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Swiss Federal Institute of Technology Zurich

Lateral Detection

Qing Zhong (ETHZ)
Martin Schindler (IMVS, FHNW)
Christoph Stamm (IMVS, FHNW)

Introduction

- A lateral connects a branch sewer to a main sewer
- The goal is to automatically detect the lateral

Pipe Inspection

- Communal sewer networks should be examined periodically because of contamination and water waste
- Robots produce analog/digital videos of sewer pipes
- A time consuming task for human inspectors
- Automatic pipe condition assessment system is needed

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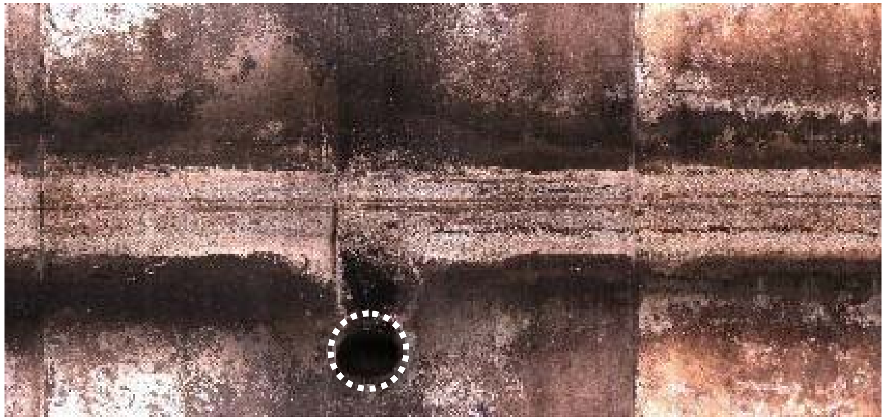
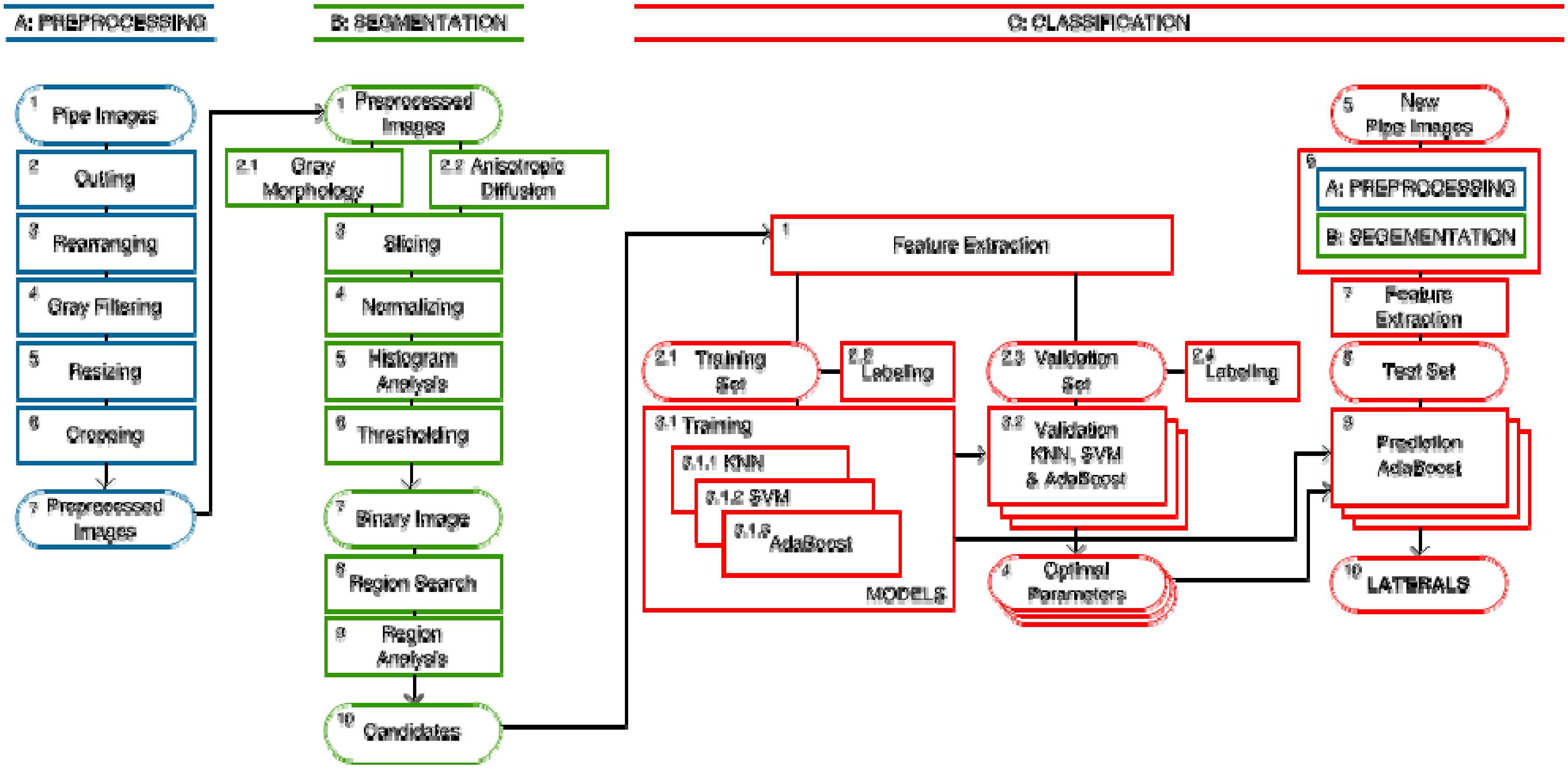
Automatic Lateral Detection



