## Roof Rlan Polygon Extraction from.



## Task description

The objective is to arrive at as precise roof plan polygons as possible.


## Example pipeline



## Related work

There's already some effort put into this, but no ultimately good solution. The approaches are:

- U-Net-style architectures

- These trained with special losses
- Special models with special losses
- Whatever and regularization
- End-to-end polygon predictors

The approach also depends on the scale.


## Datasets

Three main datasets:

- Christchurch - New Zealand $\rightarrow$
- INRIA - More cities
- Our dataset - Czechia



## Methods

From the previous work can be concluded the following:

- DeeplabV3+ > U-Net
- BCE Loss not the best for borders

Thus the first approaches are based on DLV3+ trained with some specific losses.

Trained using Adam optimizer, Ir scheduler, fraction of NZ dataset


## Proposed losses

## Region oriented losses

- Binary Cross-entropy loss

$$
L_{B D}(y, \hat{y})=1-\frac{2 \sum_{i} y_{i} \hat{y}_{i}+s}{\sum_{i}\left(y_{i}+\hat{y}_{i}\right)+s}
$$

- Binary Dice loss
- Focal loss

$$
\longrightarrow L_{F}(y, \hat{y})=-\sum_{i}\left(1-\hat{y}_{i}\right)^{\gamma} \log \left(\hat{y}_{i}\right)
$$

Differentiable boundary extraction, extension and weights

- $Y_{b}=\operatorname{maxPool}(1-Y)-(1-Y)$
- $Y_{b e}=\operatorname{maxPool}\left(Y_{b}, \theta\right)$
- $w=\operatorname{GaussianBlur}\left(Y_{b}\right)+\alpha$


## First comparison

| metric | iou | dice | dice-b1 | dice-b3 | dice-b5 |
| :--- | :---: | :---: | :---: | :---: | :---: |
| bce | $\mathbf{9 1 . 0 0}$ | $\mathbf{9 5 . 2 3}$ | 27.14 | 58.10 | 70.66 |
| bce-enc | 90.92 | 95.18 | 26.94 | 57.87 | 70.47 |
| bdc | 90.84 | 95.14 | 26.17 | 57.13 | 69.98 |
| foc | 90.61 | 95.01 | 25.97 | 56.65 | 69.43 |
| wbce-a08 | 90.60 | 95.00 | 25.85 | 56.61 | 69.53 |
| wbce-a05 | 86.66 | 92.74 | 17.85 | 44.08 | 58.35 |
| wbce-a02-enc | 90.50 | 94.94 | 24.72 | 55.81 | 69.11 |
| bl-bce-a084 | 90.92 | 95.18 | 27.74 | $\mathbf{5 9 . 4 7}$ | 71.84 |
| bl-bdc-a089 | 90.66 | 95.03 | 27.80 | 59.38 | 71.67 |
| bl-bdc-a06 | 90.91 | 95.17 | 27.61 | 59.23 | 71.66 |
| bl-bdc-a08-enc | 90.94 | 95.18 | 27.63 | 59.31 | 71.74 |
| bl-bdc-a084 | 90.94 | 95.18 | 27.63 | 59.31 | 71.74 |

## Result examples



## Regularization and polygon extraction

The segmentation mask have still quite far from polygons, so I used:

- Regularization
- SAM
- Polygon extraction



## Second comparison

| metric | iou | dice | dice-b1 | dice-b3 | dice-b5 |
| :--- | :---: | :---: | :---: | :---: | :---: |
| bce-r | $\mathbf{9 0 . 3 2}$ | $\mathbf{9 4 . 8 6}$ | 22.54 | 53.35 | 67.44 |
| bdc-r | 90.16 | 94.77 | 22.01 | 52.51 | 66.83 |
| bl-bce-a084-r | 90.27 | 94.83 | $\mathbf{2 3 . 1 3}$ | $\mathbf{5 4 . 3 6}$ | $\mathbf{6 8 . 3 6}$ |
| bl-bdc-a089-r | 90.02 | 94.68 | 23.12 | 54.27 | 68.20 |
| wbce-a08-rp | 89.68 | 94.50 | 20.50 | 50.45 | 65.21 |
| bce-rp | $\mathbf{9 0 . 1 4}$ | $\mathbf{9 4 . 7 6}$ | 21.88 | 52.34 | 66.63 |
| bdc-rp | 89.99 | 94.68 | 21.26 | 51.42 | 65.97 |
| bl-bce-a084-rp | 90.09 | 94.73 | 22.28 | $\mathbf{5 3 . 1 6}$ | $\mathbf{6 7 . 4 4}$ |
| bl-bd-a089-rp | 89.85 | 94.58 | $\mathbf{2 2 . 2 9}$ | 53.06 | 67.27 |
| bce-rp | $\mathbf{9 0 . 2 9}$ | $\mathbf{9 4 . 8 3}$ | 24.47 | 54.89 | 68.15 |
| bl-bce-a084-rp | 90.20 | 94.77 | 24.92 | $\mathbf{5 6 . 1 7}$ | $\mathbf{6 9 . 3 6}$ |
| bl-bdc-a089-rp | 89.89 | 94.58 | $\mathbf{2 4 . 9 4}$ | 56.12 | 69.22 |

## Result examples

We can see:

- Worse model (regpoly)
- Better model (reg + regpoly + poly)
- Label



## Future work

As there is still a lot to do, this are further steps:

- Add PolyWorld to comparison
- Add vertex-distance metric
- Finetune the regularization model
- Finetune Polyworld model
- Finetune all the models on our data


## Conclusion \& discussion

Conclusions

- BCE is indeed not the best loss for boundaries
- Regularization helps a lot
- SAM is not the best model

Thank you for your attention!

