Non-Local Deep Features for Salient Object Detection

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Introduction

Goal

Highlight the most relevant objects in an image (**saliency**).

Proposed method

- Novel 4 × 5 multiresolution CNN grid structure
- Contrast features
- Loss function inspired by the Mumford-Shah functional
- No CRF, no superpixels

Outcome

- Top performing method on 6 datasets
- Real-time, high performance saliency detection.

Mumford-Shah Function [5]

$$F^{MS} = \underbrace{\sum_j \lambda_j \int_{\mathbf{v}\in\Omega_j} \left|I(\mathbf{v}) - u_j\right|^2 d\mathbf{v}}_{\text{data fidelity}} + \underbrace{\sum_j \gamma_j \oint_{\mathbf{v}\in C_j} d\mathbf{v}}_{\text{boundary length}}$$

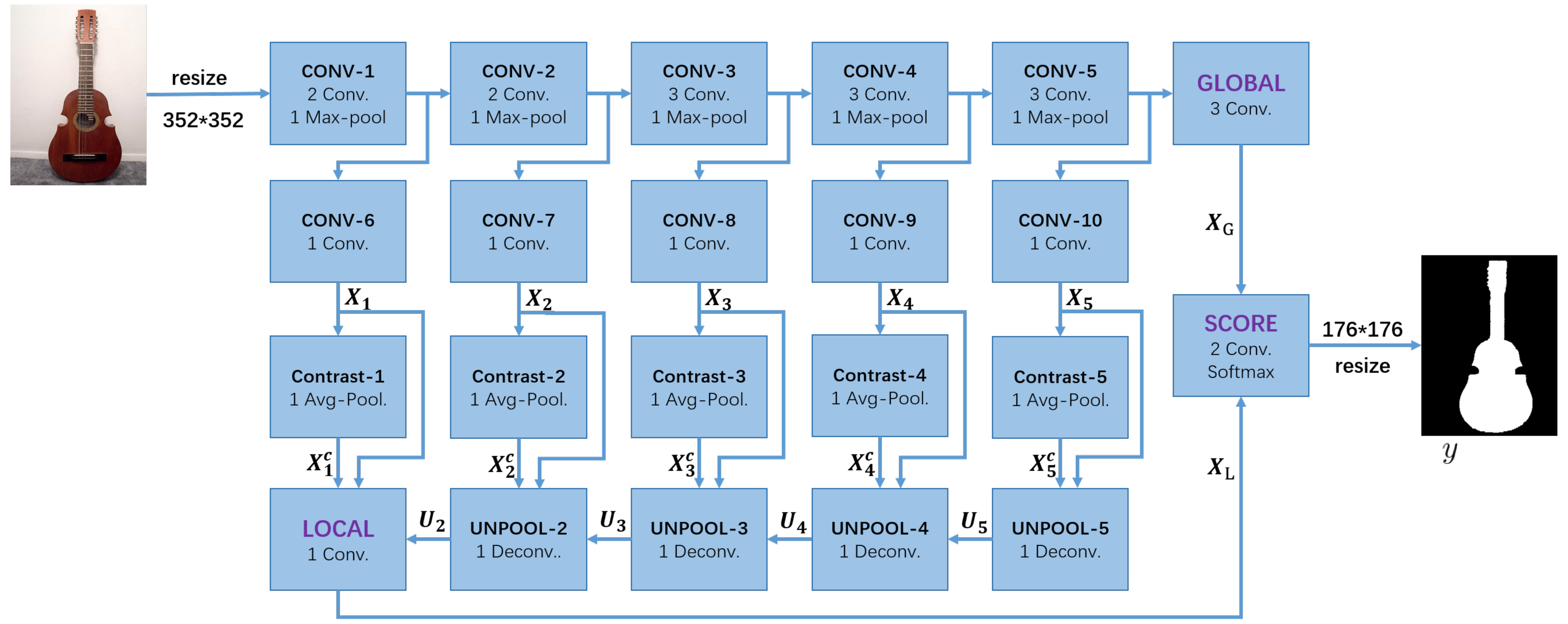
Bayesian statistical approximation [6]

$$F^{MS} \approx \underbrace{\sum_j \lambda_j \int_{\mathbf{v}\in\Omega_j} \log p_j(I(\mathbf{v}),\mathbf{v}) d\mathbf{v}}_{\text{data fidelity}} + \underbrace{\sum_j \gamma_j \oint_{\mathbf{v}\in C_j} d\mathbf{v}}_{\text{boundary length}}$$

