Bachelor Thesis

Comparison of Hamming- and Variation of Information-Loss based structured learning on the Multicut Problem

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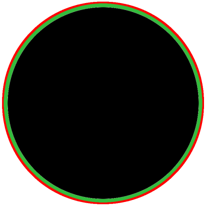
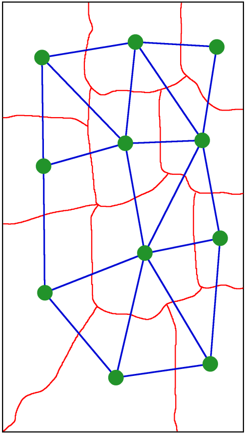
Segmentation

Motivation Variation of Information



- Hamming Loss strongly dependend on exact path of segmentation
- But: Path of segmentation often not unique
- Idea VOI: Consider labels of segmentation and penanlize area-dependend

Region Adjacency Graph (RAG)



- Image partitioned into Superpixel (SP) via SLIC
- Each Superpixel ≙ Node in RAG
- Nodes of adjacent SP are linked by an Edge

Multicut Problem (MP)

$$\begin{array}{llcll} \min\limits_{y} & \sum\limits_{y_e \in E} \langle w, \beta_e \rangle \cdot y_e & & & \\ \text{s.t.} & y - \sum\limits_{y_i \in P(y)} y_i & \leq & 0 & \forall\ y \in E \end{array}$$

- w: Weights to be learned
- β_e: Features of edge e
- y_e: Activity of edge e
- Constraint to enforce consistency

Training- and Test data

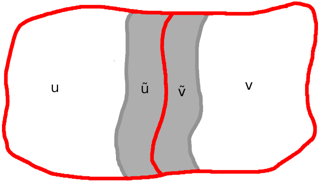
- Natural Images from Berkeley Segmentation Dataset (BSD-500)
- Took thereof the 200 images from the testset due to availability of state-of-the-art contour detectors $\rightarrow$ 100 training- and test-images
- Ground Truth as well from BSD-500 dataset (determined label of SP via majority vote)

Feature Space

- Gaussian Gradient Magnitude
- Hessian of Gaussian Eigenvalues
- Laplacian of Gaussian
- Structure Tensor Eigenvalues
- Canny Filter
- N^4-Fields [?] with and without edge length weighting
- Dollár et. al [?] Kantendetektor with and without edge length weighting

Feature Space

- Statistics in area $\tilde{u}$ und $\tilde{v}$ around edge of SP u and v:
  - Mean$(\tilde{u} + \tilde{v})$
  - Variance$(\tilde{u} + \tilde{v})$
  - $\frac{\max\{\text{Mean}(\tilde{u}),\text{Mean}(\tilde{v})\}}{\min\{\text{Mean}(\tilde{u}),\text{Mean}(\tilde{v})\}}$
  - $\frac{\max\{\text{Median}(\tilde{u}),\text{Median}(\tilde{v})\}}{\min\{\text{Median}(\tilde{u}),\text{Median}(\tilde{v})\}}$
  - Skewness$(\tilde{u} + \tilde{v})$
  - Kurtosis$(\tilde{u} + \tilde{v})$
- Random Forest Feature



Stochastic Gradient with RF Feature

- Varying configurations:
  - Domain Feature Space
  - Constraint on RF Feature
  - Subgradient Descent with/without RF Feature
- Results:
  - Decrease of VOI Loss leads to decline of Hamming Loss in Trainingsset
  - Rate of decrease sensible to configuration,
    besides strong fluctuations due to stochastic process
  - Loss decrease on Trainingset $\propto$ Loss increase on Testset
    $\Rightarrow$ Overfit of training data

Stochastic Gradient without RF Feature

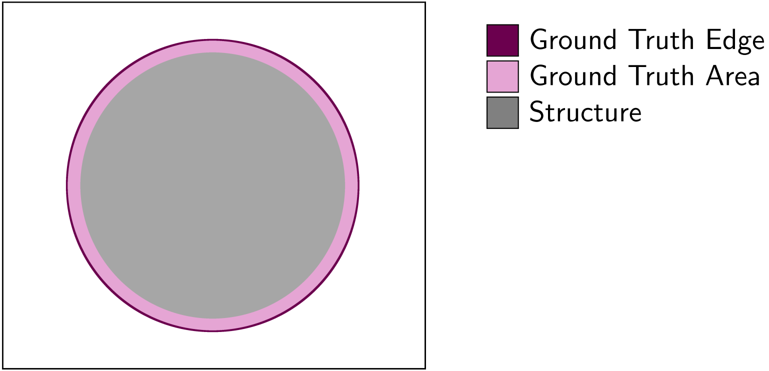
- Varying configurations:
  - Domain Feature Space
  - Constraint on N^4 Feature
- Results:
  - VOI Loss decrease on Trainingset of approximately 4%
  - Change of Loss on Testset within 1σ range of error

Cross Validation Measurement 10

- Cross validation to minimize measurement errors
- Results on Testset:
  - $\mathcal{L}_H$: $\frac{StochGrad}{SubGrad} = 0.989 \pm 0.005$
  - $\mathcal{L}_{VOI}$: $\frac{StochGrad}{SubGrad} = 1.0025 \pm 0.0084$

  $\rightarrow$ No significant change

Explanation by SLIC



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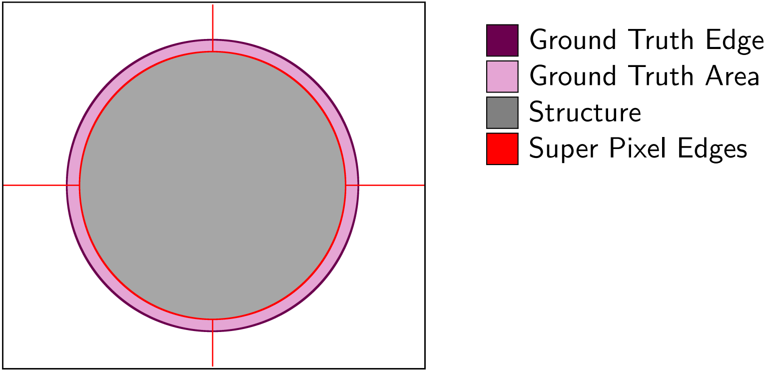

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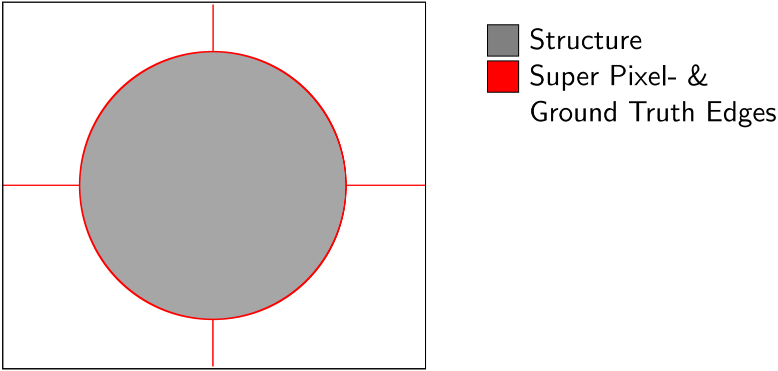

Conclusion

- Stochastic Gradient with RF Feature leads to Overfit of training data
- No significant change without RF Feature
  - Bad Ground Truth compensated by SLIC
  - Examination on Pixel-level would be interesting
- Examples were found which confirm theoretical behavior of VOI