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AUTOMATIC FEATURE LEARNING FOR ROBUST SHADOW DETECTION

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PROBLEM

- The goal is to detect shadows in unconstrained outdoor/indoor environments where no additional information about the scene lightening conditions or camera parameters is available.

- Challenges in Shadow Detection:

(a) Dark Albedo (b) Low Texture (c) Self-Shading (d) Static Shadows (e) No available information about the scene lightening conditions or camera parameters.

- Motivation:

Pros: Provide info. about ..	Cons: Degrade performance of ..
(a) Object Shape	(a) Object Recognition
(b) Object Size	(b) Shape Reconstruction
(c) Body Movements	(c) Image Segmentation
(d) Number of Light Sources	(d) Aerial Imaging
(e) Illumination Conditions	(e) Object Tracking

OUR IDEA

- Human Visual System (HVS) faces absolutely no difficulty in filtering out shadows. Probably, a deep feature learning architecture inspired by HVS will perform better!

- Use features which can classify shadow/object boundaries as well as shadow/non-shadow patches.

- Instead of using shadow variant/in-variant handcrafted features, we automatically learn these feature representations from raw images.

Figure 1: The *top row* shows two images with their detected shadow masks. The *bottom row* shows the two levels on which our feature learning approach works.

REFERENCES

[1] J. Zhu et al. Learning to recognize shadows in monochromatic natural images. In *CVPR*, pages 223–230, 2010.
[2] J.F. Lalonde et al. Detecting ground shadows in outdoor consumer photographs. In *ECCV*, pages 322–335. Springer, 2010.
[3] R. Guo et al. Paired regions for shadow detection-removal. *TPAMI*, 2012.
[4] R. Panagopoulos et al. Estimating shadows with the bright channel cue. In *ECCV wkshp*, 2010.
[5] X. Jiang et al. Shadow detection based on colour segmentation and estimated illumination. In *BMVC*, pages 1–11, 2011.

OUR APPROACH

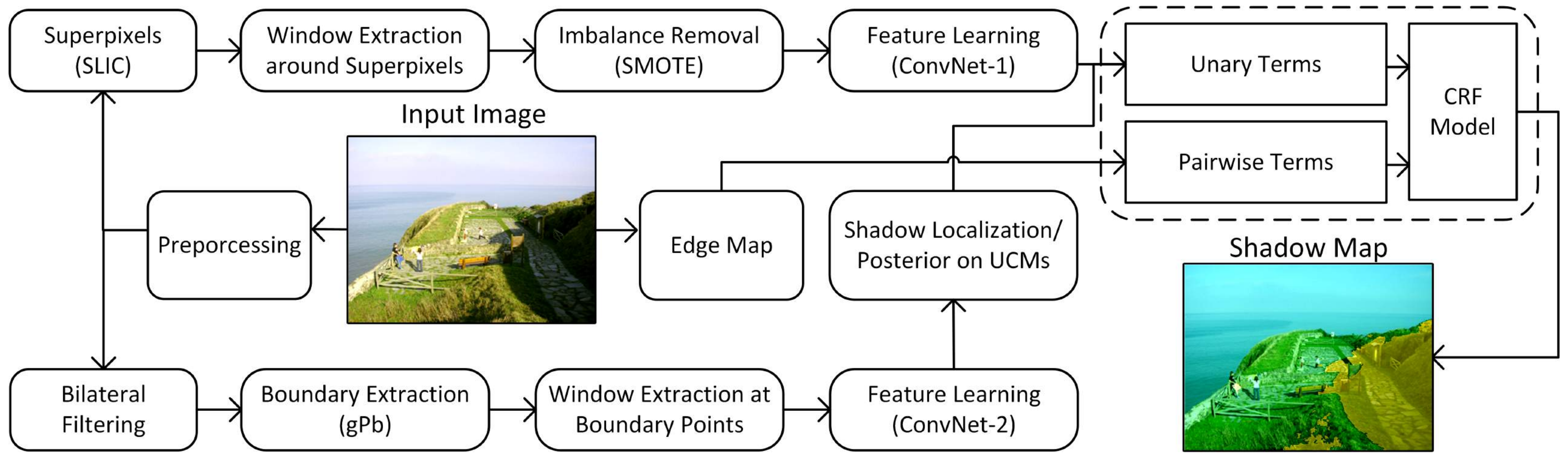


Figure 2: Block diagram of the proposed shadow detection framework.

