# Incisor Segmentation

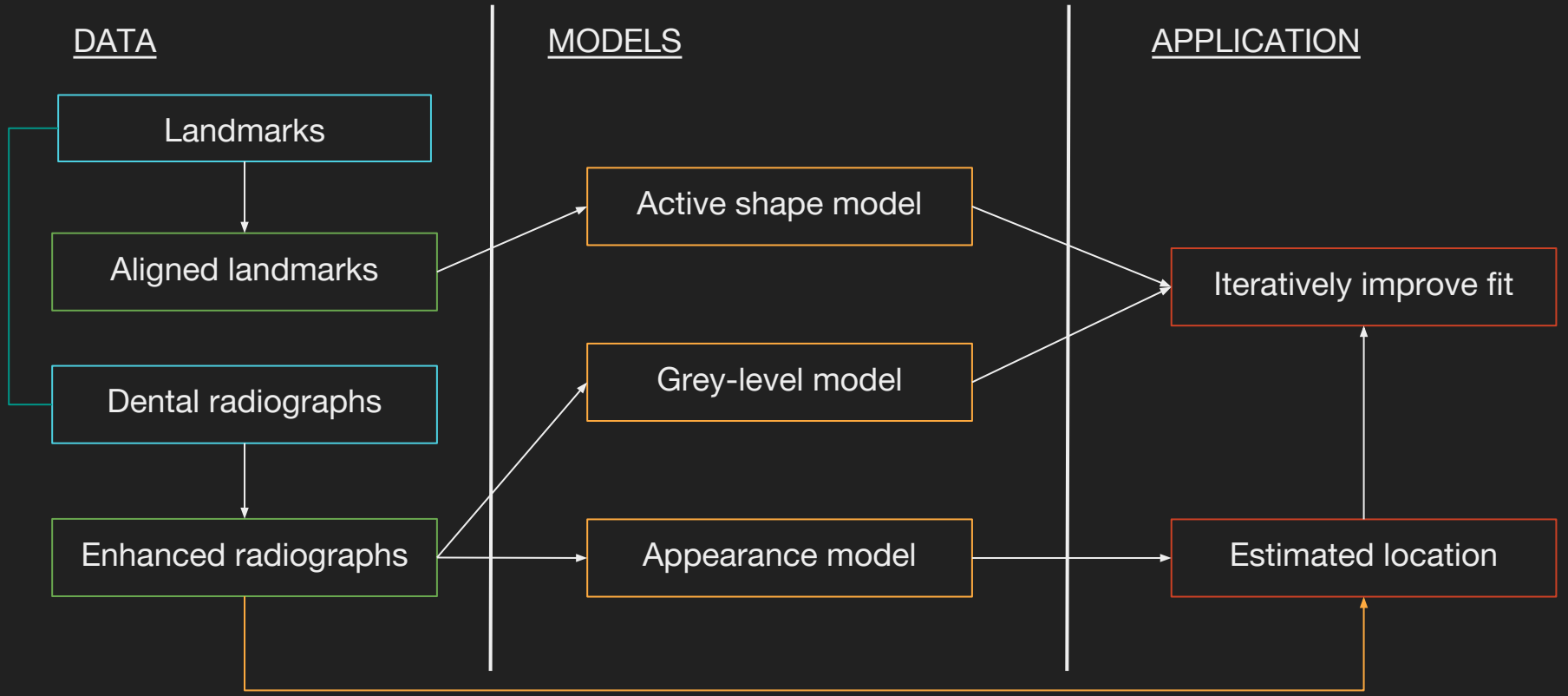
Computer Vision [H02K5a]

Pieter Robberechts
r0296915

# Implementation

## Results

# Overview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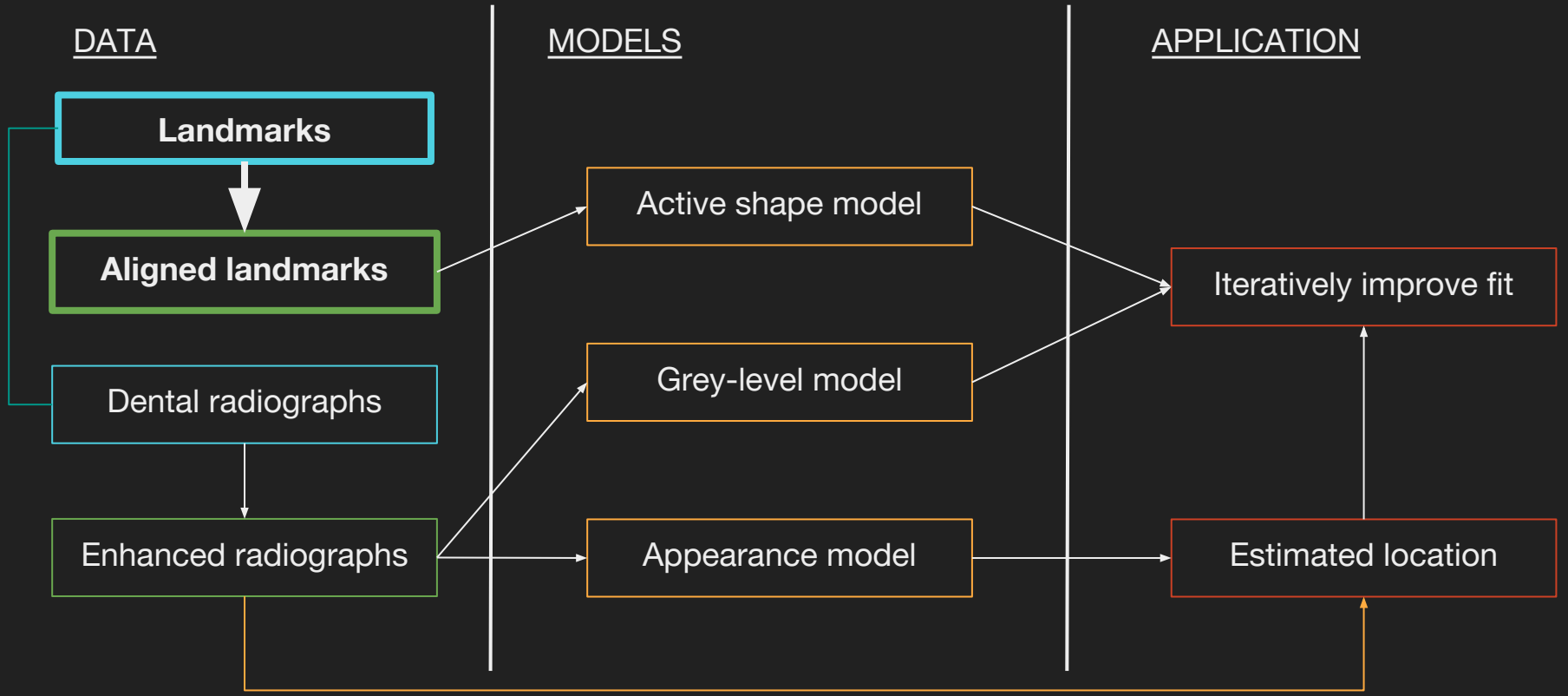
APPLICATION
Landmarks
Aligned landmarks
Dental radiographs
Enhanced radiographs
Active shape model
Grey-level model
Appearance model
Iteratively improve fit
Estimated location

# Overview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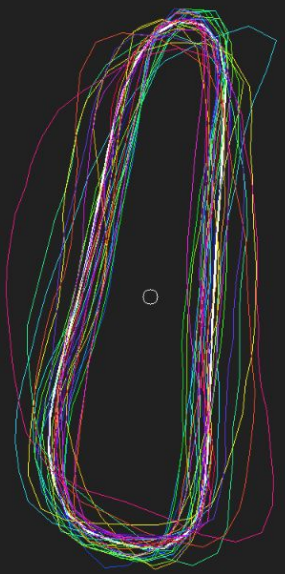
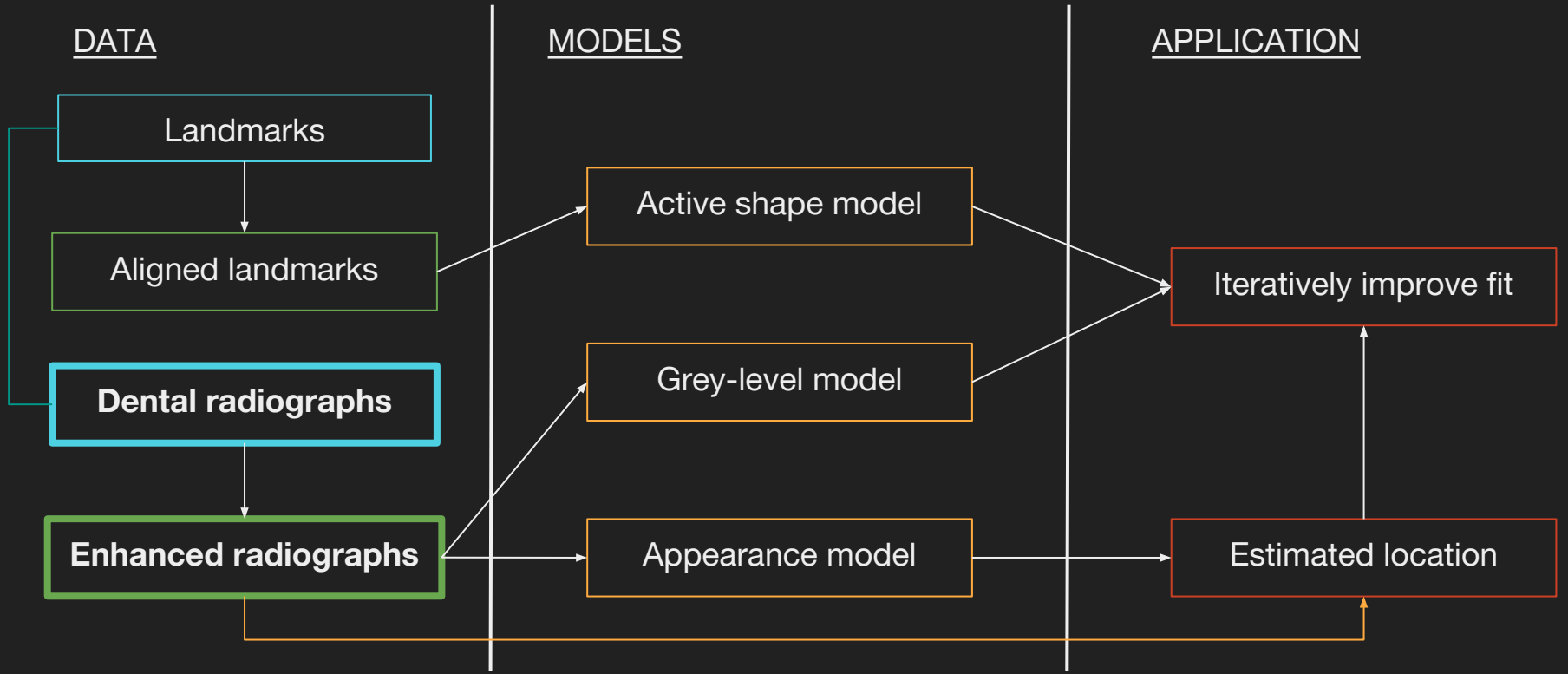
# Pre-processing landmarks: Procrustes Analyses

Normalize landmarks for translation, scale and rotation to enable comparison



*28 per incisor*
*40 landmarks*

# Overview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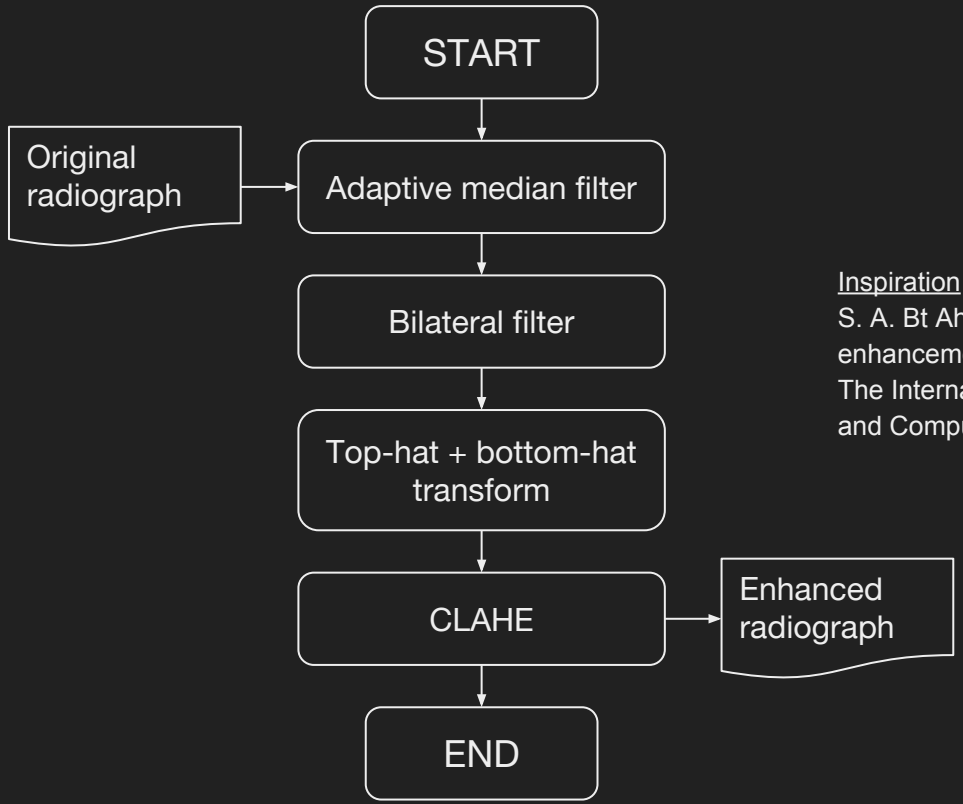
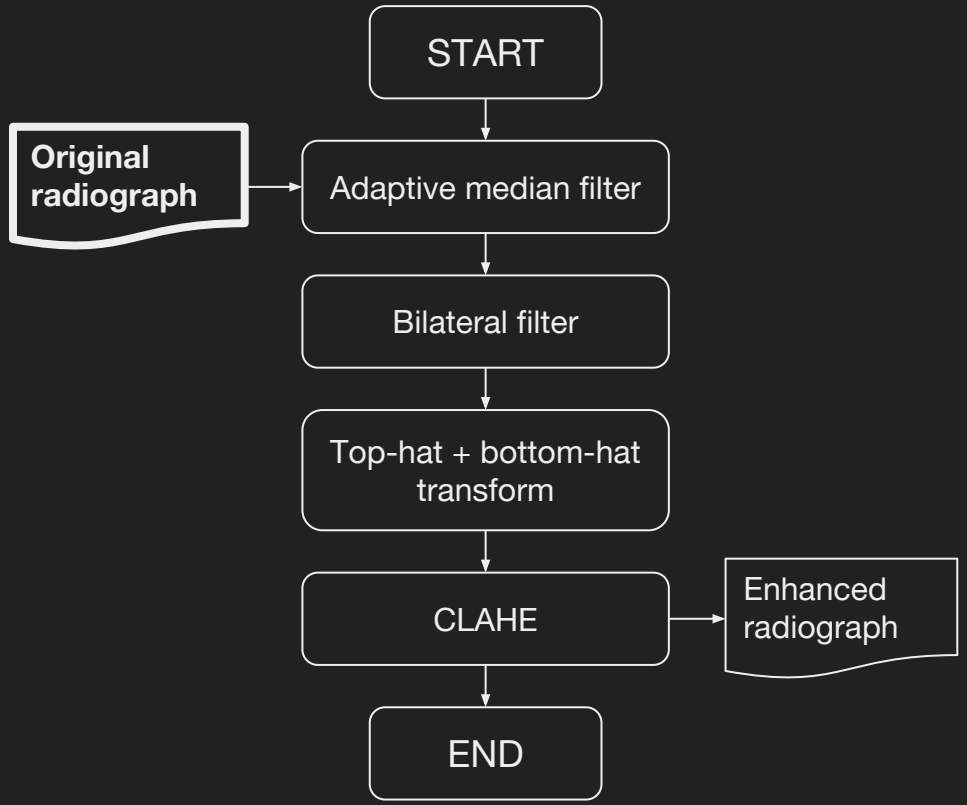
# Pre-processing dental radiographs

