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

Mohamed Baker Alawieh, Yibo Lin, Zaiwei Zhang, Meng Li, Qixing Huang and David Z. Pan
The University of Texas at Austin

Work funded in part by NSF
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
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

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]
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

- While achieving 10X runtime improvement, this approach has large room for further enhancement

[Xu et al, ISPD’16, TCAD’17]
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

- While achieving 10X runtime improvement, this approach has large room for further enhancement
  - Do we need a 2D grid and local sampling?

[Xu et al, ISPD’16, TCAD’17]
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

While achieving 10X runtime improvement, this approach has large room for further enhancement

- Do we need a 2D grid and local sampling?
- Can we avoid the feature extraction step?

[Xu et al, ISPD’16, TCAD’17]
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

While achieving 10X runtime improvement, this approach has large room for further enhancement

- 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

[Isola et al, CVPR’18]
SRAF Generation & Image Translation

What does SRAF generation have to do with Image translation?!
What does SRAF generation have to do with Image translation?!

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
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

♦ 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 straightforward, 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

Diagram:
- Encoder
- Decoder
- Generator
- Discriminator
- Real
- Fake
- Input
- Fake/Real
- Diff
CGAN Approach

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

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

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

- **After training, only the generator is used**
Results Decoding

Decoding the generated layout images consists of two steps:

- Thresholding & Excitation detection
Results Decoding

Decoding the generated layout images consists of two steps:

- Thresholding & Excitation detection
Decoding the generated layout images consists of two steps:

- Thresholding & Excitation detection
Decoding the generated layout images consists of two steps:

- Thresholding & Excitation detection
Decoding the generated layout images consists of two steps:

- Thresholding & Excitation detection

Decoding scheme is fast ➔ GPU accelerated

- Isolated pixel
- SRAF location
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

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

- LS_SVM: Xu et al, ISPD’16, TCAD’17
- MB: Model-Based Approach - Calibre
Lithography Compliance Checks

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

Histogram of PV (μm²)

Histogram of EPE (nm)
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!