- The shadow detection problem is treated as a two-class segmentation task by incorporating unary and pairwise beliefs in a CRF model:

$$E(\mathbf{y},\mathbf{x};\mathbf{w}) = \underbrace{\sum_{i\in\mathcal{V}} \psi_i(y_i,\mathbf{x};\mathbf{w}_i)}_{\text{Unary Potential}} + \underbrace{\sum_{(i,j)\in\mathcal{E}} \psi_{ij}(y_{ij},\mathbf{x};\mathbf{w}_{ij})}_{\text{Pairwise Potential}}$$

- The unary term encodes properties of both shadowy regions and shadow boundaries using ConvNets:

$$\psi_i(y_i,\mathbf{x};\mathbf{w}_i) = \underbrace{\phi_i^r(y_i,\mathbf{x};\mathbf{w}_i^r)}_{\text{region}} + \underbrace{\phi_i^b(y_i,\mathbf{x};\mathbf{w}_i^b)}_{\text{boundary}}$$

$$\phi_i^r(y_i,\mathbf{x};\mathbf{w}_i^r) = -\mathbf{w}_i^r \log \mathcal{P}_{\text{cnn-A}}(y_i|\mathbf{x}_r)$$

$$\phi_i^b(y_i,\mathbf{x};\mathbf{w}_i^b) = -\mathbf{w}_i^b \log \mathcal{P}_{\text{cnn-B}}(y_i|\mathbf{x}_b)$$

- The pairwise term consists of the class transition potential ϕ_{p_1} and the spatial transition potential ϕ_{p_2}:

$$\psi_{ij}(y_{ij},\mathbf{x};\mathbf{w}_{ij}) = \mathbf{w}_{ij}\phi_{p_1}(y_i,y_j)\phi_{p_2}(\mathbf{x}).$$

$$\phi_{p_1} = \alpha \mathbf{1}_{y_i \neq y_j},\ \phi_{p_2} = [\exp(-\frac{\|x_i - x_j\|^2}{\beta_x \langle \|x_i - x_j\|^2 \rangle})]$$

- Data augmentation is used to deal with class imbalance.
- A novel algorithm is used for shadow localization given posterior on contour maps.
- Since, energy function is sub-modular, Graph Cuts α-expansion algorithm is used for efficient inference.
- Structured learning (max-margin) is used for parameter tuning.

