Features for Image Analysis

To Craft, or to Learn: that is the question

Raghavendra Selvan

raghav@di.ku.dk
Postdoc
Data Science Lab &
Machine Learning Section
Department of Computer Science

Image Analysis as Signal Processing

Image Analysis as Signal Processing

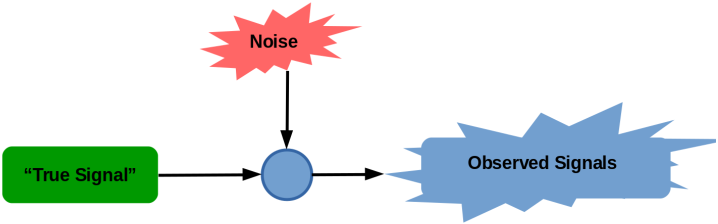
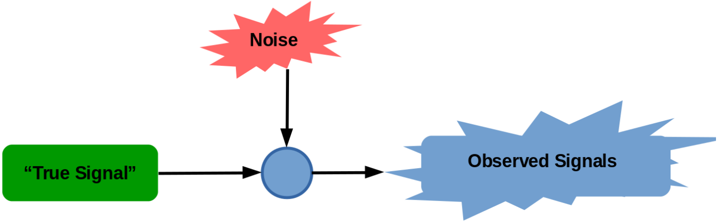
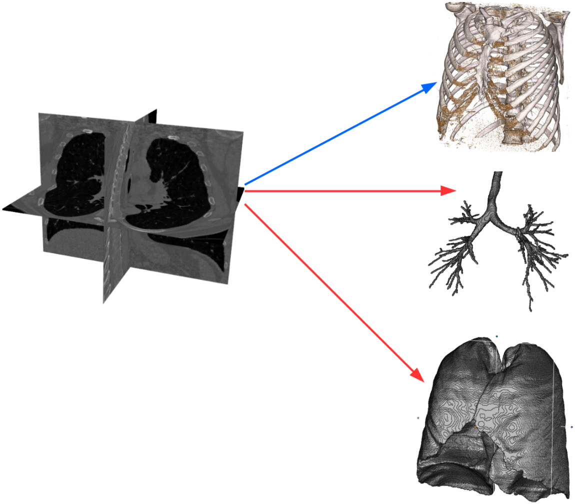


Image Analysis as Signal Processing

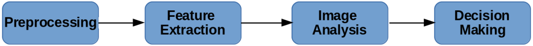


One person's noise can be another's signal!

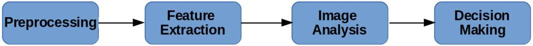
Image Analysis as Signal Processing



The “Classical” Pipeline

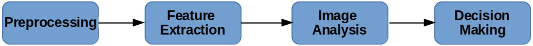


The “Classical” Pipeline



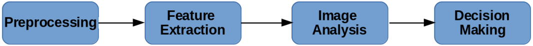
- Preprocessing: Thresholding, Morphological operations

The “Classical” Pipeline



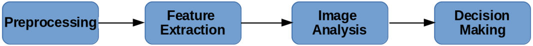
- Preprocessing: Thresholding, Morphological operations
- Feature Extraction: Primarily Filtering

The "Classical" Pipeline



- Preprocessing: Thresholding, Morphological operations
- Feature Extraction: Primarily Filtering
- Decision Making: Disease prediction, vehicle navigation, landscape change

The "Classical" Pipeline



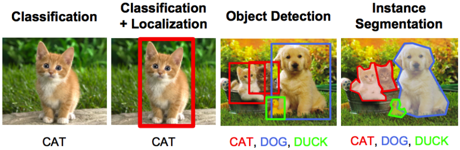
- Preprocessing: Thresholding, Morphological operations
- Feature Extraction: Primarily Filtering
- Decision Making: Disease prediction, vehicle navigation, landscape change
- Image Analysis

Common Image Analysis Tasks

- Classification
- Localisation
- Segmentation
- Registration

Common Image Analysis Tasks

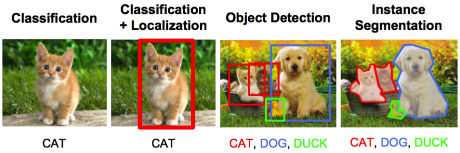
- Classification
- Localisation
- Segmentation
- Registration



http://cs224d.stanford.edu/index.html

Common Image Analysis Tasks

- Classification
- Localisation
- Segmentation
- Registration



http://cs224d.stanford.edu/index.html

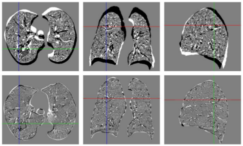


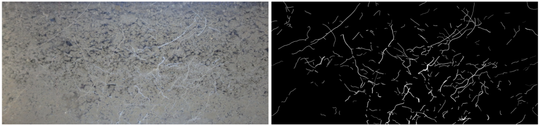
Fig. 5. Two scans of the same subject. Differences before (top) and after (bottom) registration.

