Thesis Introduction

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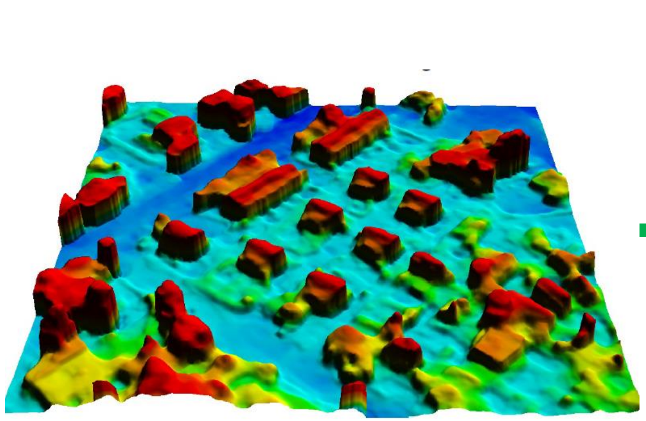
Outline

- General idea
- Methodology
- References

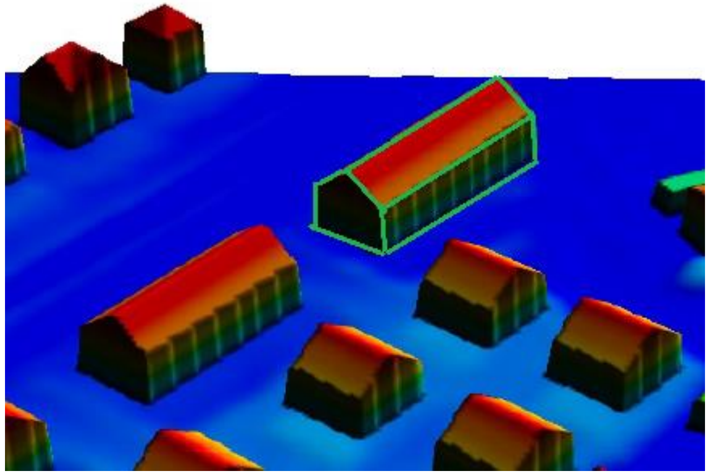
General idea

Core idea: Machine-learnt 3D vectorization of buildings from satellite imagery

- Methodology: multi-task conditional generative adversarial network (cGAN)
- Objective: refined DSM + (instances / edges) + 3D vectorization



[1]



- Source data: stereo DSM + Panchromatic image (WV-1) / RGB image (WV-4)

Methodology

Generative adversarial network:

- Given the training data, two neural networks compete with each other: the Generator learns to generate real-like samples, while the Discriminator learns to distinguish between generated samples and real data.
- In other words,
  - Discriminator: binary classifier (real or fake)
  - Generator: learns to fool the discriminator (learns real data's distribution)
- A min-max problem:

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$$ [2]

- In theory, it is proved that this game will go to Nash-equilibrium:

$$P(D(real)) = P(D(fake)) = 0.5$$

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Conditional GAN: (Generally) apart from random noise, input also other constraints (label, text, image, etc.) to control the generated outputs.

Pix2pix: train source & destination image pairs to perform image to image style translation.

$$\min_G \max_D \mathcal{L}_{\mathrm{cGAN}}(G, D) = \mathbb{E}_{\boldsymbol{x},\boldsymbol{y}\sim p_{\mathrm{real}}(\boldsymbol{y})}[\log D(\boldsymbol{y}|\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{x},\boldsymbol{z}\sim p_z(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z}|\boldsymbol{x})|\boldsymbol{x}))]$$

[3]

During training, we build generator (usually ResNet/UNet structure) and discriminator (usually simple CNN) as two independent networks, train and optimize them alternately.