RESULTS

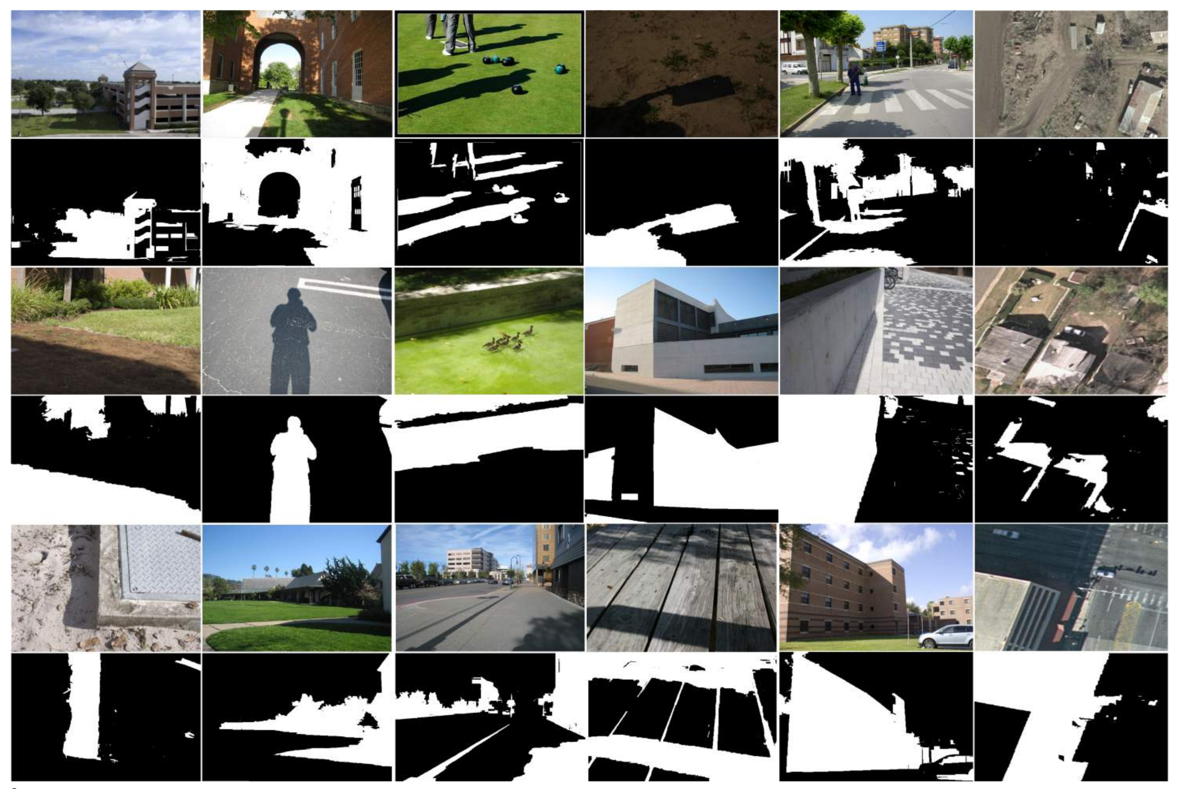


Figure 3: Examples of our results; Images (odd rows) and shadow masks (even rows); Shadows are in white.

	Methods	UCF DB	CMU DB	UIUC DB
	BDT-BCRF [1]	88.70%	–	–
	BDT-CRF-Scene Layout [2]	–	84.80%	–
	Unary SVM-Pairwise [3]	90.20%	–	89.10%
	Bright Channel-MRF [4]	85.90%	–	–
	Illumination Maps-BDT-CRF [5]	83.50%	84.98%	–
This paper	ConvNet(Boundary+Region)	89.31%	87.02%	92.31%
This paper	ConvNet(Boundary+Region)-CRF	**90.65%**	**88.79%**	**93.16%**

Table 1: Pixel-wise accuracies and comparisons for the proposed scheme.

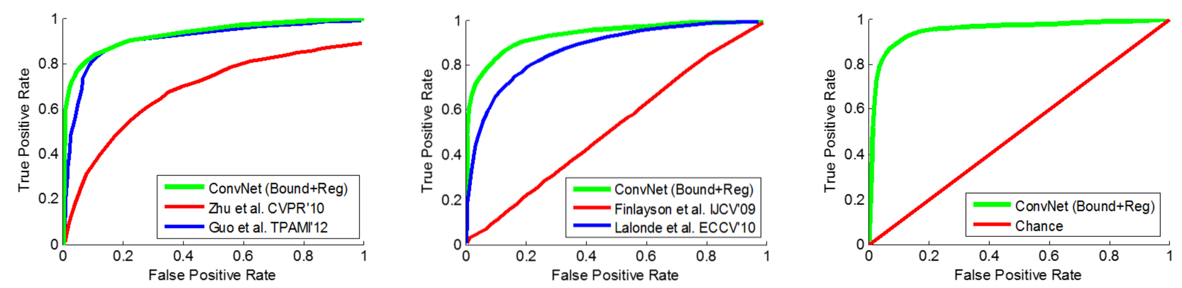


Figure 4: ROC curve comparisons for the proposed scheme.

Methods/Datasets	Shadows	Non-Shadows
UCF Dataset		
BDT-BCRF [1]	63.9%	93.4%
Unary-Pairwise [3]	73.3%	**93.7%**
Bright Channel-MRF [4]	68.3%	89.4%
ConvNet(Boundary+Region)	72.5%	92.1%
ConvNet(Boundary+Region)-CRF	**78.0%**	92.6%
CMU Dataset		
BDT-CRF-Scene Layout [2]	73.1%	**96.4%**
ConvNet(Boundary+Region)	81.5%	90.5%
ConvNet(Boundary+Region)-CRF	**83.3%**	90.9%
UIUC Dataset		
Unary-Pairwise [3]	71.6%	95.2%
ConvNet(Boundary+Region)	83.6%	94.7%
ConvNet(Boundary+Region)-CRF	**84.7%**	**95.5%**

Table 2: Class-wise accuracies of our proposed framework in comparison with the state-of-the-art techniques. Our approach gives the highest accuracy for the class *'shadows'*.