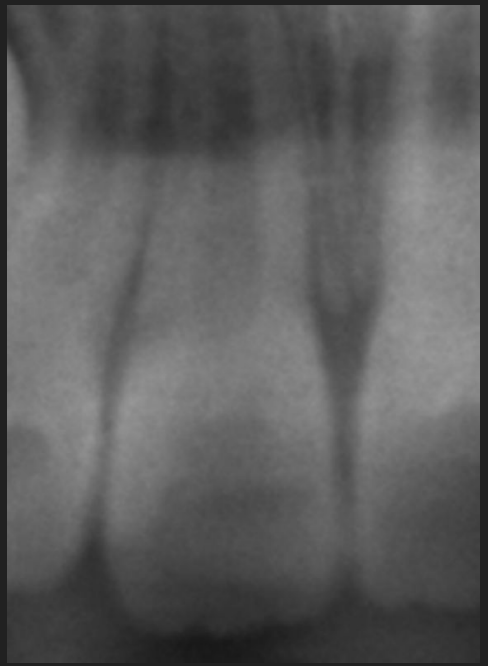



Inspiration

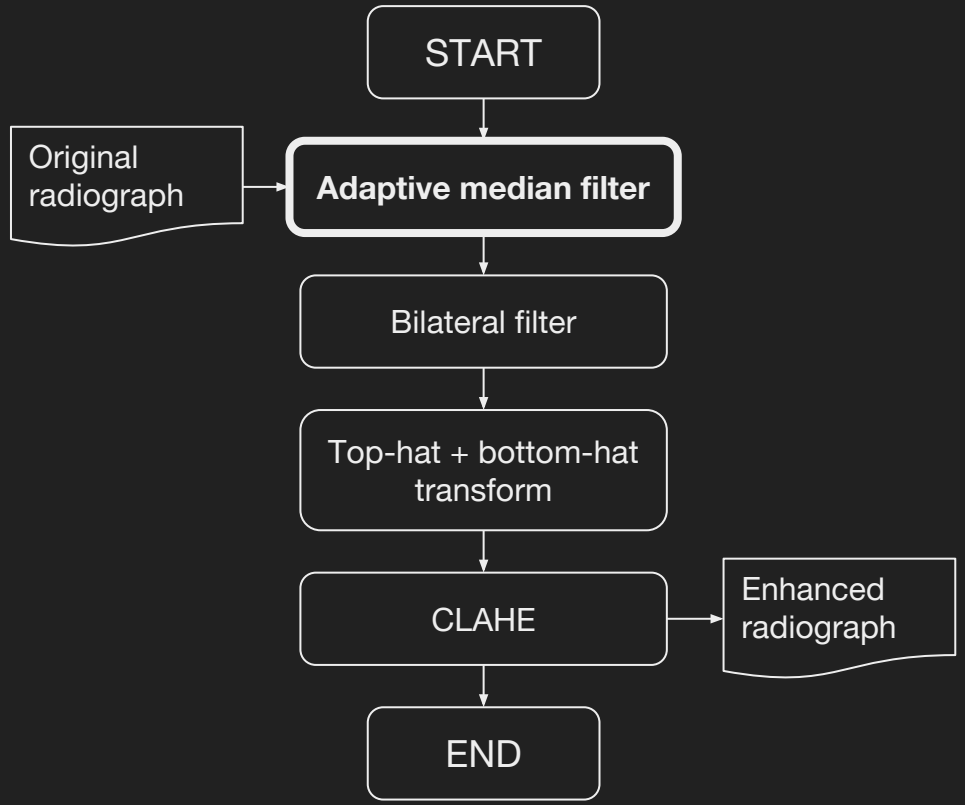
S. A. Bt Ahmad, M. N. Taib, N. E. A. Khalid, and H. Taib. Utilizing contrast enhancement algorithms (CEAs) in identification of dental abnormalities. In 2013 The International Conference on Technological Advances in Electrical, Electronics and Computer Engineering (TAEECE), pages 218–223. IEEE, May 2013.

