GAN-SRAF: Sub-Resolution Assist Feature Generation using Generative Adversarial Networks

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Motivation

♦ With the IC technology scaling, resolution enhancement techniques are becoming indispensable.

♦ Sub-Resolution Assist Feature (SRAF) generation is used to improve the lithographic process window of target patterns.

https://slideplayer.com/slide/9416386/
Conventional Approaches

♦ Rule-Based approaches:
  › Work well for simple designs with regular patterns
  › Cannot handle complex shapes

♦ Model-Based (MB) approaches:
  › Achieve high quality results
  › Suffer from exorbitant computational cost

♦ Machine Learning (ML) Based approach:
  › Achieves results quality similar to MB
  › Results in 10X reduction in runtime
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Can we do better?!
ML Based Approach

- Proposes local sampling scheme with a classification model
- On a 2D grid, the classifier predicts the presence of SRAF in each grid

[Xu et al, ISPD’16, TCAD’17]
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While achieving 10X runtime improvement, this approach has large room for further enhancement

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- Can we avoid the feature extraction step?

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- Do we need a 2D grid and local sampling?
- Can we avoid the feature extraction step?
- Most importantly, with all advancements in Computer Vision, can we recast this problem to leverage these advancements?

[Xu et al, ISPD’16, TCAD’17]
CGAN for Image Translation

♦ GANs have been proposed to produce images similar to those in training data set
♦ CGAN, takes as an input a picture in one domain and translates it to a new one
  › During training it sees pairs of matched images
SRAF Generation & Image Translation

What does SRAF generation have to do with Image translation?!
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Can we define the problem as translating images from the Target Domain ($D_T$) to the SRAF Domain ($D_S$)?
Challenges

♦ Layout images have sharp edges which pose a challenge to GANs
  › Model is not guaranteed to generate polygon SRAF shapes
  › Sharp edges can complicate gradient propagation

♦ Generated images need ultimately be changed to layout format
  › Images cannot be directly mapped to ‘GDS’ format
  › Post-processing step should not be time consuming
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♦ Hence, a proper encoding is needed to address these challenges!
Multi-Channel Heatmap Encoding

Key Idea: encode each type of object on a separate channel in the image
- Channel index carries object description (type, size,...)
- Excitations on the channel carry objects location

Original Layout

Encoded Layout
Challenges Revisited

- Layout images have sharp edges which pose a challenge to GANs
  - Model is not guaranteed to generate polygon SRAF shapes
  - Polygon shapes are not needed, the objective of model is to predict locations on different channels
  - Sharp edges can complicate gradient propagation
  - No sharp edges in encoded image

- Generated images need ultimately be changed to layout format
  - Images cannot be directly mapped to ‘GDS’ format
  - Decoding is straight forward, it suffices to detect excitation location on each channel to get full GDS information
CGAN Approach

♦ Generator:
  › Trained to produce images in $D_S$ based on input from $D_T$
  › Tries to fool the Discriminator

♦ Discriminator:
  › Trained to detect ‘fakes’ generated by the Generator

♦ The two networks are jointly trained until convergence
CGAN Approach

- **Generator:**
  - Encoder: Downsampling
  - Decoder: Upsampling
CGAN Approach

- **Generator:**
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  - Decoder: Upsampling

- **Discriminator:**
  - CNN trained as a classifier

- **After training, only the generator is used**
Decoding the generated layout images consists of two steps:
  › Thresholding & Excitation detection
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Decoding scheme is fast ➔ GPU accelerated
Sample Results

- LS_SVM: Xu et al, ISPD’16, TCAD’17
- MB: Model-Based Approach - Calibre
Sample Results

A post processing legalization step is applied

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Sample Results

- LS_SVM: Xu et al, ISPD’16, TCAD’17
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Lithography Compliance Checks

- LS SVM: Xu et al, ISPD’16, TCAD’17
- MB: Model-Based Approach - Calibre

**Histogram of PV ($\mu m^2$):**

**Histogram of EPE (nm):**
**Comparison Summary**

<table>
<thead>
<tr>
<th></th>
<th>No SRAF</th>
<th>MB</th>
<th>LS_SVM</th>
<th>CGAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV Band ((\mu m^2))</td>
<td>0.00335</td>
<td>0.002845</td>
<td>0.00301</td>
<td>0.00291</td>
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<tr>
<td>EPE (nm)</td>
<td>3.9287</td>
<td>0.5270</td>
<td>0.5066</td>
<td>0.541</td>
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<tr>
<td>Run time (s)</td>
<td>-</td>
<td>6910</td>
<td>700</td>
<td>48</td>
</tr>
</tbody>
</table>

*The proposed CGAN based approach can achieve comparable results with LS_SVM and MB with **14.6X** and **144X** reduction in runtime*
Conclusions

• GAN-SRAF, a novel SRAF generation framework, is presented featuring:
  › Novel problem formulation as image translation
  › Smart heatmap encoding scheme and GPU accelerated decoding

• Results demonstrate significant speedup when compared to ML and MB
  › While achieving comparable lithography performance
Thank You!