Final loss function

$$F^{MS} \approx \underbrace{\sum_j \lambda_j \int_{\mathbf{v}\in\Omega_j} \mathrm{H}_j(y(\mathbf{v}),\hat{y}(\mathbf{v}))}_{\text{cross entropy}} + \underbrace{\sum_j \gamma_j (1 - \mathrm{IoU}(C_j,\hat{C}_j))}_{\text{boundary IoU loss}}$$

Network Architecture



Cross-Entropy Loss

$$\hat{y}(\mathbf{v}) = p\big(y(\mathbf{v}) = c\big) = \frac{e^{\overbrace{W_L^c X_L(\mathbf{v}) + b_L^c}^{\text{Local}} + \overbrace{W_G^c X_G + b_G^c}^{\text{global features}}}}{\sum_{c'\in\{0,1\}} e^{W_L^{c'} X_L(\mathbf{v}) + b_L^{c'} + W_G^{c'} X_G + b_G^{c'}}}$$

(Local & global features)

$$H_j(y(\mathbf{v}),\hat{y}(\mathbf{v})) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c\in\{0,1\}} (y(\mathbf{v}_i) = c)\big(\log(\hat{y}(\mathbf{v}_i) = c)\big)$$

IoU Boundary Loss (Dice Loss)

$$\text{IoU Loss} = 1 - \frac{2|C_j \cap \hat{C}_j|}{|C_j| + |\hat{C}_j|},$$

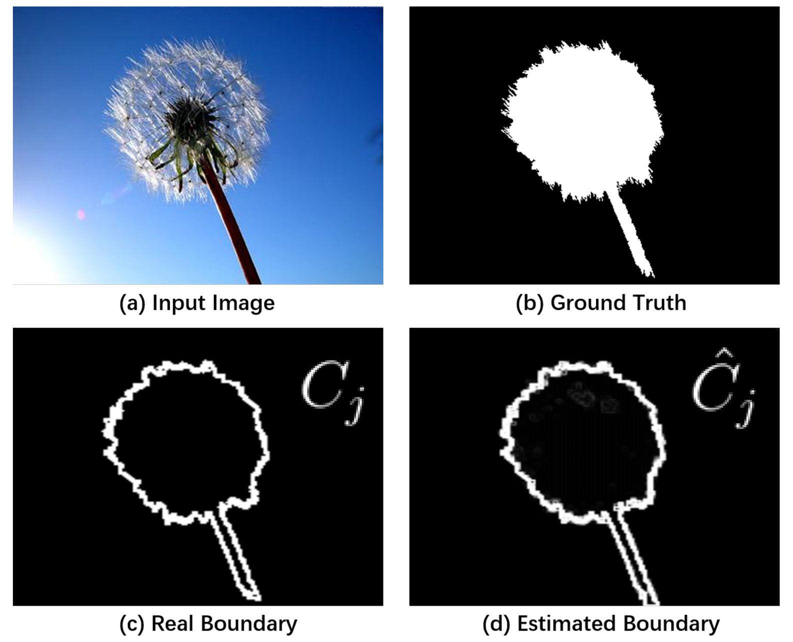


Figure 1. The IoU boundary loss, end-to-end trainable.

Figure 2. Visual comparison of saliency detection results with and without the boundary loss term.