# Pre-processing dental radiographs



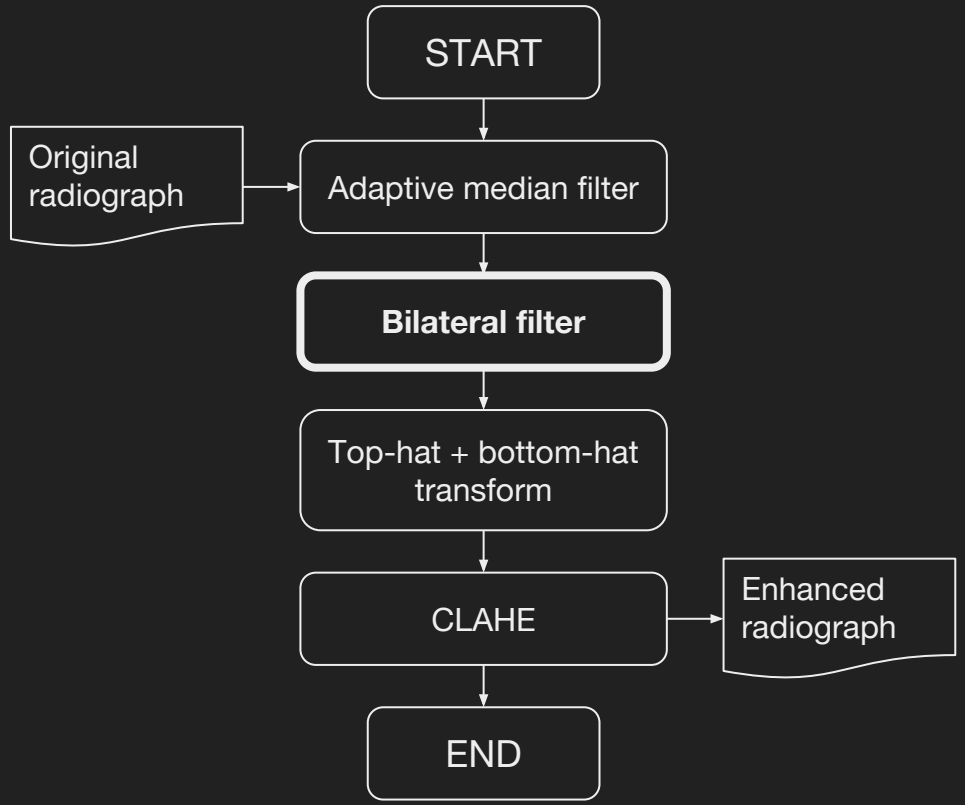



# Pre-processing dental radiographs



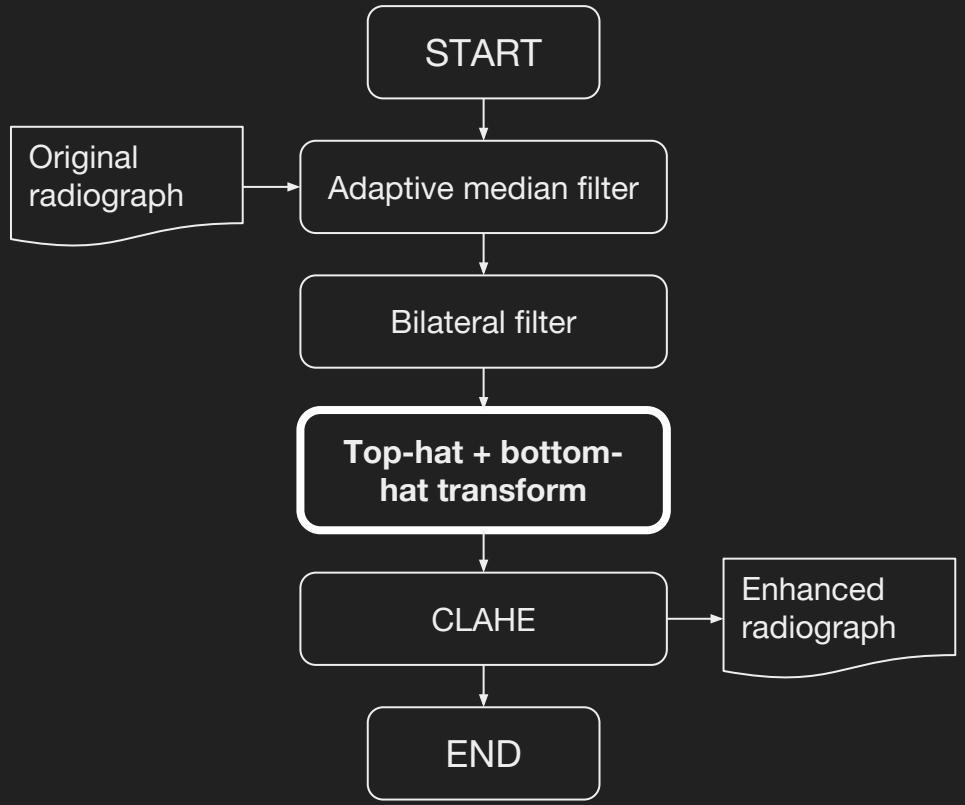

Suppress impulsive noise

# Pre-processing dental radiographs



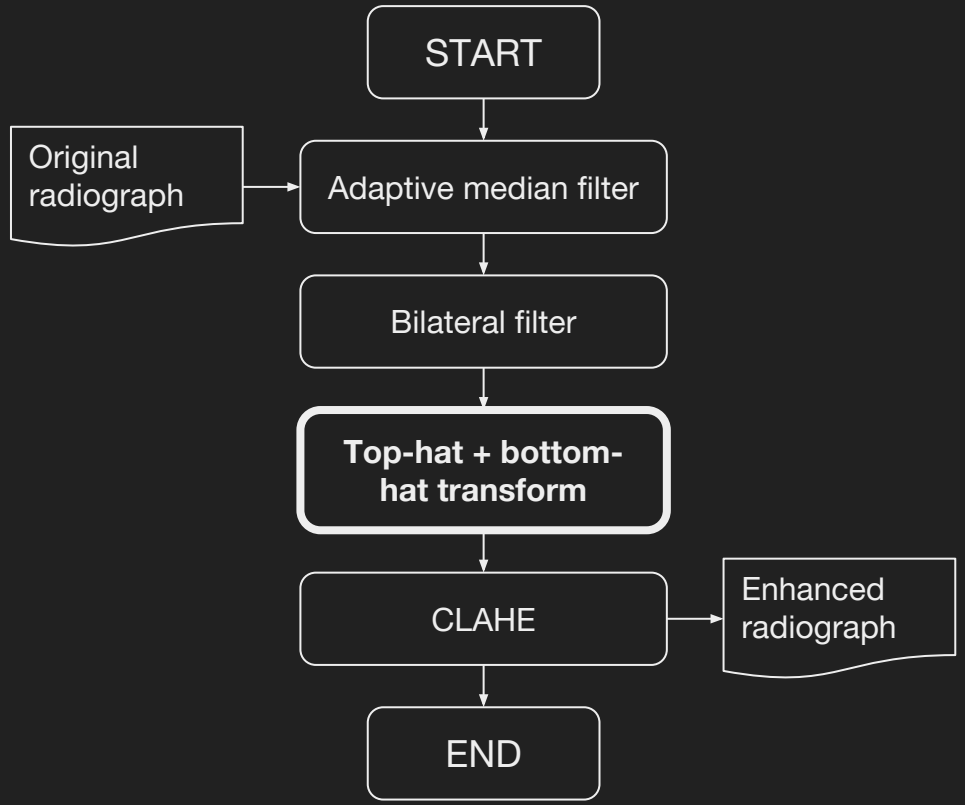

Suppress Gaussian noise

# Pre-processing dental radiographs



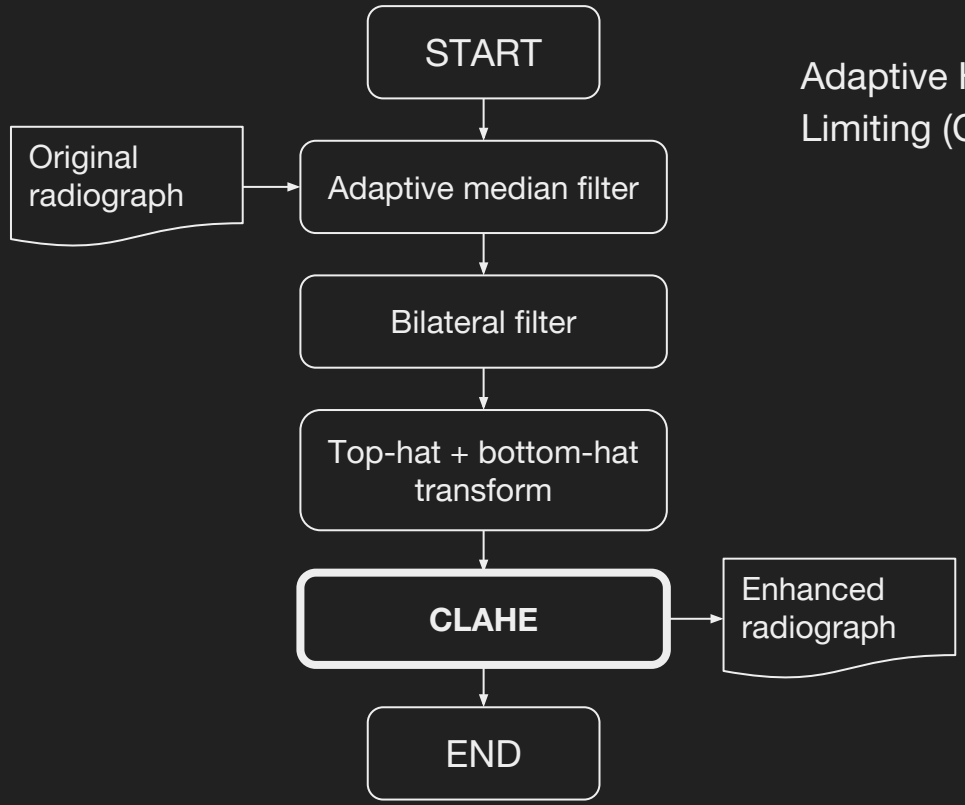

Top-hat: enhance brighter structure
Bottom-hat: enhance darker structure

# Pre-processing dental radiographs



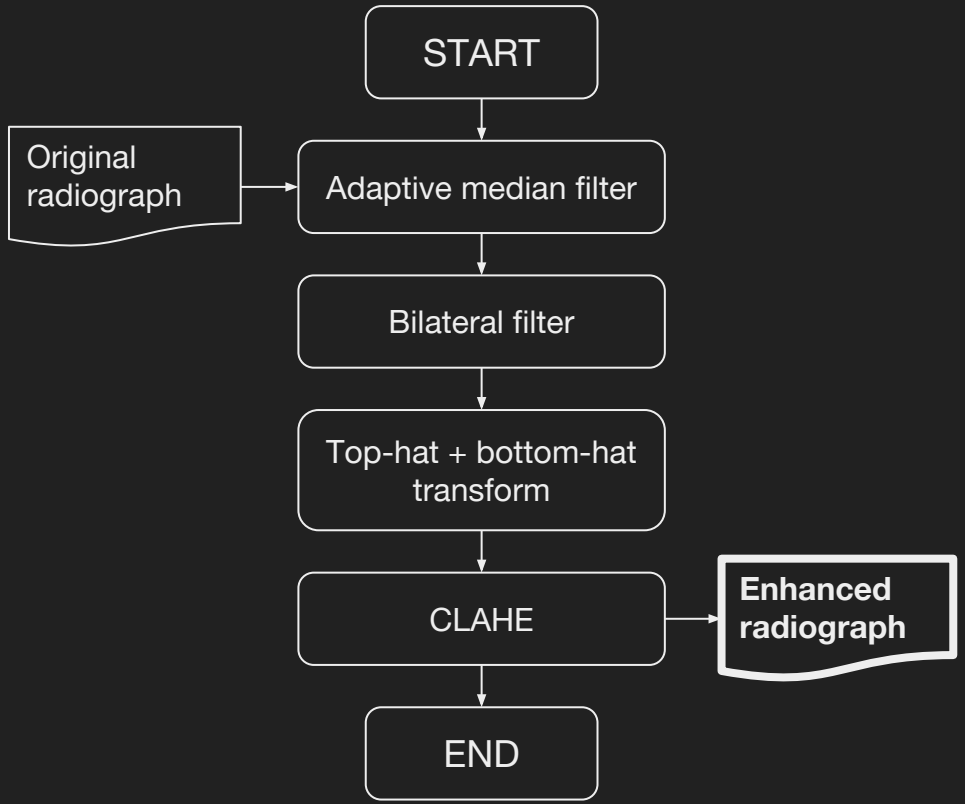

Sharpens the image

# Pre-processing dental radiographs

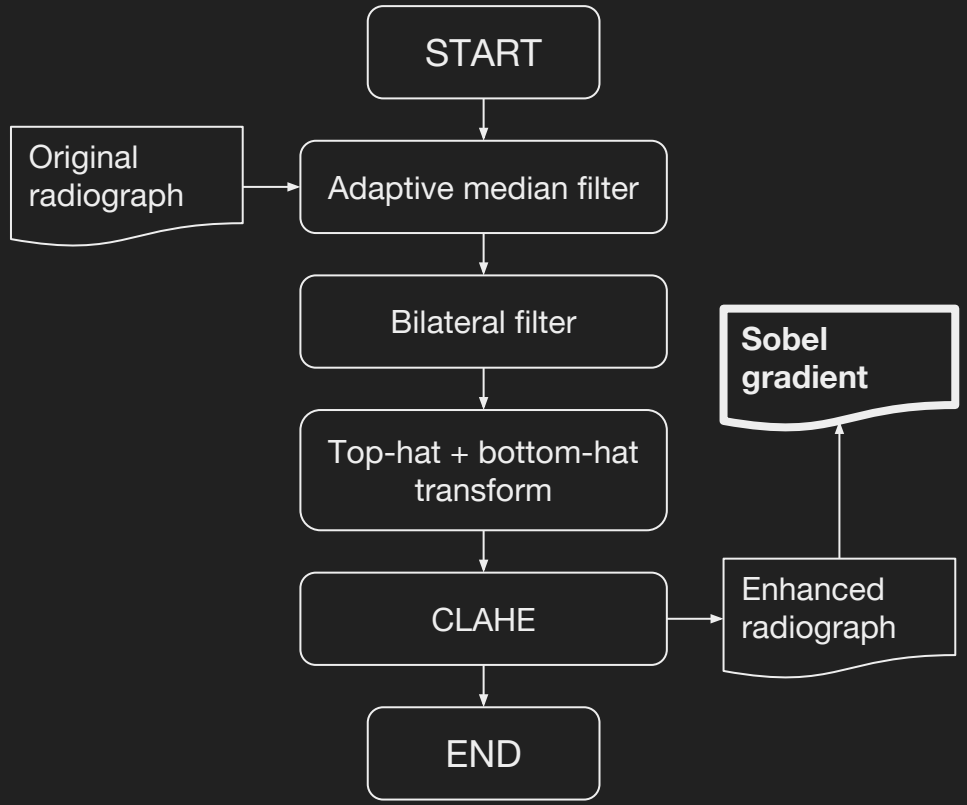



Adaptive Histogram Equalization (AHE) + Contrast Limiting (CL)

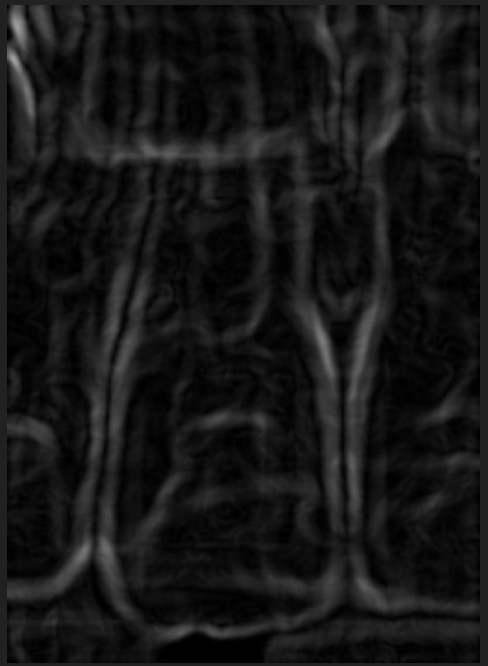
# Pre-processing dental radiographs




# Pre-processing dental radiographs




Detect edges



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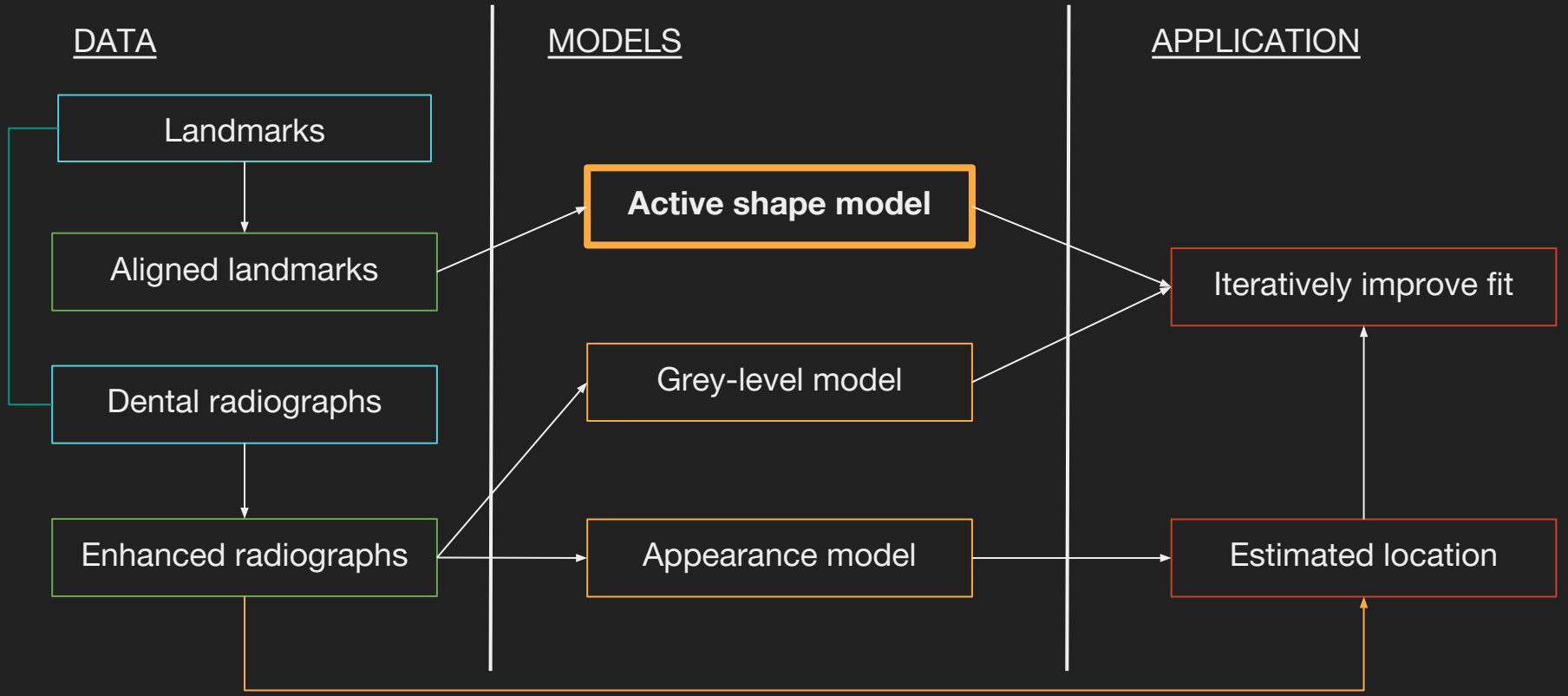
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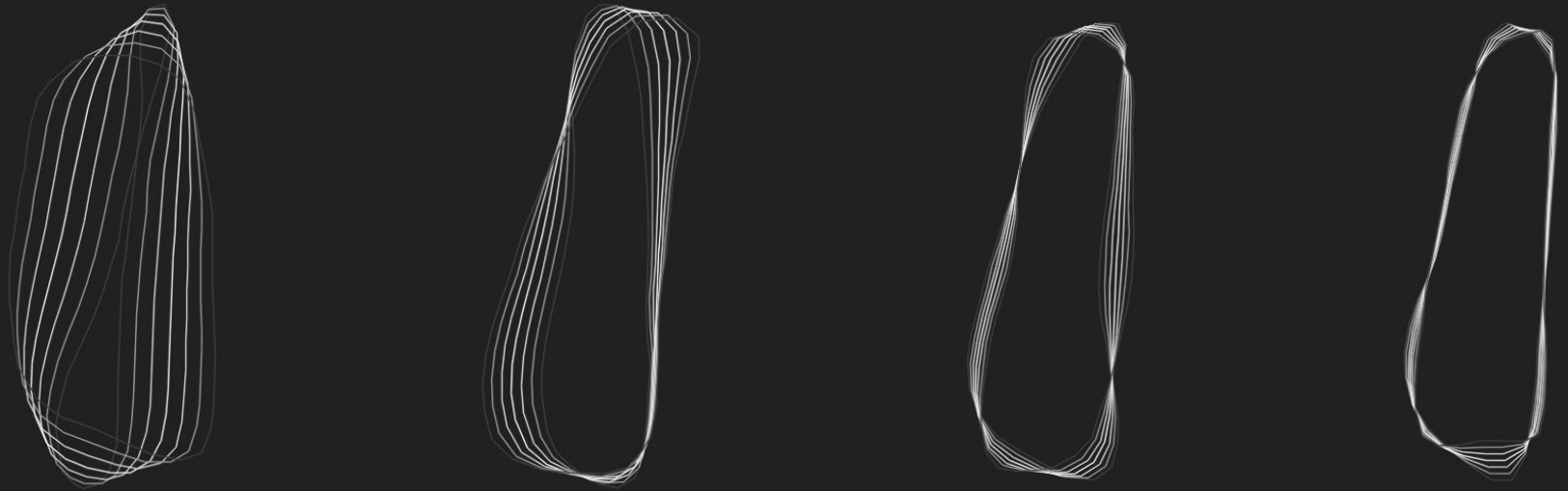
# Active Shape Model

- Mirror training data to increase number of examples
- Apply PCA to the aligned shapes to capture incisors' main axes of variance in few parameters → $x \approx \dot{x} + Pb$
- By varying b, we can generate plausible variations to  the mean shape