FEATURE LEARNING

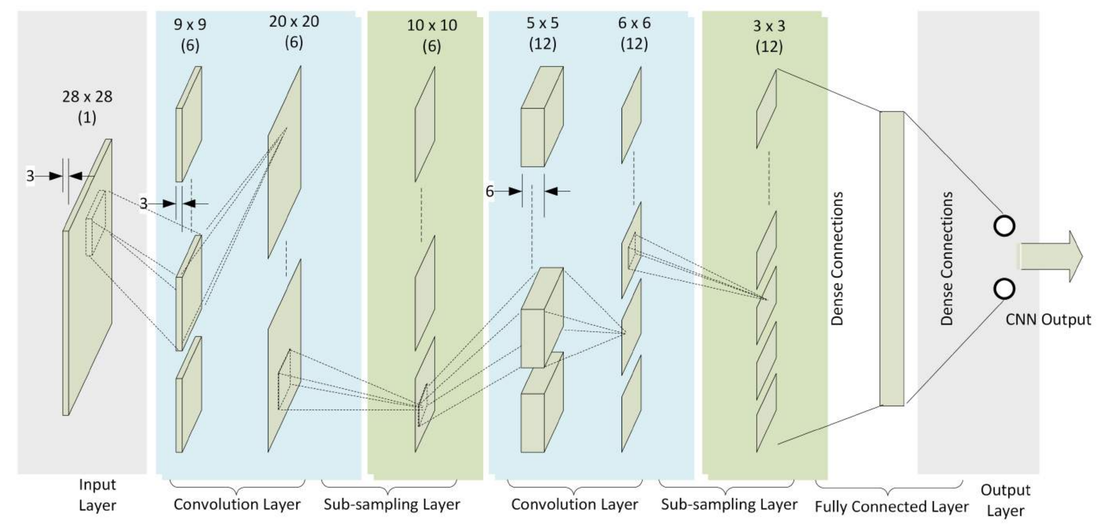
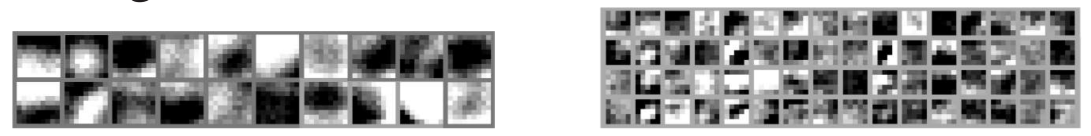


Figure 5: The ConvNet architecture used in this work.



(a) Examples of 9x9 learned kernels for left convolution layer. (b) Examples of 5x5 learned kernels for right convolution layer.

- Training is done with stochastic gradient descent algorithm. Epochs are set by an early stopping criterion.
- We empirically found that pixel decorrelation methods do not work for shadow detection.

ANALYSIS

- Cross-dataset Evaluation: Experiments (Tab. 3) show that the learned feature representations are generalizable.

Tested on	Trained on UCF	Trained on CMU	Trained on UIUC
UCF	–	80.3%	80.5%
CMU	77.7%	–	76.8%
UIUC	82.8%	81.5%	–

Table 3: Results when ConvNets were trained and tested across different datasets

- Failure cases were due to complex self shading patterns created by tree leaves, objects with dark albedo and inconsistencies in the ground-truths.

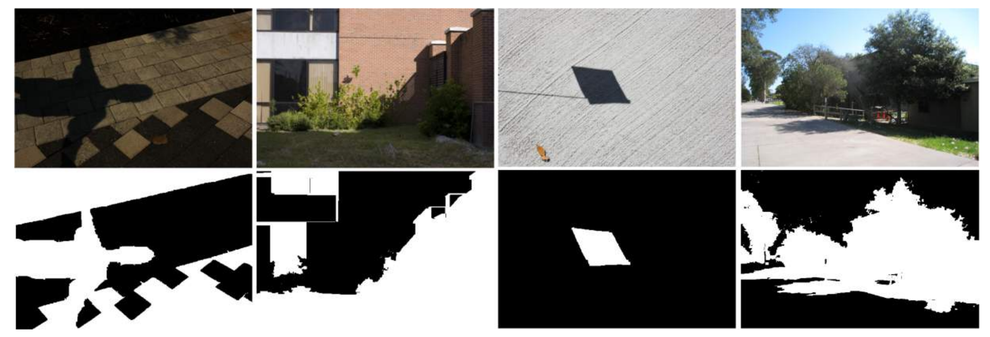


Figure 6: Examples of ambiguous cases: (From *left* to *right*) Our framework misclassified a dark non-shadow region, texture-less black window glass, very thin shadow region and trees due to complex self shading.

CONTACT INFORMATION

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