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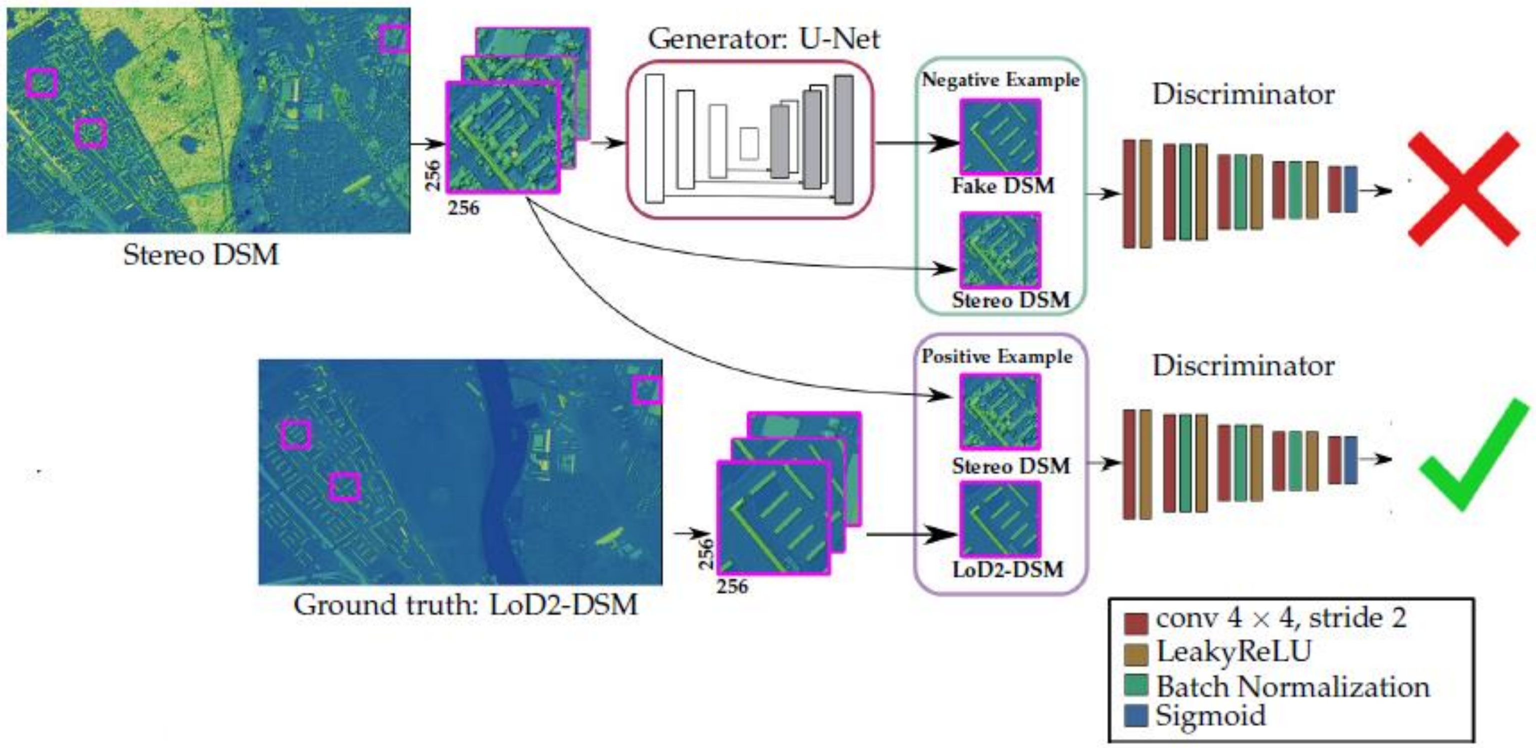
Methodology

cGAN -> DSM refinement (base):



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Methodology

Building vectorization (new):
- previous research --- 2D polygonization; my task --- 3D vectorization
- Step1: Extract corners and edges from satellite image (DSM+orthophoto)
- Step2: Connect the corners and edges as polygons and combine these polygons for vectorized building

Multi-task learning (new):
- multiple learning tasks are solved at the same time, while exploiting commonalities and differences across tasks.
- In our case, the building instance masks (optional), the edge extraction and the DSM refinement should have useful commonalities, thus we expect the combination of all tasks can improve each other.