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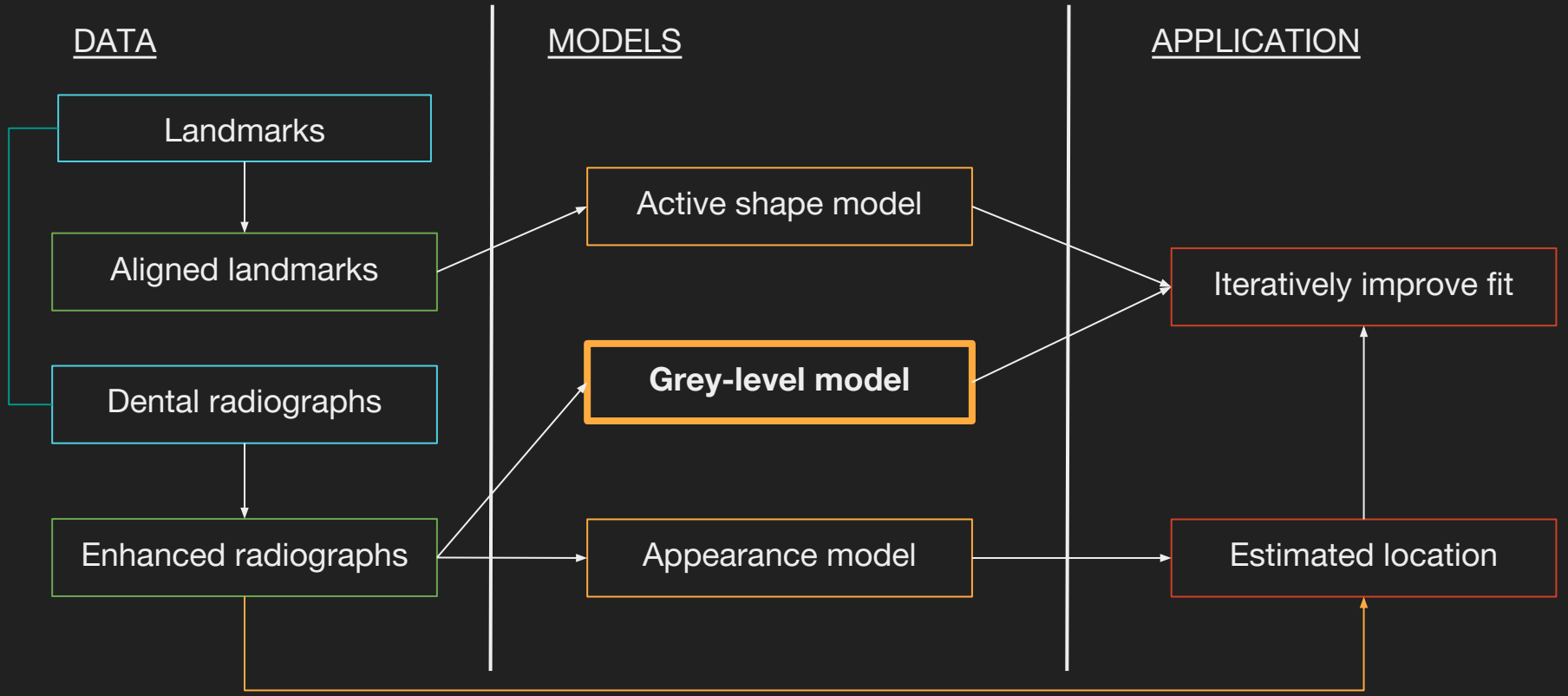
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# Grey-level model

= a model for the local grey-level structure of each landmark point

**Algorithm 2:** Grey-level Model Construction Algorithm

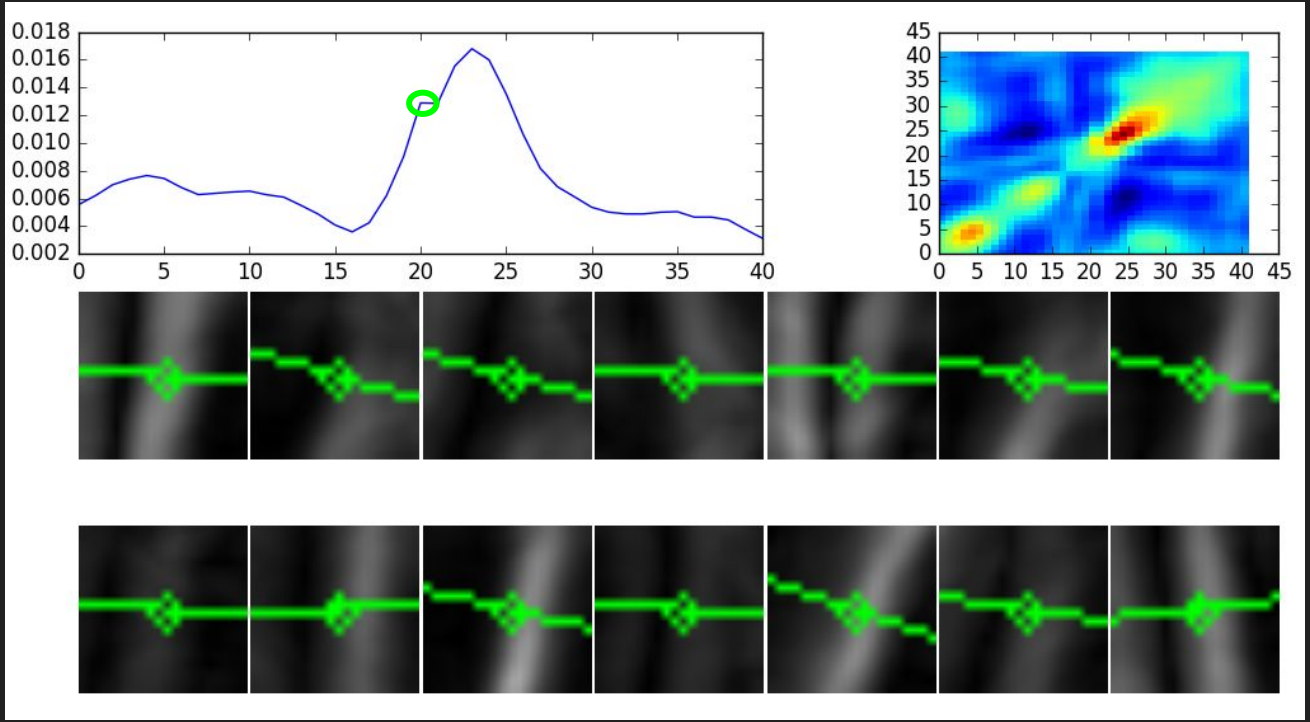
**Step 1** For each model point, repeat the following steps for every training image:

(a) Sample the gradients (to reduce effects of global intensity changes) of $k$ pixels along each side of the profile through the model point.

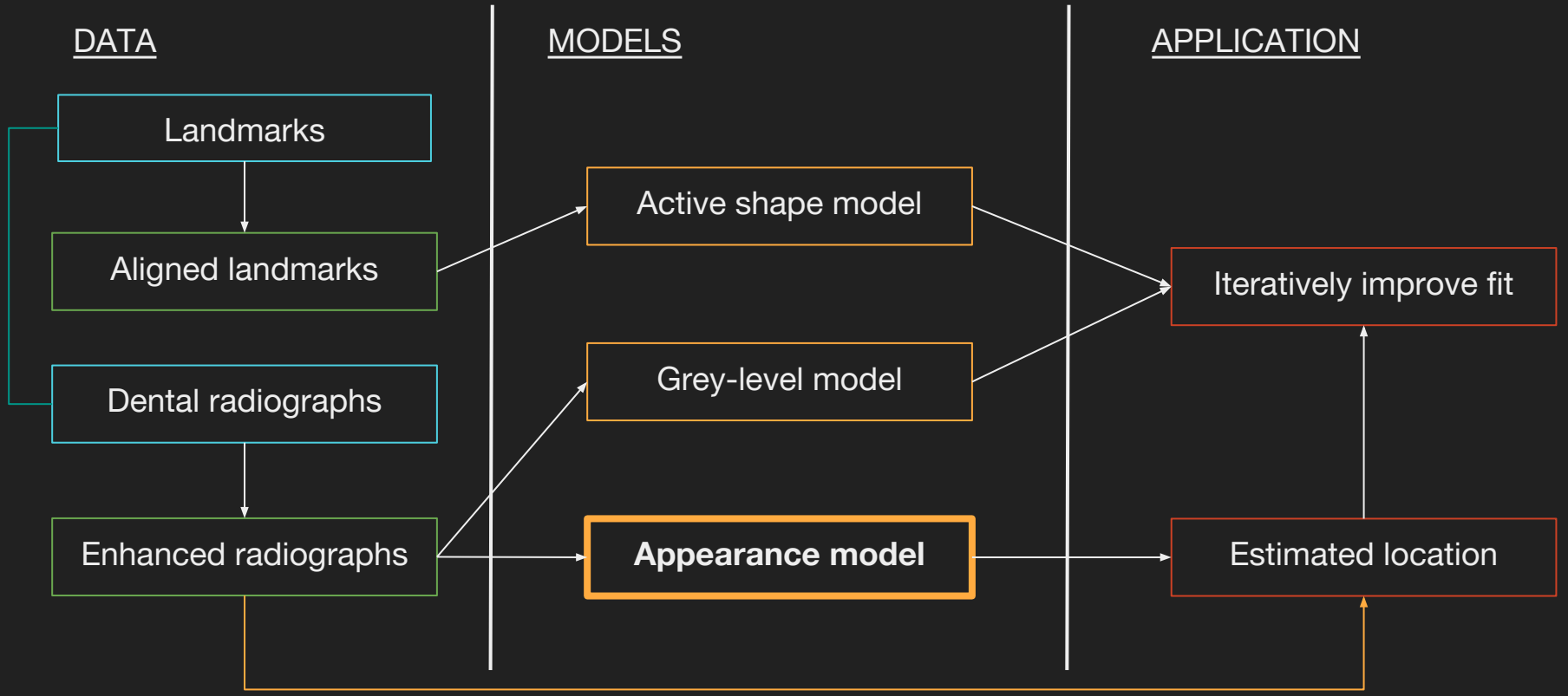
(b) Normalise the sample by dividing it by the sum of its values.

**Step 2** Combine the data for all training images and calculate the mean and covariance matrix. This is the grey-level model for one landmark in the training data.

# Grey-level model



# Overview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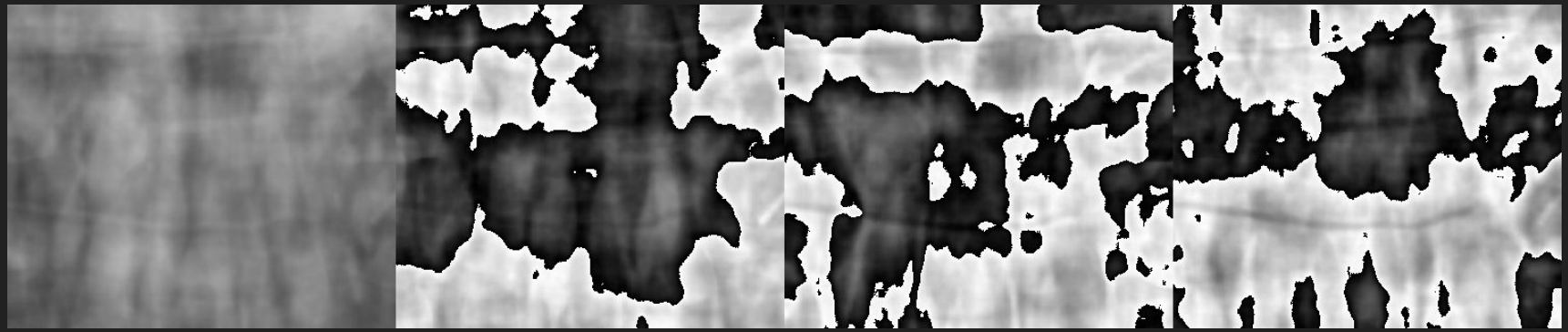
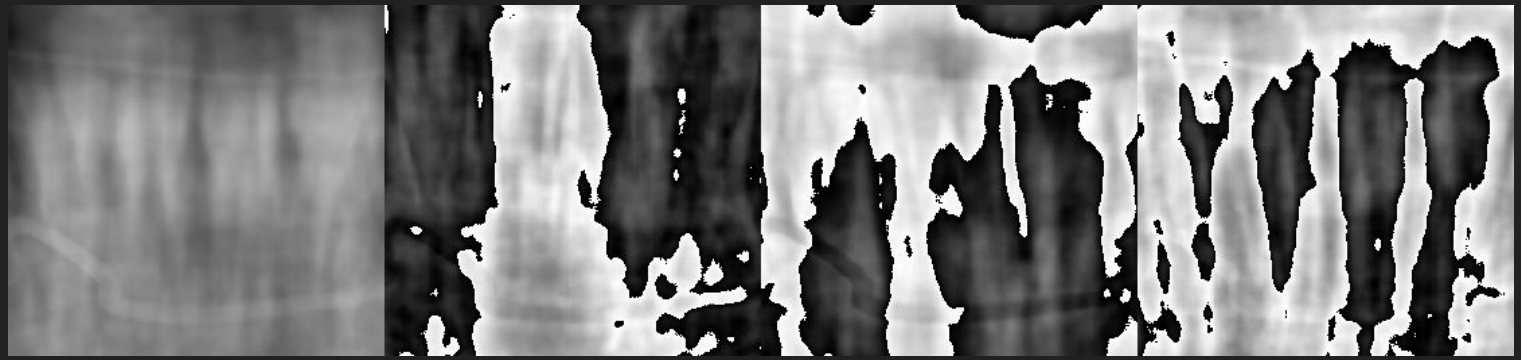
# Appearance model

Extract region of four upper incisors in all examples → PCA → Model for upper



# Appearance model

Extract region of four lower incisors in all examples → PCA → Model for lower



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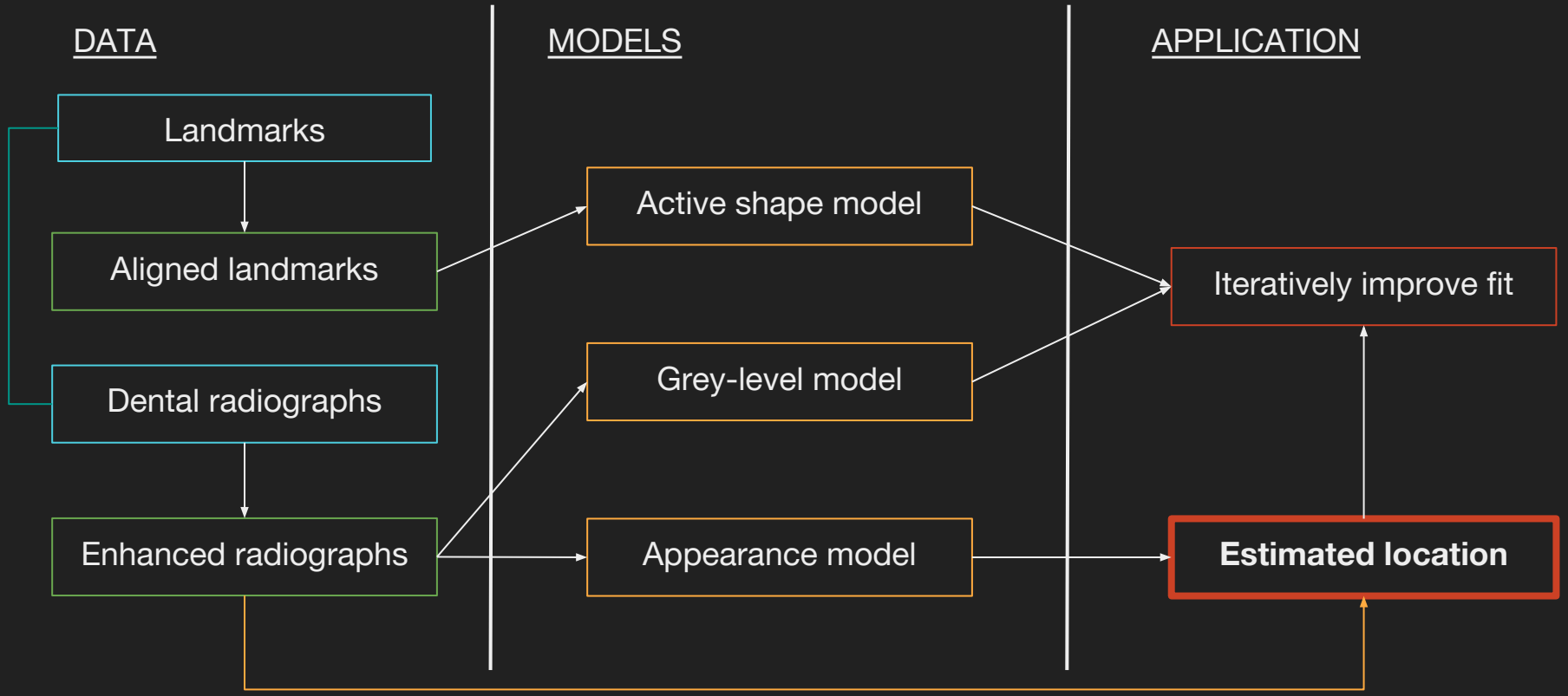
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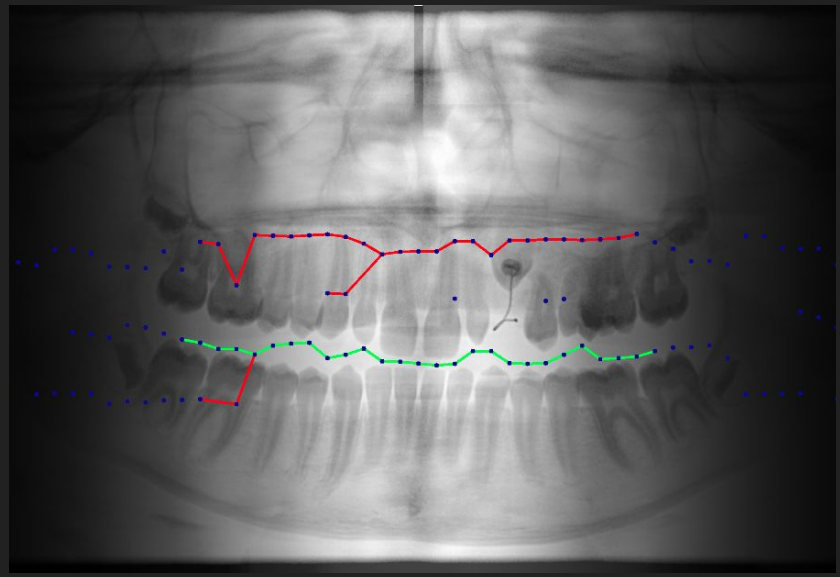
# Estimate incisor location

