B.Tech. Project: Autumn 2021 Study of Methods for Power Lines Monitoring

Lalit Saini
Roll no. 180070030

Supervisor: Prof. V. Rajbabu

Department of Electrical Engineering
IIT Bombay

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Outline

1. **Improved Radon Transform for Power line detection**
2. **Road Detection using Color Features**
3. **Road Detection Using Unet**
4. **Road Detection using DeepResUNet**
5. **Change Detection**

Improved Radon Transform for Power line detection[1]

- Image Enhancement

[1] Yunping Chen, Yang Li, Huixiong Zhang, et al. "Automatic power line extraction from high resolution remote sensing imagery based on an improved Radon transform". In: *Science Direct Pattern Recognition* 49 (2016), pp. 174–186. URL: http://dx.doi.org/10.1016/j.patcog.2015.07.004

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Improved Radon Transform for Power line detection[1]

- Image Enhancement
- Edge Detection
- Cluster Radon Transform
  - Normal Radon Transform doesn't work well when some high intensity useless feature is present.
  - CRT assign weight $I_{\phi,r}$ to the pixels in direction ϕ and range r, the value is bigger if there are more pixels cluster in the specified direction.
  - Decreases influence of the dispersed pixels efficiently.

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  - Decreases influence of the dispersed pixels efficiently.
- Imposing rules on detected linear features to select only power lines.

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Improved Radon Transform for Power line detection

Performance

- The algorithm is slow for large size images, images need to resized before using the algorithm.
- The algorithm need hyper-parameters like distance between lines and minimum deviation angle, these parameters affect the accuracy very much.
- Presence of potential linear features can lead to false lines detection.

Figure 1: Results obtained using CRT

Road Detection using Color Features[1]

- Training:
  - Extract L, a, b color features of CIELab color space for each image.
  - Estimate a^*, b^* representing a and b features for road.

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- Thresholding

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Road Detection using Color Features

Performance

- Very simple algorithm taking advantage of color feature of roads, ignoring illumination factor.
- Objects having similar color feature as the roads will be detected as roads.
- Post processing required to get continuous road prediction from patches predicted by the algorithm.
- Dependency on hyperparameter used in thresholding heavily affects the accuracy.

Figure 2: Roads detection using CIELab color space chroma features.

Road Detection Using Unet

- ResNet50 pre trained weights for encoder part of UNet[1].

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- Dice Loss for training and IoU score for validation.
- Used Adam as optimizer and Cosine Annealing Warm Restarts as learning rate scheduler.
- Achieved IoU score of **0.9033** and Dice loss of **0.1309** on test dataset.

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Road Detection Using Unet

Performance

- Simple segmentation model, easy to train.
- Fails to predict continuous road, discontinuity can be seen in the results.
- Experimented with small dataset to see performance variations. Introduced Conditional Random Fields to improve results for small dataset.
- Obtained weights can be fine tuned to use for power line detection task.

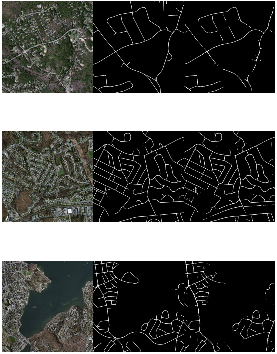

Figure 3: Roads detection using UNet

Road Detection using DeepResUNet

- Loss function landscape for UNet is rough, possibility of stucking in local minimum. DeepResUNet[1]uses residual connections which gives smooth landscape and makes it easy to find global minimum[2].

[1] Zhengxin Zhang, Qingjie Liu, and Yunhong Wang. "Road Extraction by Deep Residual U-Net". In: *IEEE Geoscience and Remote Sensing Letters* 15.5 (2018), pp. 749–753. DOI: 10.1109/LGRS.2018.2802944

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- Used Adam as optimizer and Cosine Annealing Warm Restarts as learning rate scheduler.
- Achieved IoU score of **0.9129** and Dice loss of **0.0475** on test dataset.

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Road Detection using DeepResUNet

Performance

- Better performance than plain UNet. Very small increase in model size.
- More continuous predictions as compared to UNet.

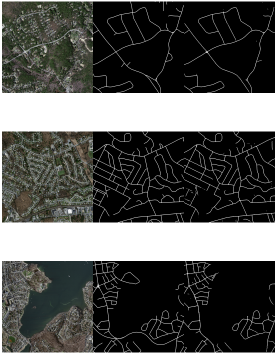

Figure 4: Roads detection using DeepResUNet

Comparisons

	UNet	DeepResUNet	SegNet[1]
IoU Score	0.9033	0.9129	0.7191

Table 1: Comparison between different models

[1]Scores as mentioned in : Zhengxin Zhang, Qingjie Liu, and Yunhong Wang. "Road Extraction by Deep Residual U-Net". In: *IEEE Geoscience and Remote Sensing Letters* 15.5 (2018), pp. 749–753. DOI: 10.1109/LGRS.2018.2802944

Change Detection

- In power lines monitoring it is required to detect the change in the corridor brought by growing vegetation or human activities.

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- We concatenated an image's all features and made prediction on sum features of both the images.
- Used Adam for optimizing and StepLR for learning rate scheduling. Dice loss for traning and IoU score for validation.
- Obtained IoU score of **0.3159** and dice loss of **0.5525** on Levir-CD dataset.

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Change Detection

Performance

- Performance lower than that reported on paper on different dataset, the IoU score reported was 0.7735.
- Predictions are in patches, the boundaries are not sharp which lead to lower IoU score.
- In vegetation detection task sharp boundaries are not required, it is expected that the model will work better in that case.

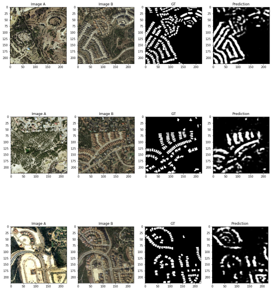

Figure 5: Change detection results

Thank you