Faster Region-based Hotspot Detection

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1. Background

- What you see is what you get
- RET: OPC, SRAF, MPL
- Worse on designs under 10nm or beyond

2. Previous Solutions

- A binary classification problem.
- Scan over whole region.
- Single stage detector.
- Scanning is time consuming and single stage is not robust to false alarm.

3. Region Based Approach

- Learning what and where is hotspot at same time.
- Multi-task on Classification and Regression.

4. Feature Extraction

- Encoder-decoder preprocess
  - Symmetric Structure for feature encoding and decoding.
  - Much faster than discrete cosine transformation.
- Inception based structure
  - Multi thread feature extraction.
  - Prune the depth of the output channel for each stage.
  - Downsample the feature map size in height and width direction.

5. Clip Proposal Network

- Definition
  - Clip: Predefined box to crop hotspot features in region.
  - Proposal: Selected clip which contribute to classification and regression.
- Based on extracted features, Clip Proposal Network is designed to locate and classify hotspots.
- Classification and regression branches share features.

6. Details on Clip Proposal Network

- To a classifier, we have to balance the positive and negative samples.
- As a regression task on location, we need to select reasonable clips as proposals.
- We also need to consider efficiency and quality of features.

7. Loss Function Design

- Parameterizations of coordinates
  - Origin parameters may affect the training stability.
  \[ l_x = x - x_g \]
  \[ l_y = y - y_g \]
  \[ \theta_w = \tan^{-1}(w / h) \]
  \[ \theta_h = \tan^{-1}(h / w) \]
(1)
- Classification and Regression Loss
  - L2 regularization penalizes peaky weight vectors and prefers diffuse weight vectors, which has appealing property of encouraging the network to use all of its inputs rather than skewed on partial of its inputs.
  \[ L_{CR}(h, \theta) = \frac{1}{2} \sum h_{prev}(h, \theta) + \frac{1}{2} \| \theta_{hotspot} \|^2 \]
(2)
  - Smooth L1 loss for robust regression, which makes gradient smooth when offset is small.
  \[ L_{W2}(h, \theta) = \begin{cases} \frac{1}{2} (h - \theta)^2, & \text{if } |h - \theta| < 1 \\| h - \theta \| - \frac{1}{2}, & \text{otherwise} \end{cases} \]
(3)
  - Cross Entropy loss:
  \[ L_{CE}(h, \theta) = - (h \log(h_x) + h_y \log(h_y)) \]
(4)

8. Experimental Results

- Comparison with State-of-the-art
  - ICCAD CAD Contest 2016 Benchmarks
  - Three different design styles
  - 45 times faster and 6.14 % accuracy improvement compared to [Yang, TCAD'18].
  - Much better than two well known object detection based frameworks.

9. Ablation Study

- Comparison among different settings
  - (a) average accuracy and (b) average false alarm.

10. Visualized Result

- Visualized different hotspot detection results.