1. **Determine jaw split**
2. Pass a sliding window of different sizes over the image
   a. Project each window on the first five components of the appearance model
   b. Retain the window with the smallest reconstruction error
3. Split the found region in four equal width parts
4. Fit the mean shape in this box



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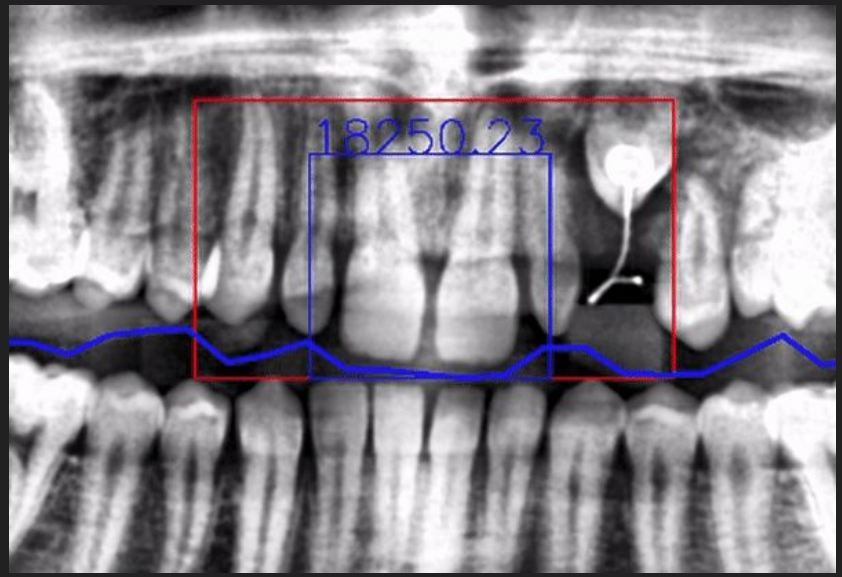

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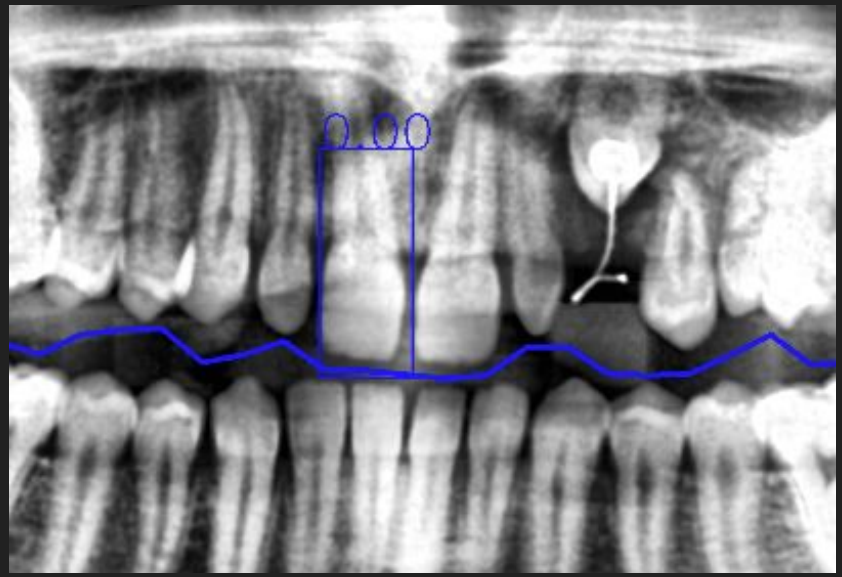

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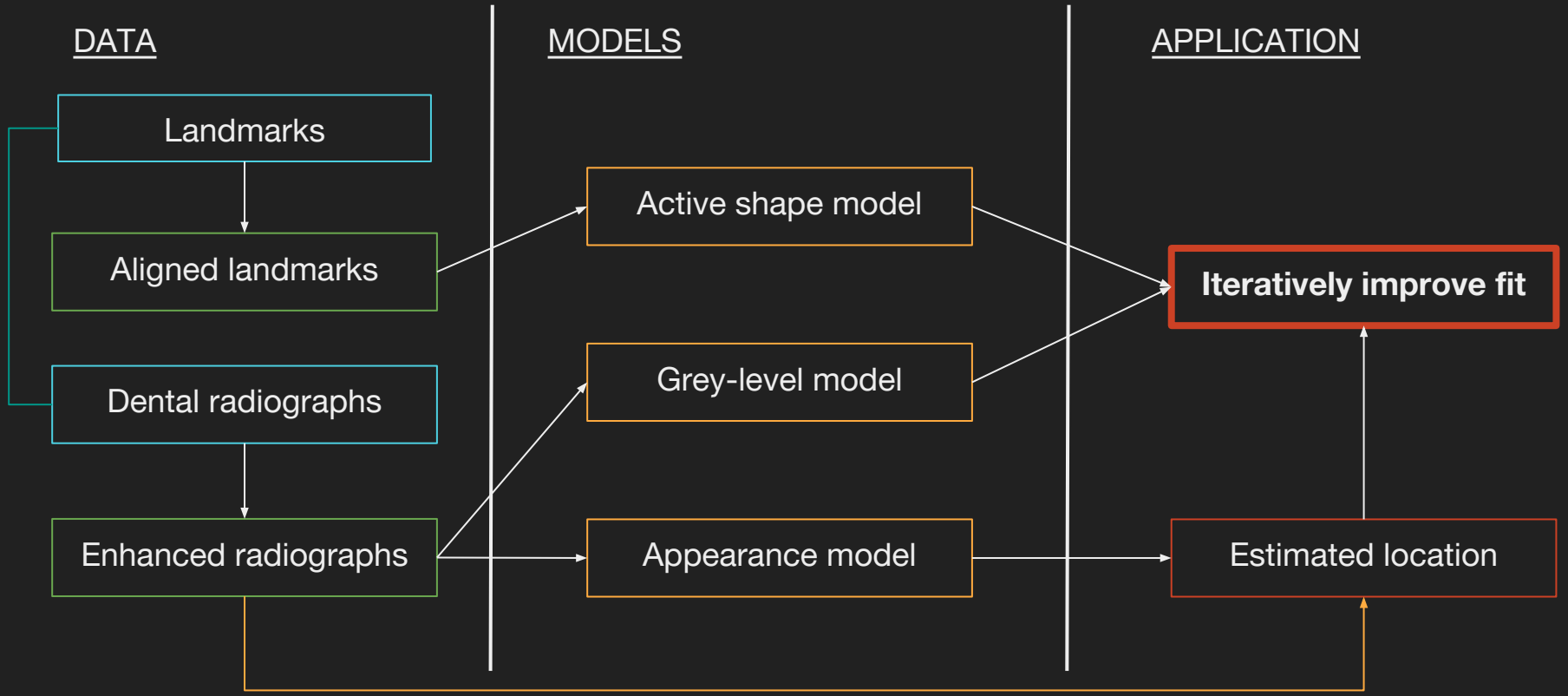
# Overview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# Iteratively improve fit

Tim Cootes - An Introduction to Active Shape Models

… with some small additions

**Algorithm 2:** Model Fitting Algorithm

**Step 1** Use the previously obtained initial estimate as the first current fit $X'_i$.

**Step 2** For each point $X'_i$ of the current fit, find the best point $X_i$ in the neighbouring image region.

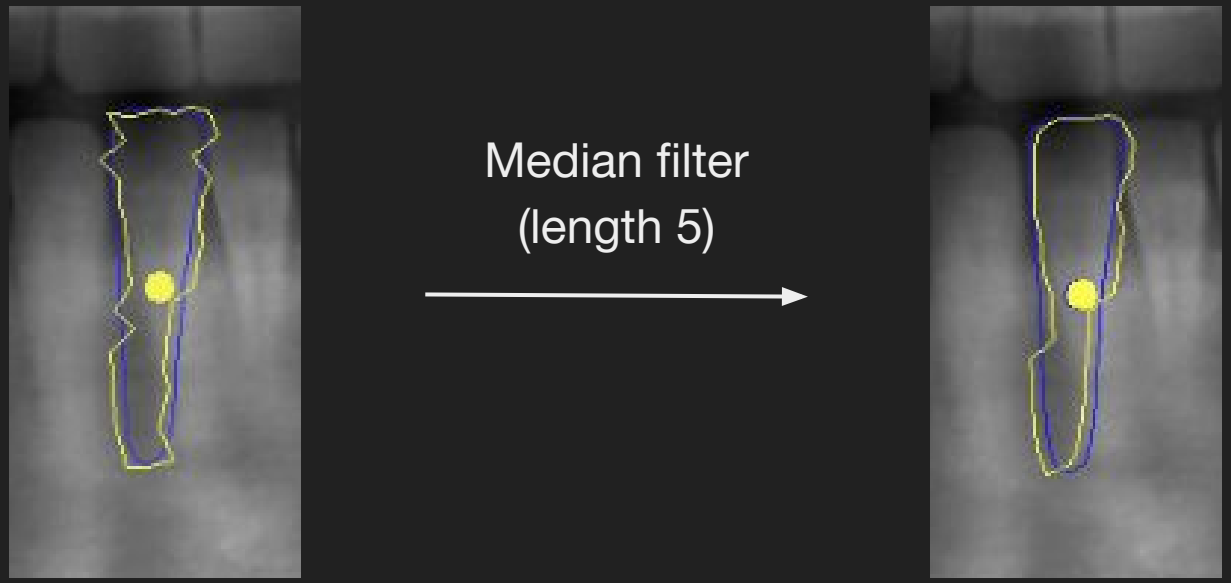
**Step 3** Update the model's parameters $(X_t, Y_t, s, \theta, b)$ such that the new fit $X$ is best approximated.

**Step 4** Apply constraints to shape parameters $b$ in the object-centred coordinate frame. Ensure plausible shapes by allowing $|b_i|$ to vary no more than three standard deviations.

**Step 5** If not converged, then re-iterate from **Step 2**.

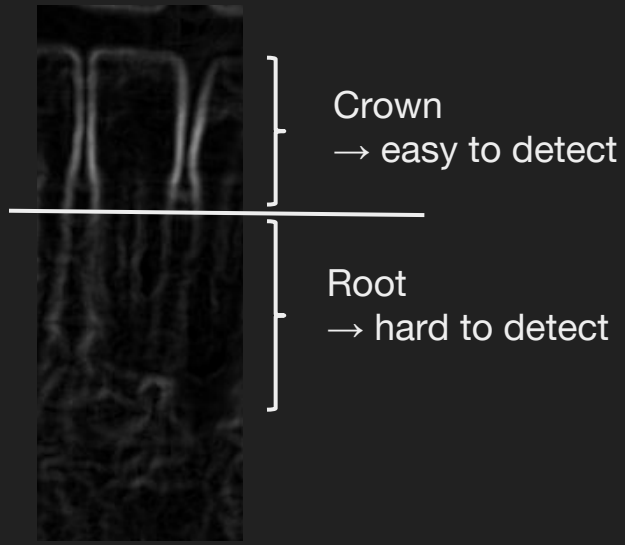
# Iteratively improve fit

1. Outlier removal



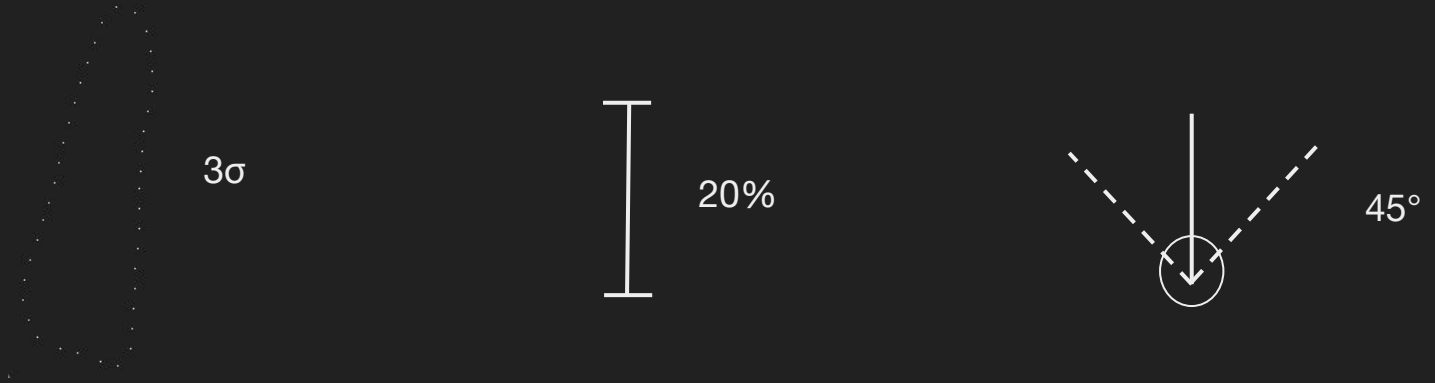
# Iteratively improve fit

2. Only consider the crown part of the tooth to determine the translation ([Xt, Yt]), scale (s) and rotation (θ) parameters.