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Whole Process:

- For the GAN network,
  - Input: Panchromatic/RGB image + stereo DSM
  - Output: refined DSM + extracted core points + (optional, building instance mask)
- Afterwards,
  - Connect the core points with the help of all outputs to get vectorized 3D buildings

- To be mentioned, the ground truth consists of:
  - Ground truth DSM
  - Ground truth core points
  - Ground truth instance mask (optional)

  All these three are to be generated from cityGML data

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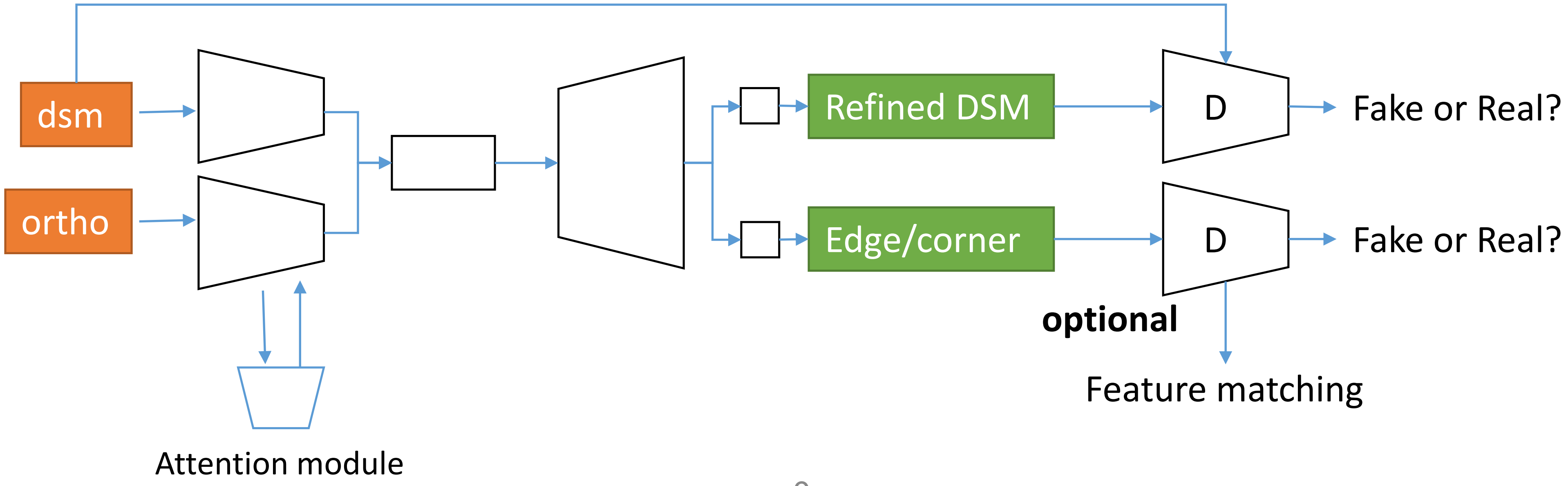
Ideas for the network structure:

- Generator: U-Net with residual block, Discriminator: PatchGAN
- Several 1x1 conv layers for edge detection task
- Attention module in encoder → importance weight → attention feature map
- Fine tune GAN based on pretrained CNN: Network interpolation [5]
- Optional: Give a Discriminator to edge-detection (segmentation GAN)?



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Ideas for the objective function:

- DSM refinement: LSGAN loss + L1 loss + Surface Normal loss [1]
- Edge detection:
  - CrossEntropy (weighted?)
  - multi-scale edge-detection loss
    - Encoder? → HED[6]
    - Discriminator? → Feature Matching Loss [7]
- Loss weights: Learnable multi-task loss weights [8]

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References

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[1] Bittner, Ksenia, Peter Reinartz, and Marco Korner. "Late or Earlier Information Fusion from Depth and Spectral Data? Large-Scale Digital Surface Model Refinement by Hybrid-cGAN.“ Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. 2019.

[2] Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014.

[3] Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

[4] Bittner, Ksenia, et al. "Dsm-to-lod2: Spaceborne stereo digital surface model refinement." Remote Sensing 10.12 (2018): 1926.

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References

[5] Wang, Xintao, et al. "Esrgan: Enhanced super-resolution generative adversarial networks." Proceedings of the European Conference on Computer Vision (ECCV). 2018.

[6] Xie, Saining, and Zhuowen Tu. "Holistically-nested edge detection." Proceedings of the IEEE international conference on computer vision. 2015.

[7] Nazeri, Kamyar, et al. "Edgeconnect: Generative image inpainting with adversarial edge learning." arXiv preprint arXiv:1901.00212 (2019).

[8] Kendall, Alex, Yarin Gal, and Roberto Cipolla. "Multi-task learning using uncertainty to weigh losses for scene geometry and semantics." Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.