The “Classical” Pipeline: Root Segmentation Task

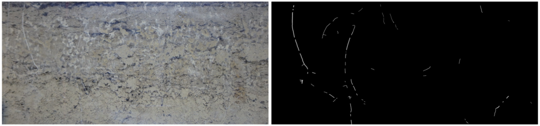
Objective: Detect and measure roots from soil

The “Classical” Pipeline: Root Segmentation Task

Objective: Detect and measure roots from soil



(c) Set: Validation, ID: P8222813, Panel: 2



(d) Set: Training, ID: P7181902, Panel: 10

The "Classical" Pipeline: Root Segmentation Task

Method: Frangi Vesselness filter plus region growing

The "Classical" Pipeline: Root Segmentation Task

Method: Frangi Vesselness filter plus region growing

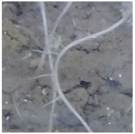


Figure 13: Original

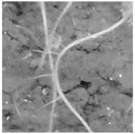


Figure 14: Grey scale

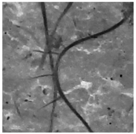


Figure 15: Inverted

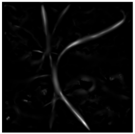


Figure 16: Frangi output

The "Classical" Pipeline: Root Segmentation Task

Method: Frangi Vesselness filter plus region growing

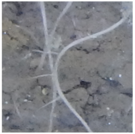


Figure 13: Original

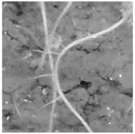


Figure 14: Grey scale

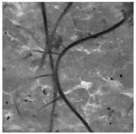


Figure 15: Inverted

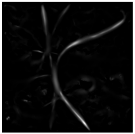


Figure 16: Frangi output

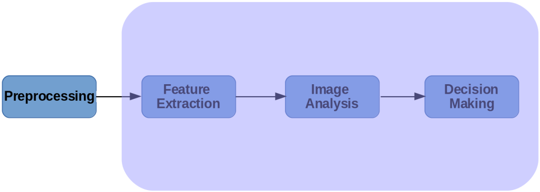
Figure 18: Annotation

Figure 19: Threshold 0.4

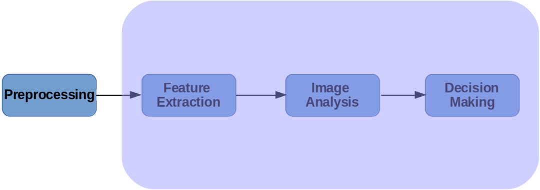
Figure 20: Threshold 0.2

Figure 21: Threshold 0.1

End-to-End Pipeline

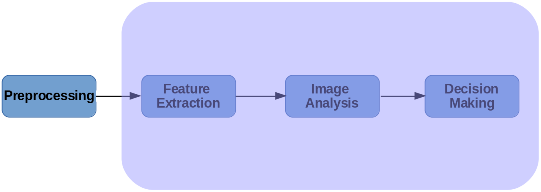


End-to-End Pipeline



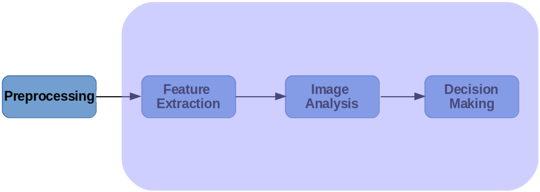
- Reduce error propagation

End-to-End Pipeline



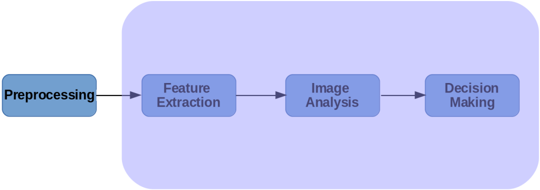
- Reduce error propagation
- Learn features from examples

End-to-End Pipeline



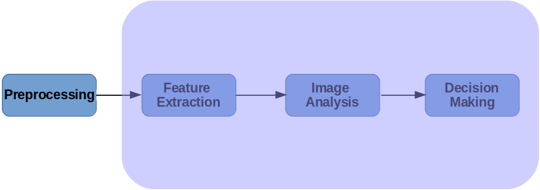
- Reduce error propagation
- Learn features from examples
- Objective from final decision making

End-to-End Pipeline



- Reduce error propagation
- Learn features from examples
- Objective from final decision making
- **Conditioned on labels**, can be powerful

End-to-End Pipeline



- Reduce error propagation
- Learn features from examples
- Objective from final decision making
- **Conditioned on labels**, can be powerful