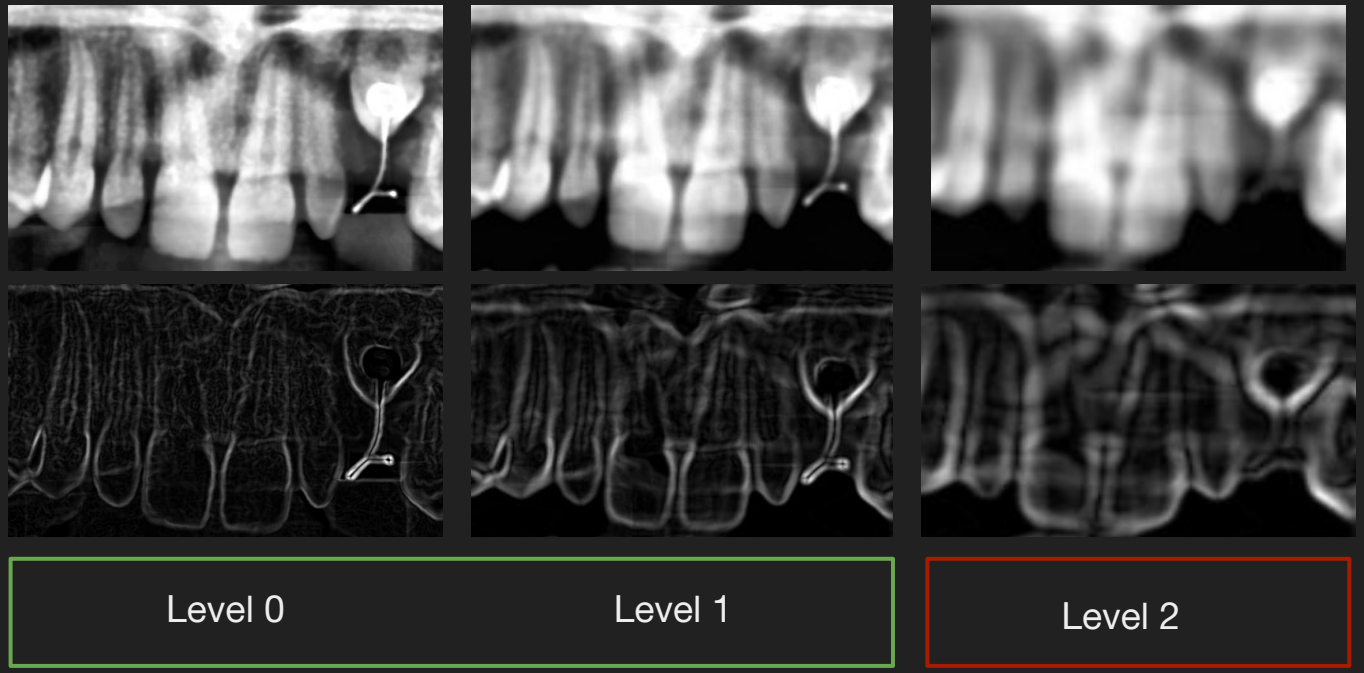
# Iteratively improve fit

3. To ensure plausible shapes we
    - allow shape parameters $|b_i|$ to vary no more than three standard deviations
    - limit scaling to 20% increase or decrease compared to the mean shape
    - limit the rotation to 45°.



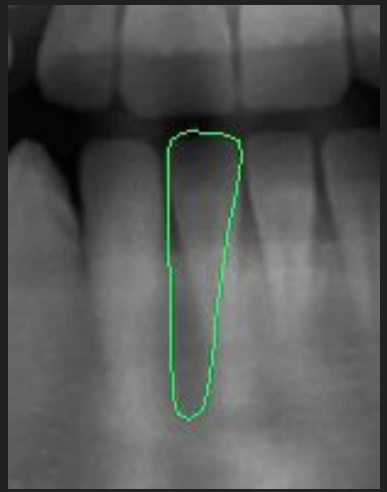
# Iteratively improve fit

4. A multi-resolution framework



# Iteratively improve fit

5. Iterate
    - until 90% of the best found pixels along a search profile is within the central 25% of the profile
    - backtrack to best fit if not converged after 50 iterations



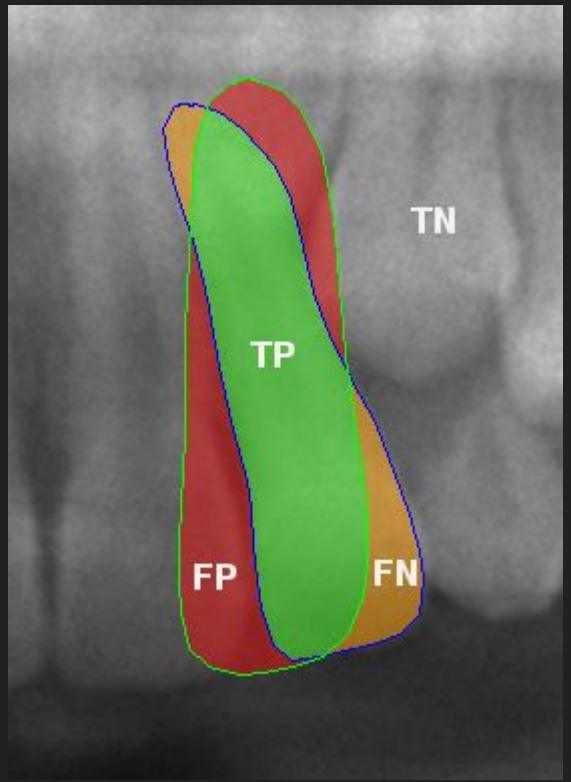
Implementation

# Results

# Evaluation: F-measure

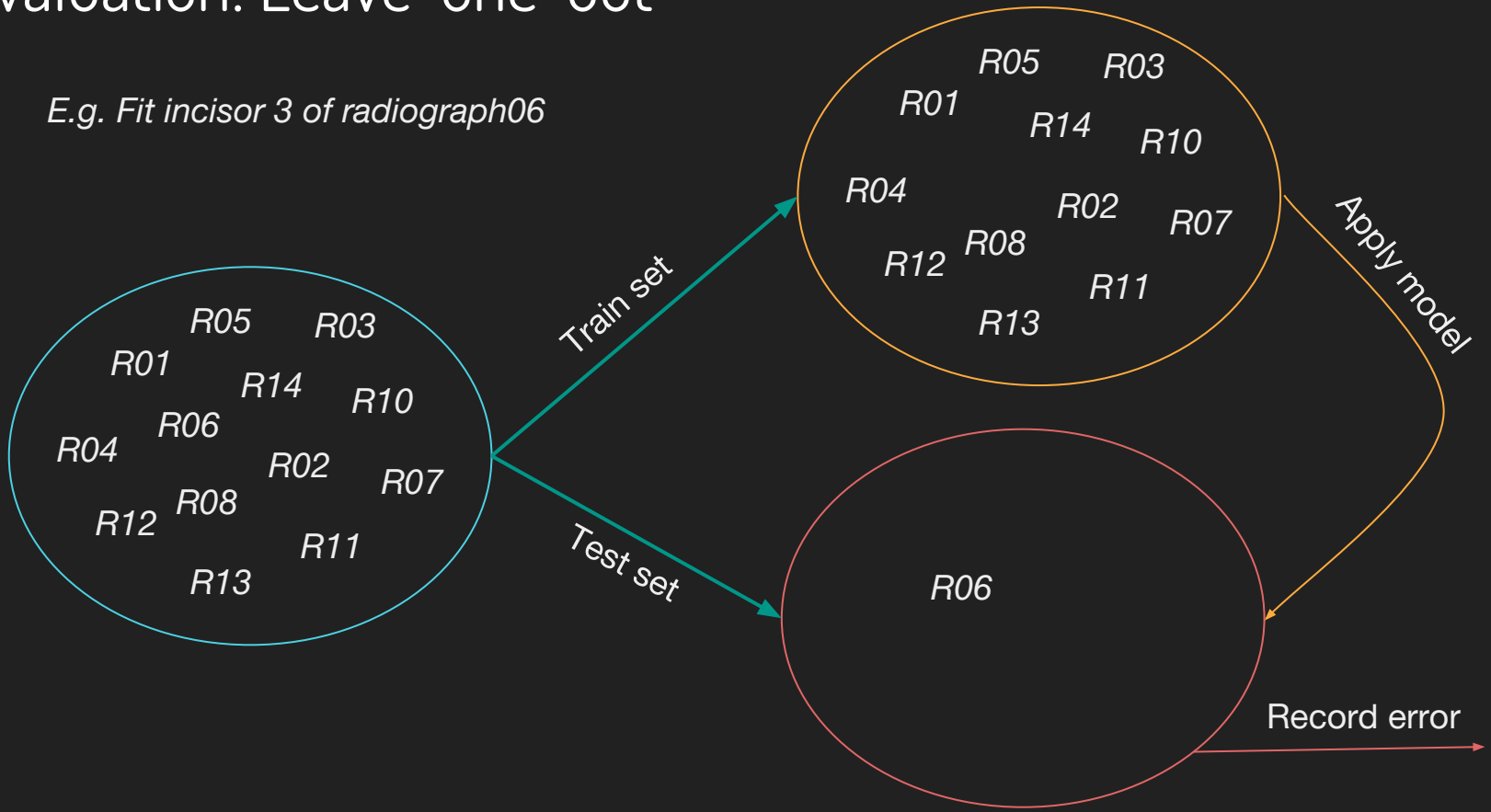
$$F = \frac{P + R}{2 * P * R} = \frac{2 * TP}{2 * TP + FP + FN}$$

P = Precision
R = Recall
TP = True Positives
FP = False Positives
FN = False Negatives
TN = True Negatives

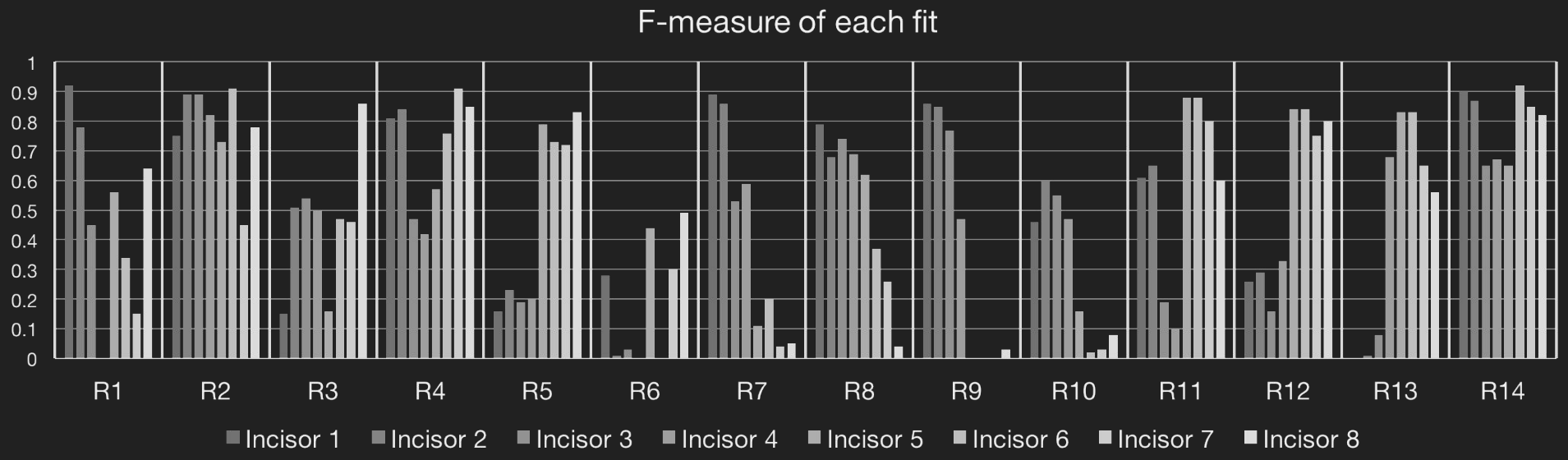


# Evaluation: Leave-one-out

*E.g. Fit incisor 3 of radiograph06*



# Results (automatic initialization)



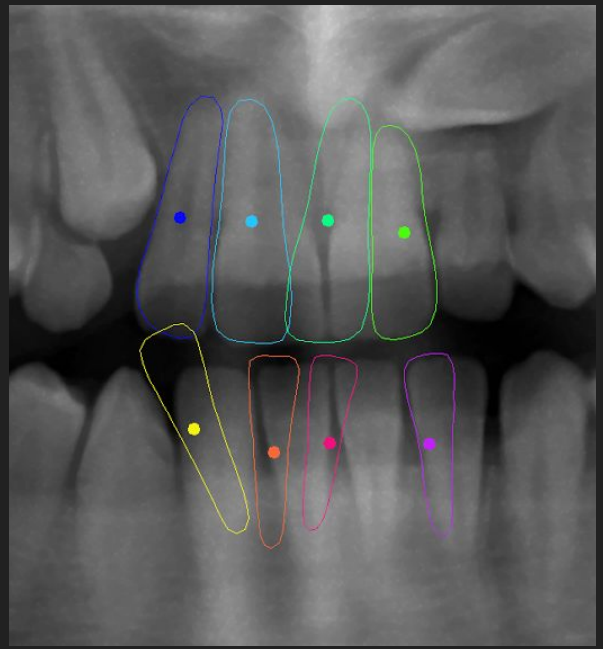
# Difficulties

1) Poor initial estimate of the position
   → fit diverges to neighboring tooth

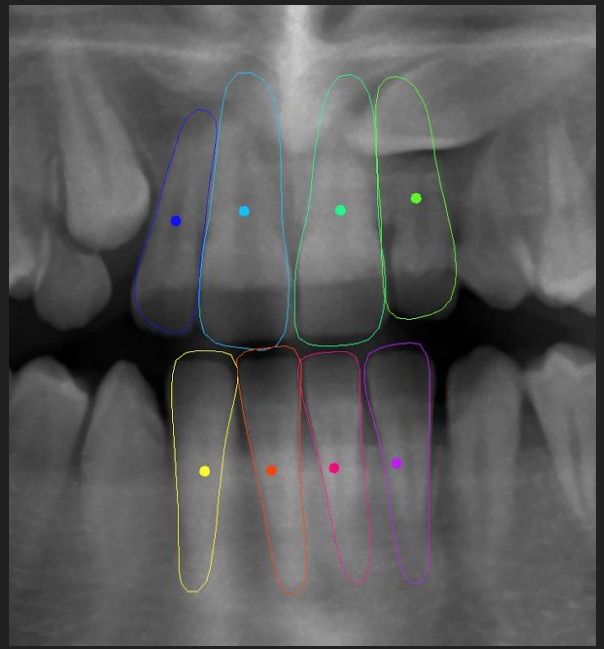
2) Rather small training set
   → incisors with unique shape don’t fit well