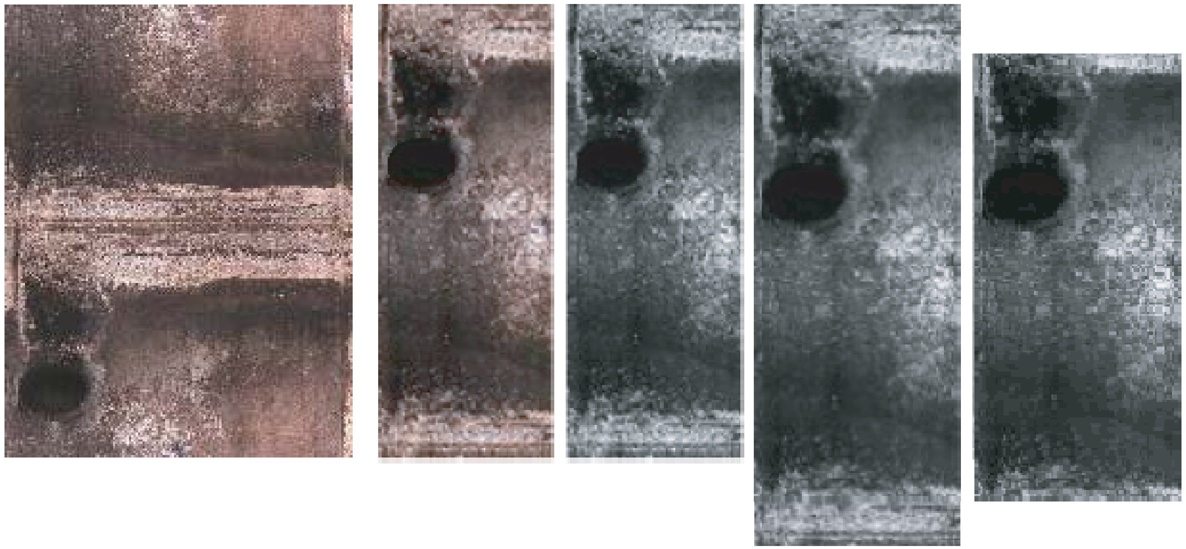
- Circular and dark objects with a given radius
- LD is a twofold challenge
  - Distinguish the different objects, i.e., to delineate regions in pipe images corresponding to candidate laterals
  - Discriminate real laterals from false ones in the set of candidate laterals
- Three-step algorithm, preprocessing, segmentation and classification