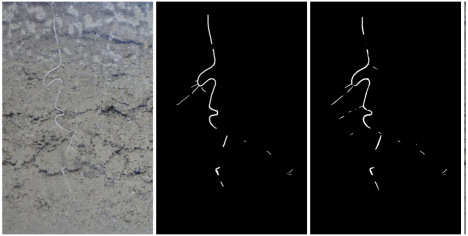
End-to-End Pipeline: Root Segmentation Task

End-to-End Pipeline: Root Segmentation Task

- U-Net based segmentation
- Extensive data augmentation
- Specialised loss function

End-to-End Pipeline: Root Segmentation Task

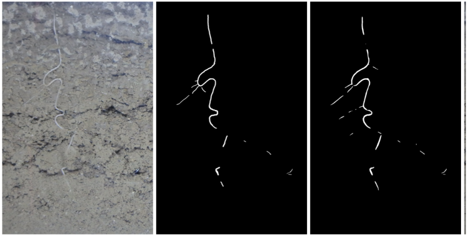
- U-Net based segmentation
- Extensive data augmentation
- Specialised loss function



(a) photo (b) annotation (c) U-Net segmentation (

End-to-End Pipeline: Root Segmentation Task

- U-Net based segmentation
- Extensive data augmentation
- Specialised loss function



(a) photo (b) annotation (c) U-Net segmentation

F1 Score: Frangi=0.462, U-Net=0.701

Learning features is good! But....

Learning features is good! But....

https://xkcd.com/1838/

Learning features is good! But....

https://xkcd.com/1838/

- High quality labelled data
- Or, artifical data
- Domain knowledge not utilised
- Generalisation problems

Between Crafting and Learning features?

- Incorporate useful domain knowledge (Priors)
- Reduce dependency on high quality labels (Weak Labels)

Between Crafting and Learning features?

- Incorporate useful domain knowledge (Priors)
- Reduce dependency on high quality labels (Weak Labels)

Additionally,

- Uncertainty estimation
- Intepretability
- Tractability

Between Crafting and Learning features?

- Incorporate useful domain knowledge (Priors)
- Reduce dependency on high quality labels (Weak Labels)

Additionally,

- Uncertainty estimation
- Intepretability
- Tractability

One such example...

Recent work: Airway Tree Segmentation

- Approximate Bayesian Inference
- Mean-Field Networks
- Graph Neural Networks

Visual Summary of Airway Extraction using GNNs

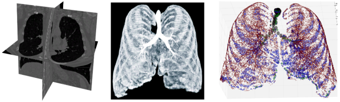


Figure 1: The preprocessing to transform the input image (left) into a probability image (center) and then into graph format (right). Nodes in the graph are shown in scale (as different colours) to capture the variations in their local radius.

Visual Summary of Airway Extraction using GNNs

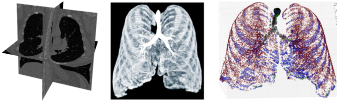


Figure 1: The preprocessing to transform the input image (left) into a probability image (center) and then into graph format (right). Nodes in the graph are shown in scale (as different colours) to capture the variations in their local radius.

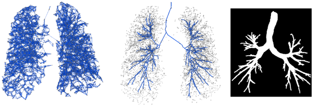


Figure 2: Input graph derived from a chest scan depicting the initial connectivity based on $\mathbf{A}_{\text{in}}$ between nodes (left). Nodes of the input graph (grey dots) overlaid with connections derived from the reference adjacency matrix, $\mathbf{A}_r$ (center). Binary volume segmentation obtained from the reference adjacency matrix and the corresponding node features (right).

To summarise.

- Image analysis has evolved extensively in recent years

To summarise.

- Image analysis has evolved extensively in recent years
- Classical model based methods have limitations

To summarise.

- Image analysis has evolved extensively in recent years
- Classical model based methods have limitations
- Powerful feature extraction possible using end-to-end learning

To summarise.

- Image analysis has evolved extensively in recent years
- Classical model based methods have limitations
- Powerful feature extraction possible using end-to-end learning
- Heavy dependency on labelled data

To summarise.

- Image analysis has evolved extensively in recent years
- Classical model based methods have limitations
- Powerful feature extraction possible using end-to-end learning
- Heavy dependency on labelled data
- A bridge between these two can be good trade-off

To summarise.

- Image analysis has evolved extensively in recent years
- Classical model based methods have limitations
- Powerful feature extraction possible using end-to-end learning
- Heavy dependency on labelled data
- A bridge between these two can be good trade-off

Acknowledgements

- Abraham Smith, PLEN, KU
- Camilla Rasmussen, PLEN, KU
- Jens Petersen, DIKU
- Marleen de Bruijne, DIKU

Acknowledgements

- Abraham Smith, PLEN, KU
- Camilla Rasmussen, PLEN, KU
- Jens Petersen, DIKU
- Marleen de Bruijne, DIKU

Questions? More details on my methods?