# Results: *Radiograph01*

Automatic initialization

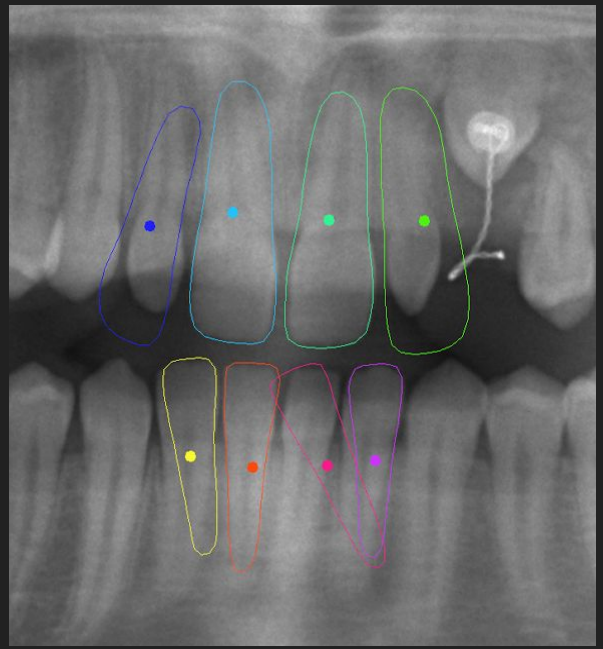


Manual initialization

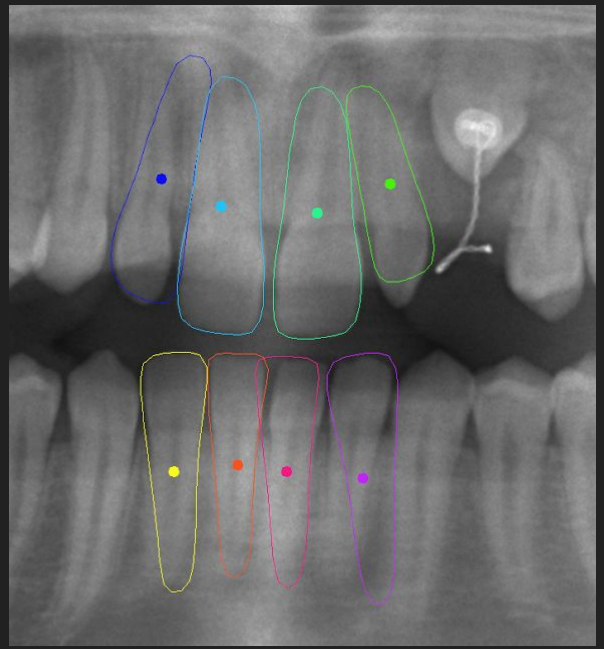


# Results: *Radiograph02*

Automatic initialization

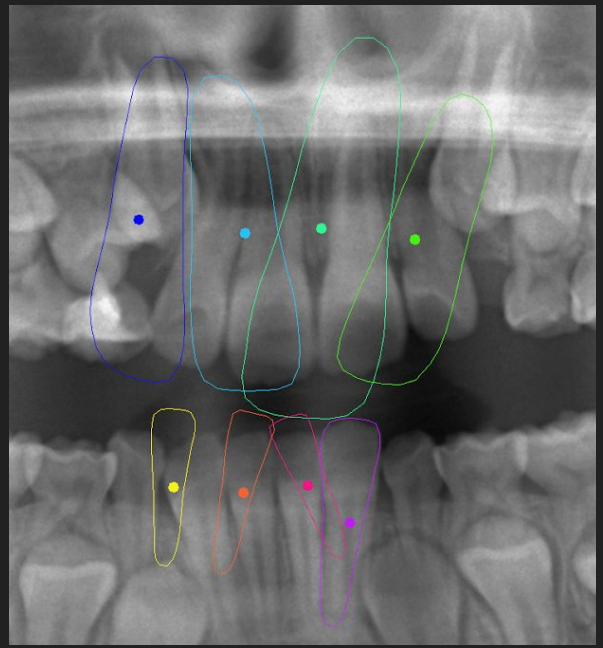


Manual initialization

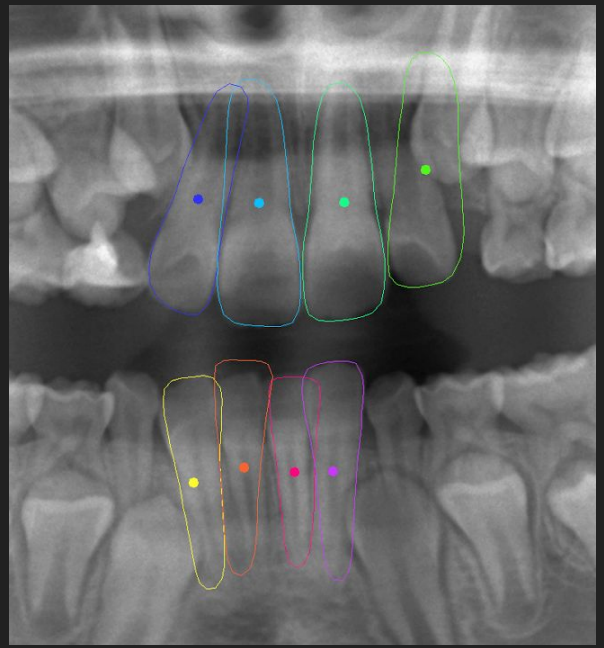


# Results: *Radiograph03*

Automatic initialization

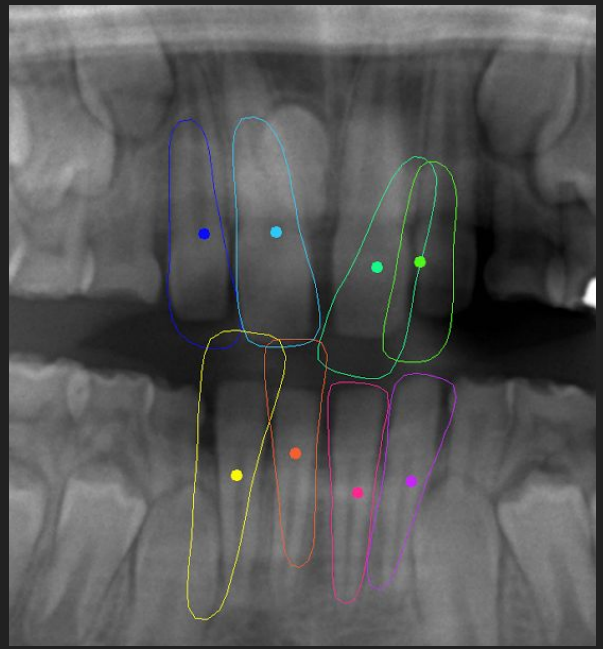


Manual initialization

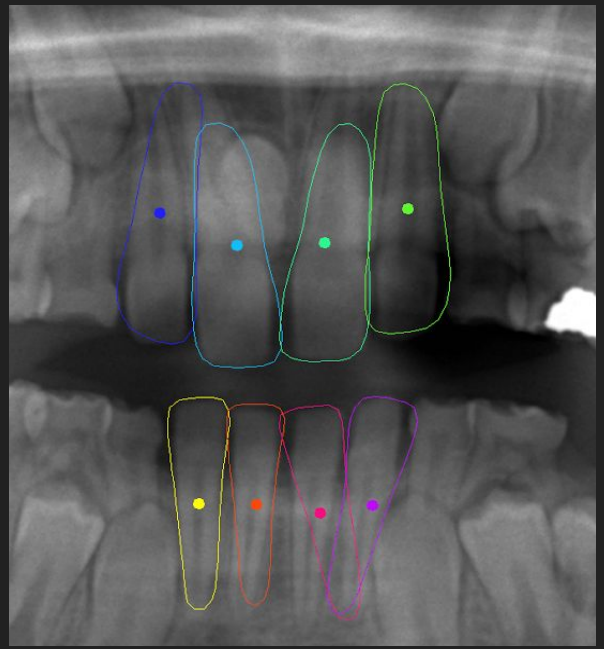


# Results: *Radiograph04*

Automatic initialization

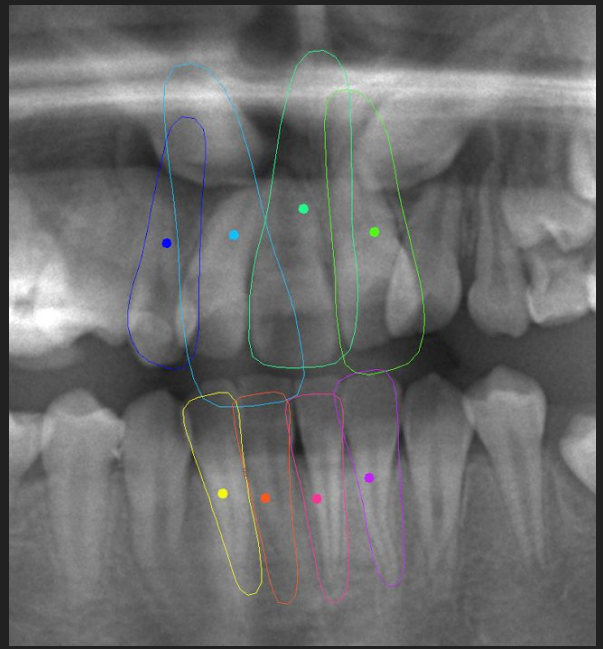


Manual initialization

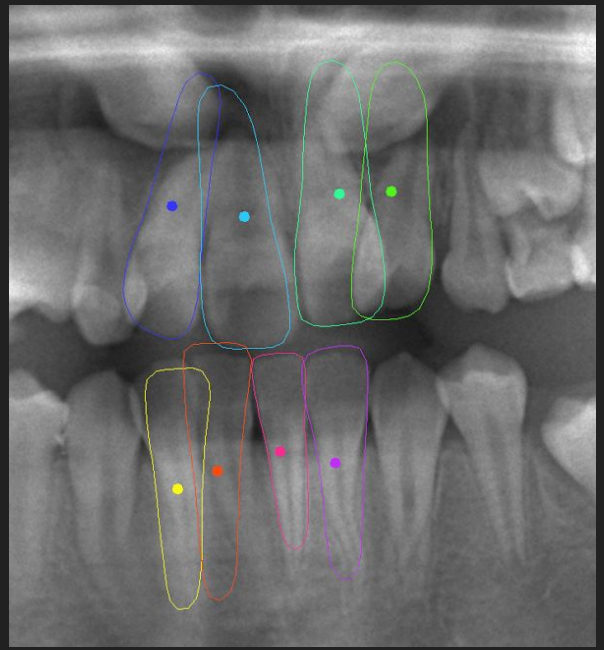


# Results: *Radiograph05*

Automatic initialization

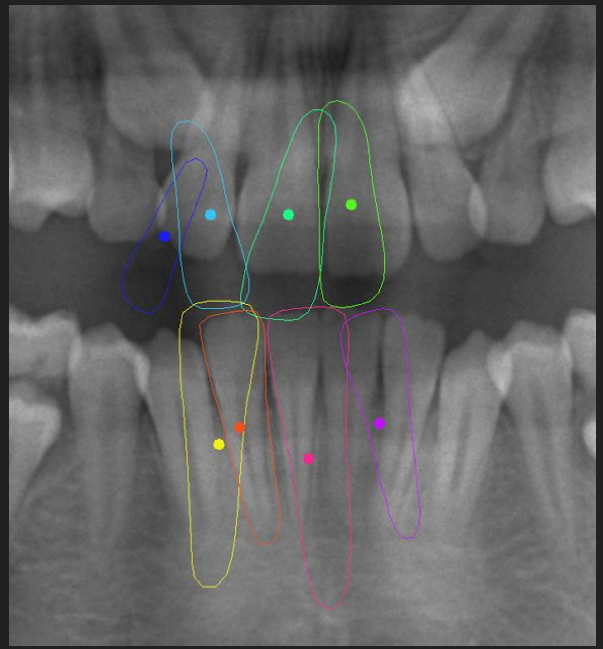


Manual initialization

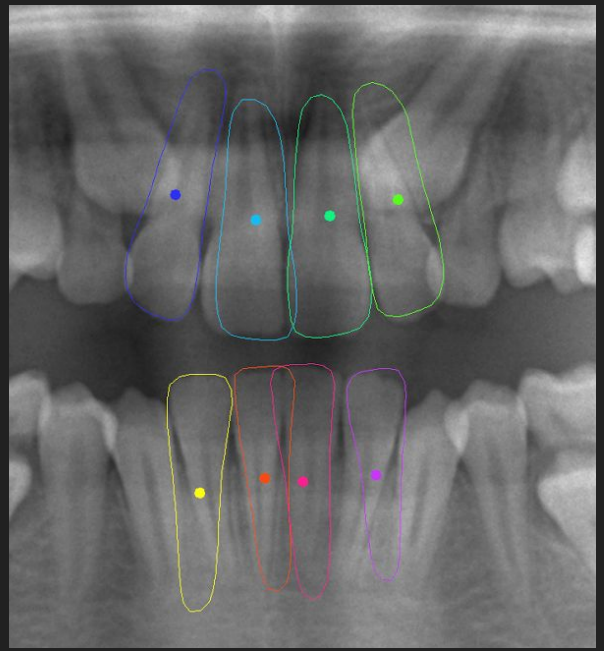


# Results: *Radiograph06*

Automatic initialization

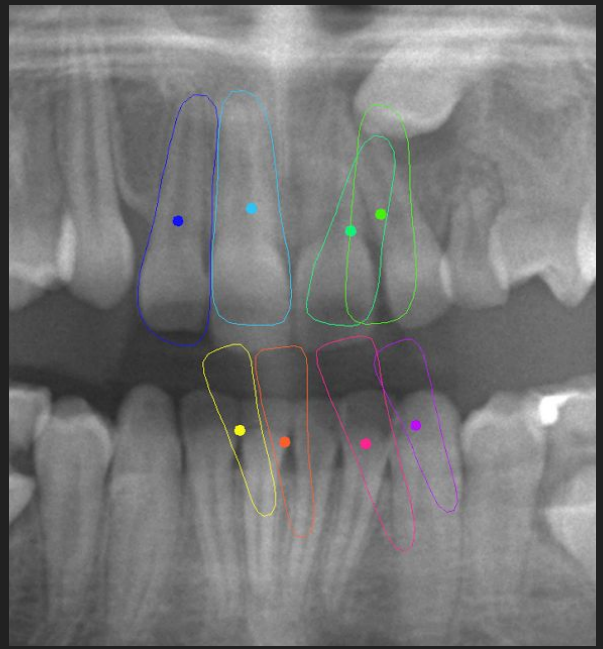


