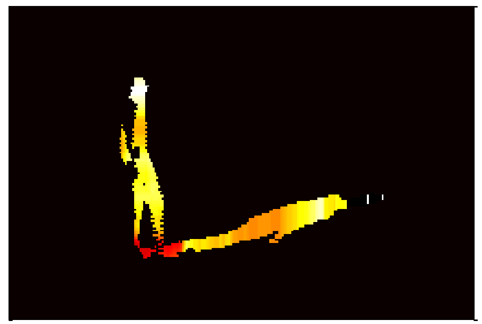
- Finally, we get:

$$\boxed{D(p,w) = \frac{1}{m \cdot \mathrm{var}(w)}\left[\|w\|^2 - \sum_j \frac{1}{|p^j|}(p^j \cdot w)^2\right]}$$

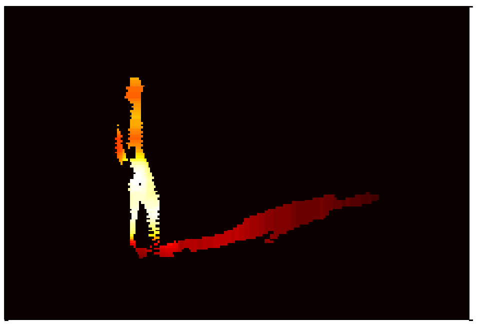
Distance Map



(a)



(b)



(c)

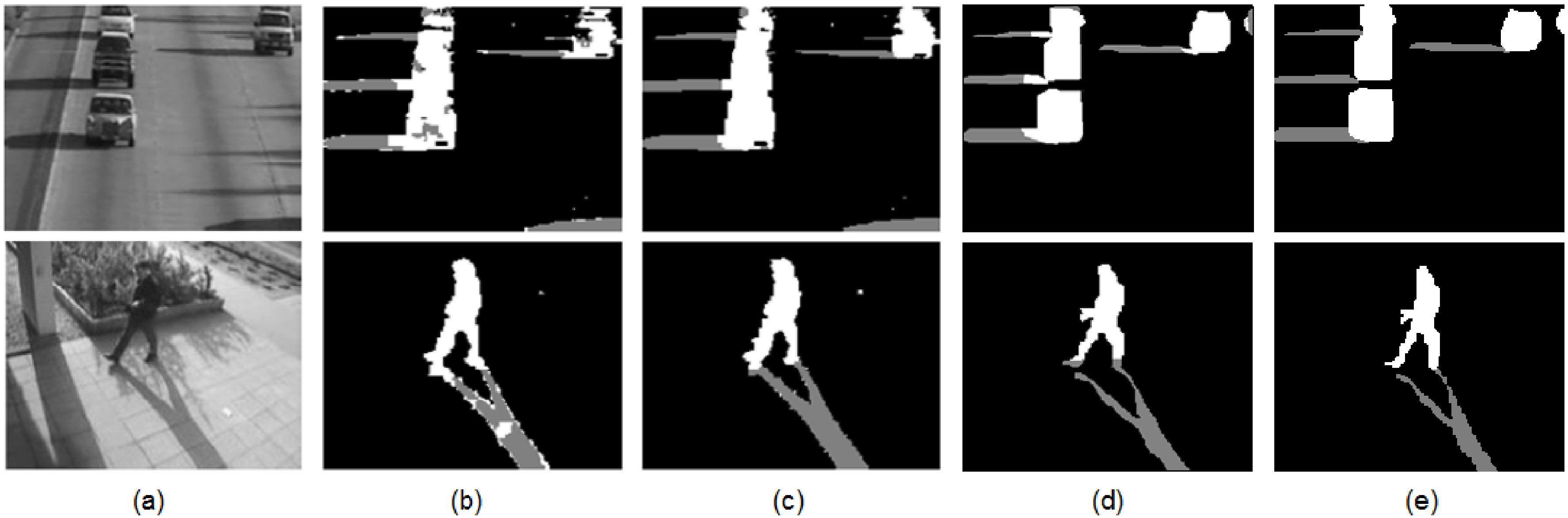
Original

Distance maps using Normalized Cross Correlation (linear tone mapping)

Distance maps using proposed technique

Clear separation between foreground and shadow

Results



Original | CR - Constant ratio (Stander et al., 1999) | SS - Statistical shadow (Benedek & Sziranyi, 2011) | **Proposed** | Ground truth

Images are taken from "**SZTAKI Benchmark Set for Foreground and Shadow Detection in Video Sequences**". (http://cvrr.ucsd.edu/aton/shadow/)

Results

- Better than state of the art

	Precision			Recall			F-measure		
Sequence	CR	SS	MTM -PWC	CR	SS	MTM -PWC	CR	SS	MTM -PWC
Highway	0.644	0.805	0.925	0.866	0.890	0.914	0.746	0.845	**0.920**
Seam	0.596	0.774	0.971	0.946	0.968	0.947	0.731	0.861	**0.959**
Senoon	0.742	0.833	0.935	0.980	0.963	0.953	0.845	0.894	**0.944**
Sepm	0.621	0.830	0.908	0.972	0.961	0.914	0.756	0.891	**0.911**

Conclusion

- A novel moving shadow detection technique
- Based on nonlinear tone mapping between shadows and background
- Uses the Matching by Tone Mapping (MTM) approach for efficiently comparing patches

√ Low computational complexity

√ Robust

√ Substantially outperforms state-of-the-art shadow detection techniques in typical surveillance scenarios