Three-step algorithm



Preprocessing

- Raw pipe images are quite different
- To make input pipe images as homogenous as possible



original image | cut and rearranged | gray scaled | resized | cropped

Segmentation I

- Apply edge preserving filters beforehand
- Gray-scale morphology (closing operator, radius = 5 pixels)
- Anisotropic diffusion, (diffusion coefficient $\exp(-f_i^2/2\kappa^2)$, step size 0.2 and k = 15)

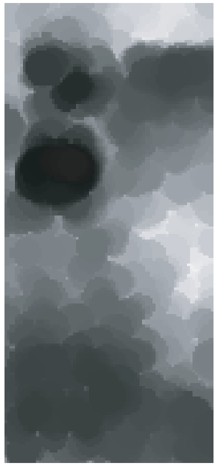


Image after Morphology

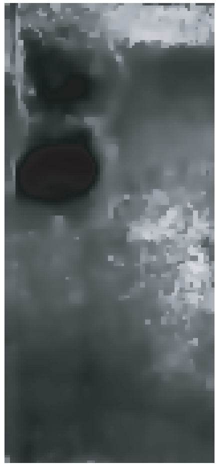
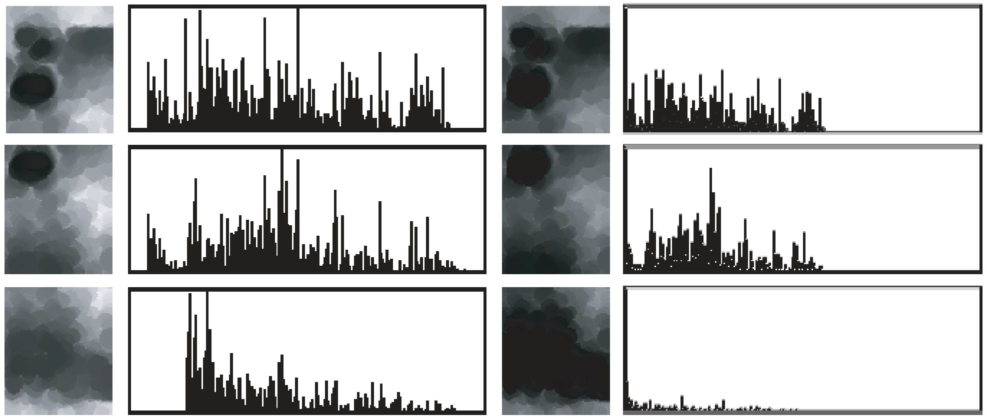


Image after anisotropic diffusion

Segmentation II

- Normalization and segmentation

$$\tilde{I}_n \leftarrow (\tilde{I}_{ROI} - q_{\min}) \cdot \frac{\min(z, q_{\max} - q_{\min})}{q_{\max} - q_{\min}}$$