Results and Evaluation

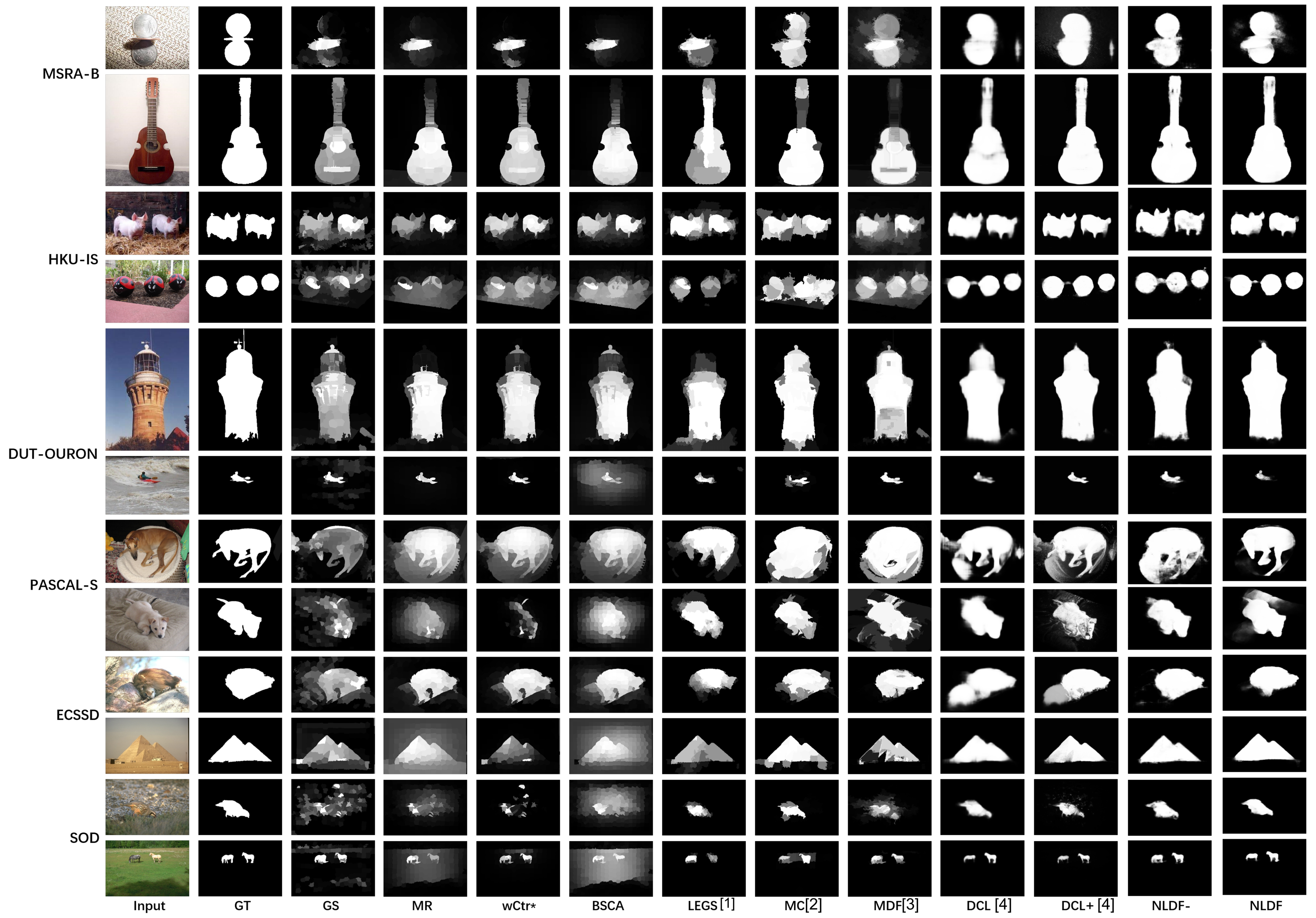


Figure 3. Visual comparison between previous approaches and our method (NLDF).

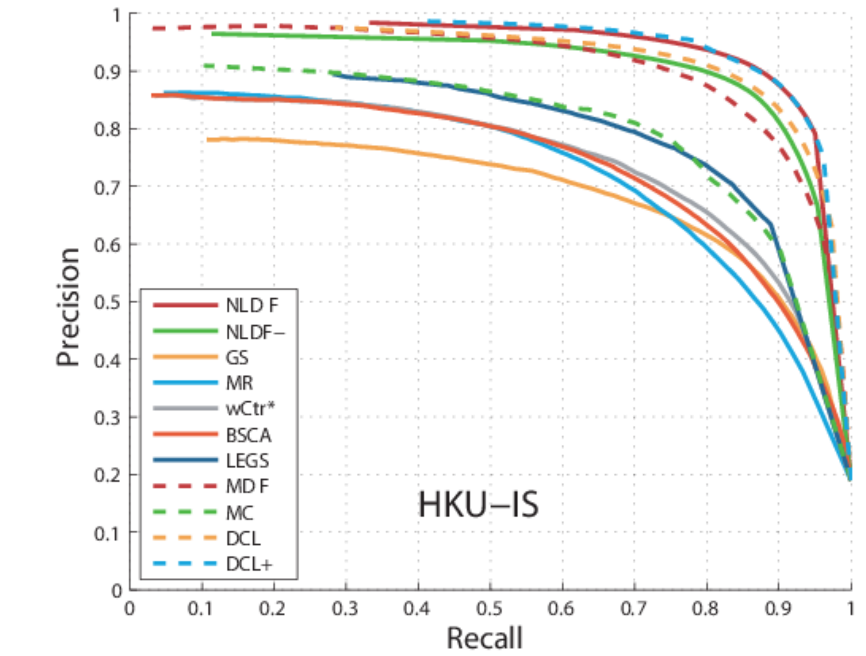


Figure 4. Precision and recall curve for the HKU-IS datasets

	LEGS[1]	MC[2]	MDF[3]	DCL[4]	DCL+[4]	**NLDF**
s/img	2	1.6	8	1.5	2.3	**0.08**

Table. Average execution time to process an image

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