Layout Hotspot Detection with Feature Tensor Generation and Deep Biased Learning

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Introduction

- RET: OPC, SRAF, MPL
- Still hotspot: low fidelity patterns
- Simulations: extremely CPU intensive
- Hotspot Detection: Predicting patterns or regions with low printability

Preliminaries and Related Works

Accuracy

The ratio between the number of correctly predicted hotspot clips and the number of all real hotspot clips.

False Alarm

The number of non-hotspot clips that are predicted as hotspots by the classifier.

Pattern matching based hotspot detection

- Fast and accurate
- Fuzzy pattern matching [Ven., TCAD'15]
- Hard to detect non-seen pattern

Machine learning based hotspot detection

- Predict new patterns
- Decision-tree, ANN, SVM, Boosting, Bayesian, ...
- Deep learning issues: compatibility with CNN
- Feature tensor generation and deep biased learning

Why Deep Learning?

1. Feature Crafting vs. Feature Learning
   - Manually designed feature → inevitable information loss
   - Learned feature → Reliable
2. Scalability
   - More pattern types
   - More complicated patterns
   - Hard to fit millions of data with simple ML model
3. Mature Libraries
   - Caffe [Jia+ ACM/14]
   - Tensorflow [Martín, TR'15]

Deep Learning Issues on Hotspot Detection

Layout image size is large (≈ 1000 x 1000)
- Compared to ImageNet (≈ 200 x 200)
- Associated CNN model is large
- Not storage and computational efficient

Hotspot detection accuracy is more important
- Hotspot → Circuit Failure
- False Alarm → Runtime Overhead
- Consider methods for better trade-off between accuracy and false alarm

The Overall Detection Flow

Training Layout
Biased Learning Extraction CNN
Validation Phase
Convergence

Testing Layout
Feature Tensor Extraction

Biased Learning Algorithm

Recall the training procedure
- Minimize difference with ground truths
  \[ y^* = [1, 0], \quad F_{\theta}(y(0)) = 0.5 \]

\[ F_{\theta}(y(1)) = 0.5 \]

Solutions to increase the detection accuracy

1. Shifting decision boundary
   \[ F_{\theta}(y(1)) = 0.5 + \lambda \]

   - Straightforward
   - At the cost of much false alarm penalties
2. Biased ground truth
   \[ y^* = [1 - \epsilon, \epsilon] \]

Assumption of the Biased Ground Truth

Given a trained convolutional neural network with ground truth \( y^* = [1, 0] \) and \( y^* = [0, 1] \) and hotspot detection accuracy \( \alpha \) on a given test set. Fine tune the network with \( y^* = [1 - \epsilon, \epsilon], \quad \epsilon \in (0, 0.5) \), and obtain the hotspot detection accuracy \( \alpha' \) of the new model. We have \( \alpha' \geq \alpha \).

The training procedure

Algorithm: Biased Learning

Input: \( \{ F_{\theta}(y(0)), F_{\theta}(y(1)) \} \), \( \epsilon \), \( \alpha \), \( \lambda \), \( W \), \( \alpha, k_1, k_2, y^*_1 \)

\( n \) if \( \epsilon < \alpha \) then

\( \alpha' = \text{MSE}(W, \alpha, k_1, k_2, y^*_1) \)

\( \epsilon = \epsilon + \lambda \)

end if

Effectiveness of the Biased Learning Algorithm

- The above neural network is trained with \( \epsilon = 0 \) to obtain an initial model, and is fine-tuned with \( \epsilon = 0.1, 0.2, 0.3 \) on Industry3. Then we perform boundary shifting on initial model to achieve the same test accuracy with three fine-tuned models.

Experimental Results

- Using Python on Intel Xeon Platform with Nvidia K620 Graphic card.
- Based on Tensorflow Library
- Benchmarks from ICCAD Contest 2012 and Industry

Benchmark Statistics

<table>
<thead>
<tr>
<th></th>
<th>Training Set</th>
<th>Testing Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICCAD</td>
<td>1204 17096</td>
<td>2524 3500</td>
</tr>
<tr>
<td>Industry 1</td>
<td>34281 15635</td>
<td>71175 7801</td>
</tr>
<tr>
<td>Industry 2</td>
<td>5197 48758</td>
<td>7520 24457</td>
</tr>
<tr>
<td>Industry 3</td>
<td>54776 49515</td>
<td>2228 8487</td>
</tr>
</tbody>
</table>

- ICCAD contains all the 28nm clips in the original contest benchmark
- Industry1-Industry3 are from industry design and correspond to different OPC level

Result comparison with two state-of-the-art hotspot detectors

- Accuracy improved from 89.9% to 95.5% (Ours vs. Other)
- Comparable false alarm penalty

Conclusions

- Propose the feature tensor representation of layout clips
- Propose the biased learning algorithm
- Demonstrate the feasibility of deep learning solutions for advanced DFM research