a) Images after morphology and their histograms

b) Images after normalization and their histograms

- Region Analysis

a) Image after morphology

b) Image after morphology and binari-zation

c) Image after anisotropic diffusion

d) Image after anisotropic diffusion and binarization

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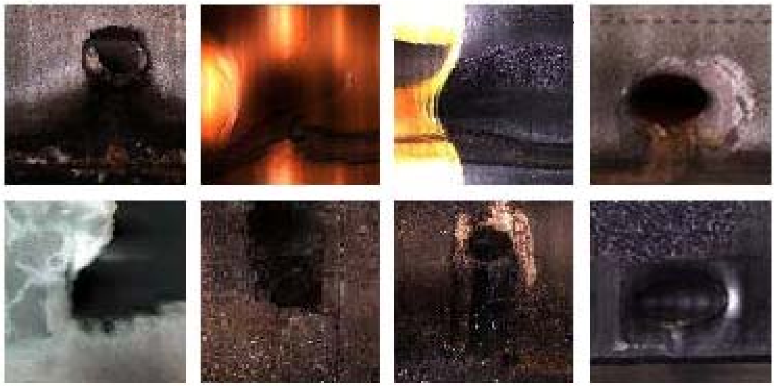
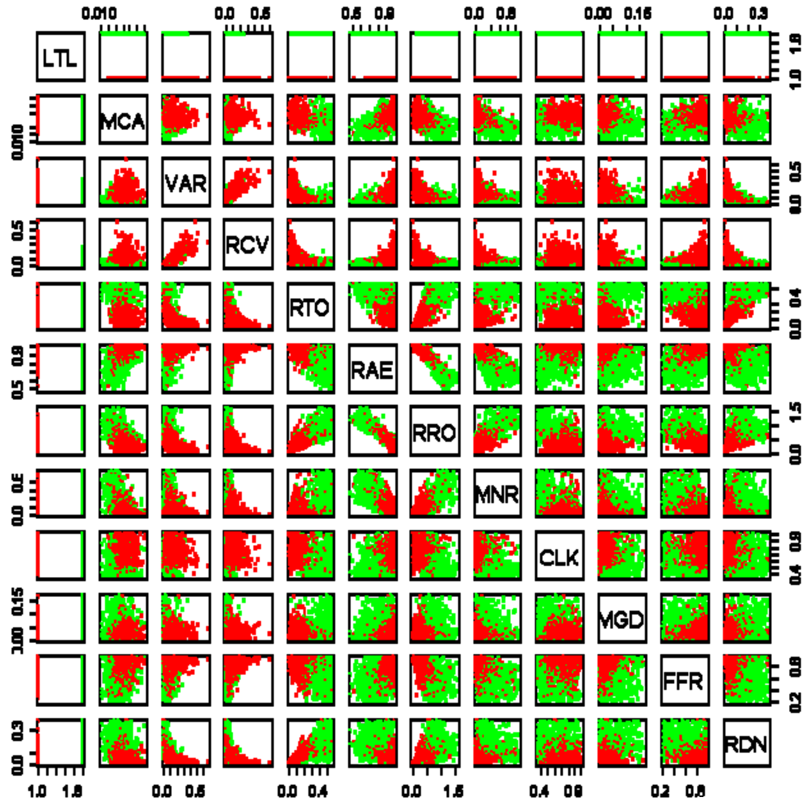
Classification I

- Candidate laterals





- Feature Extraction
  - Geometric properties (Binary image)
  - Color properties (RGB image)
  - Monte Carlo estimation (Gray-scale)

Classification II

- AdaBoost with decision stump as weak classifier

$$\hat{c}_B(\mathbf{x}) = \operatorname{sign}\left(\sum_{b=1}^{B} \alpha_b c_b(\mathbf{x})\right) \quad c_b(x_{k,p}, \theta_p) = \begin{cases} +1 & x_{k,p} > \theta_p \\ -1 & \text{otherwise} \end{cases}$$

- Tenfold cross validation to estimate the test error

$$10^{-1} \sum_{i=1}^{10} |d_i|^{-1} \sum_{k \in d_i} \mathbf{1}\{y_k \neq (\hat{c}_B)_{n-|d_i|}^{-(d_i)}(\mathbf{x}_k)\}$$

- The optimal model is found by calculating:

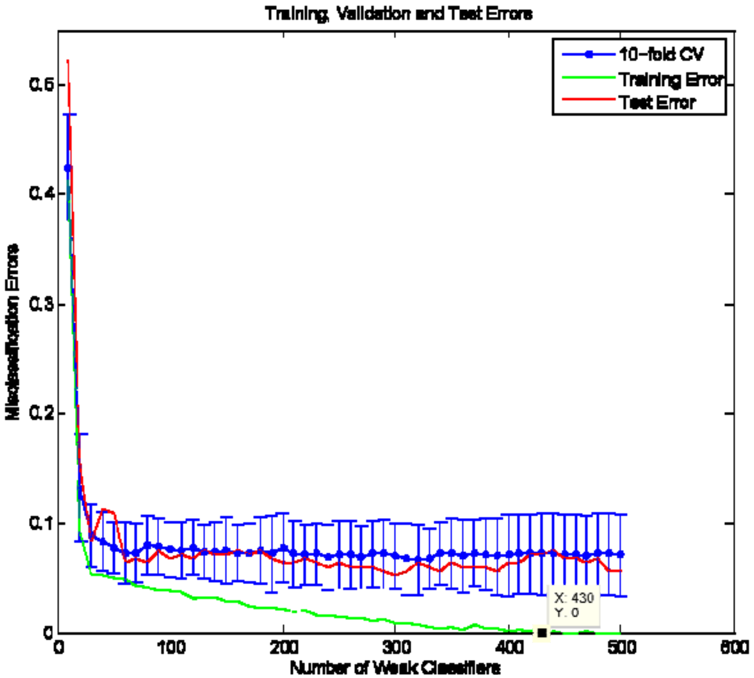
$$\hat{c}_B^* = \arg \min_{\hat{c}_B \in C} \mathrm{CV}$$

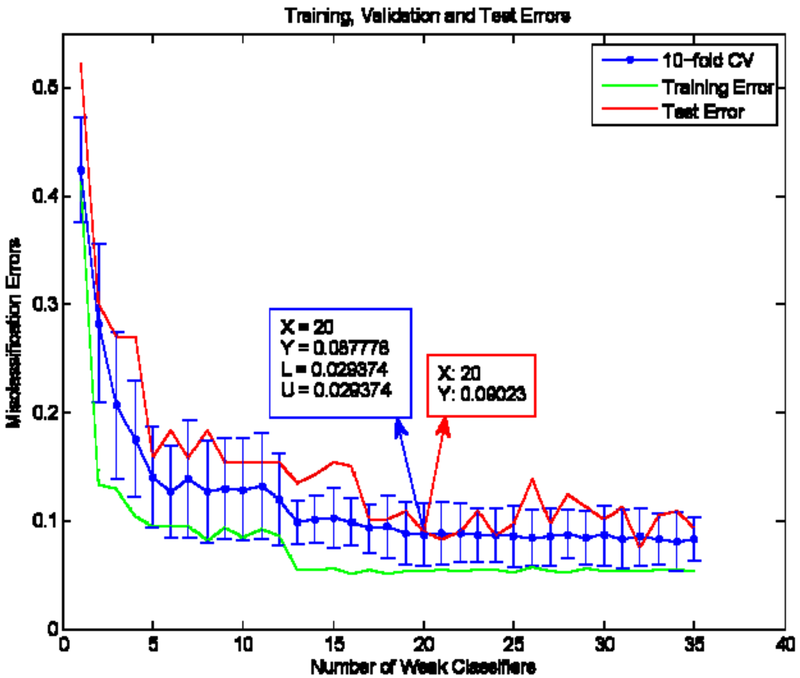
Experiments

- Apply three-step algorithm to about 6,000 scanned images (10,000 meters in length)
- Preprocessing and Segmentation, where preprocessing and segmentation cause about one percent error
- Feature extraction
- Training set (validation set 10-fold CV) and test set
- AdaBoost with decision stumps
- Compare to SVM with Gaussian RBF kernel and 1-NN and 3-NN, based on tenfold CV and the test errors

Results

- Parsimonious model: AdaBoost with 20 weak classifiers
- AdaBoost outperforms the others
- Test Error: - AdaBoost 9.0% - 1-NN 18.1%
  - SVM 15.2% - 3-NN 16.3%





Conclusion

- A three-step algorithm
- A plug-in algorithm
- Each step may be improved by other methods
  - Bilinear filter vs. gray-scale morphology or anisotropic diffusion
  - K-Means vs. simple histogram thresholding
  - SVM as weak classifier in AdaBoost

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Thank for your attention!

Q & A

- Performance: ~30m/s (Pentium 4 dual core 3GHz)
- In practice, the algorithm works well
- Laterals about 520, candidate laterals 1300