Manual initialization

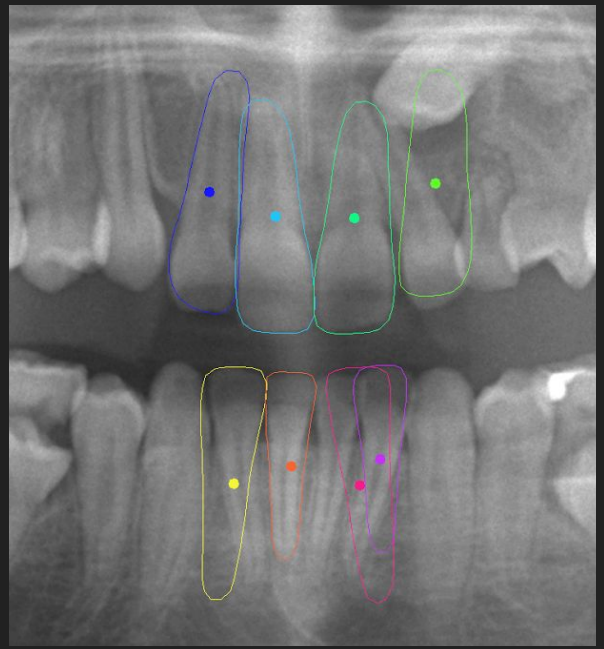


# Results: *Radiograph07*

Automatic initialization

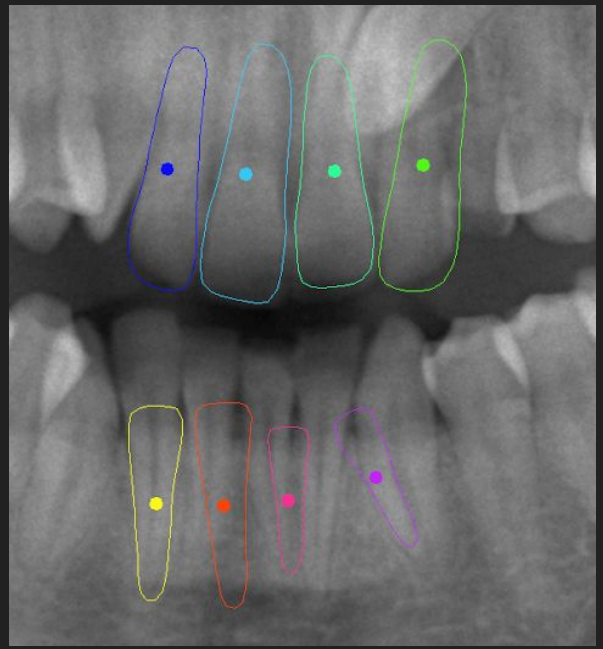


Manual initialization

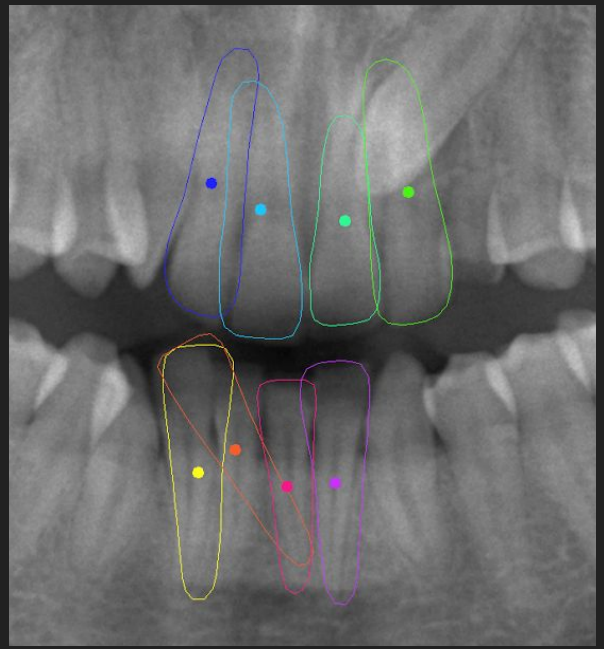


# Results: *Radiograph08*

Automatic initialization

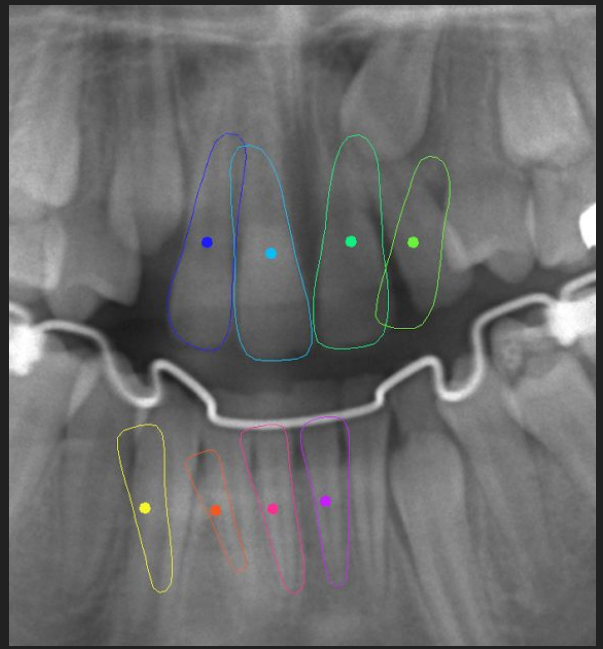


Manual initialization

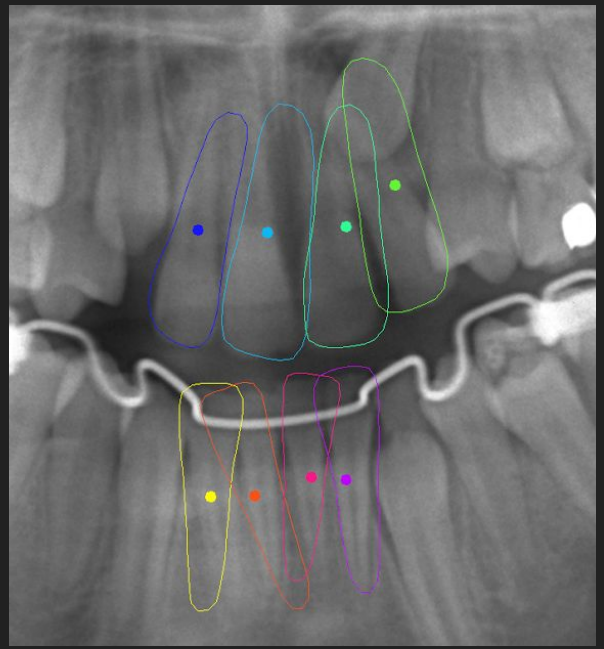


# Results: *Radiograph09*

Automatic initialization

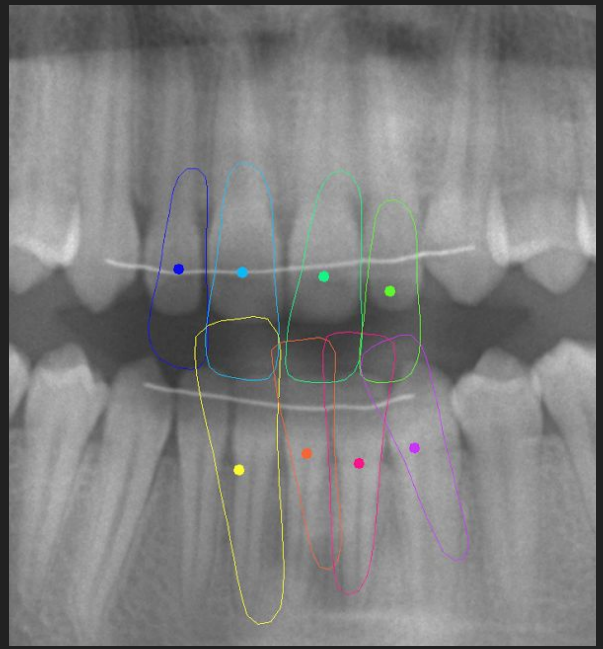


Manual initialization

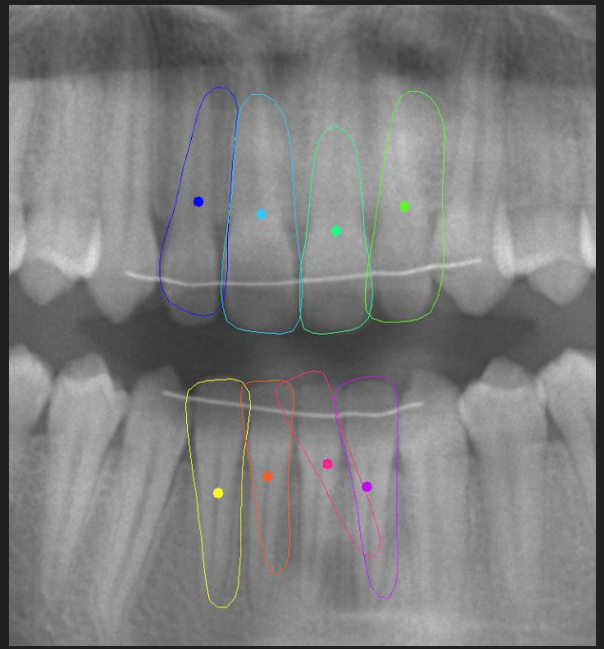


# Results: *Radiograph10*

Automatic initialization

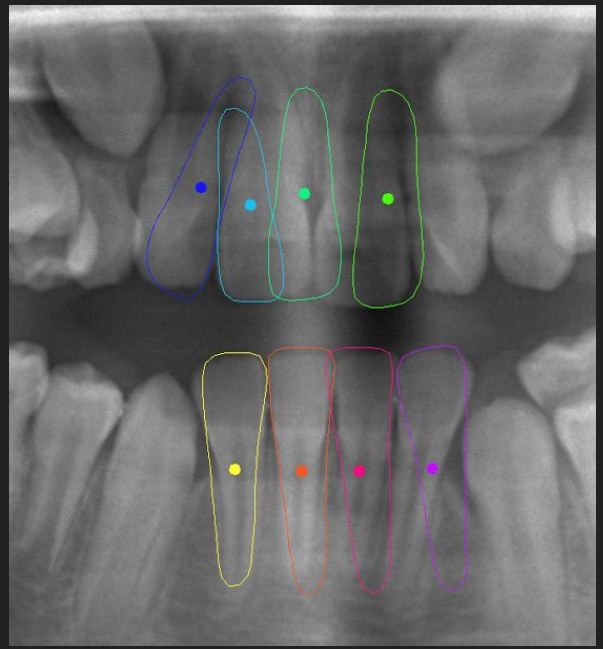


Manual initialization

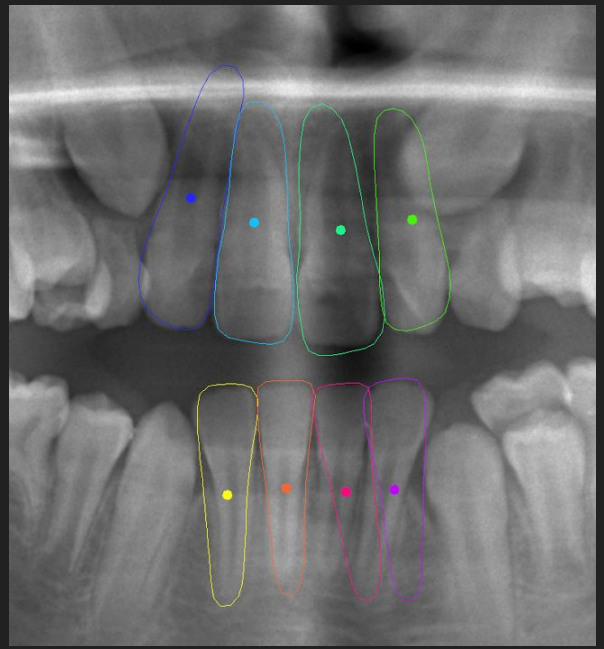


# Results: *Radiograph11*

Automatic initialization

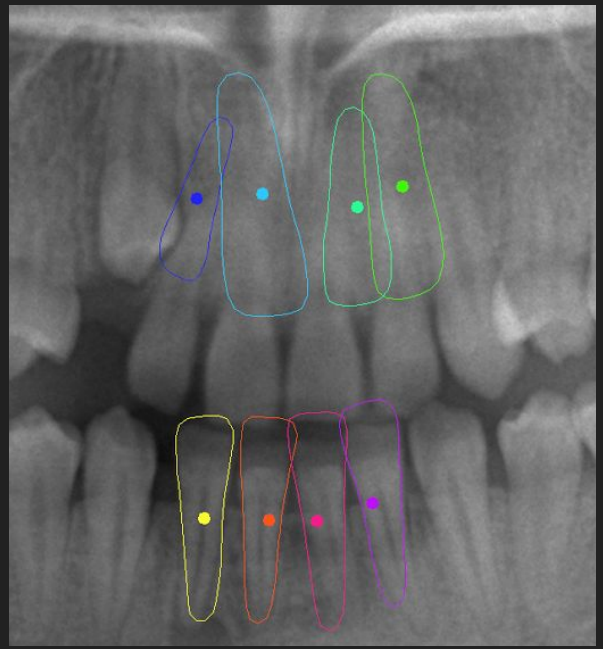


Manual initialization

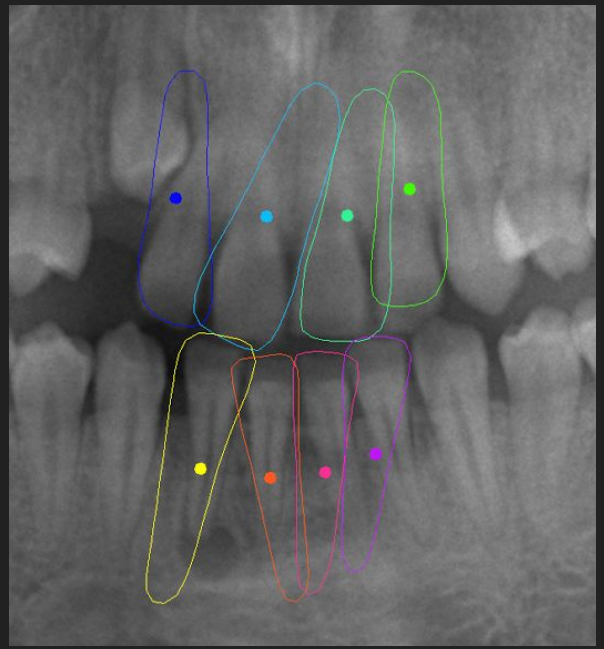


# Results: *Radiograph12*

Automatic initialization

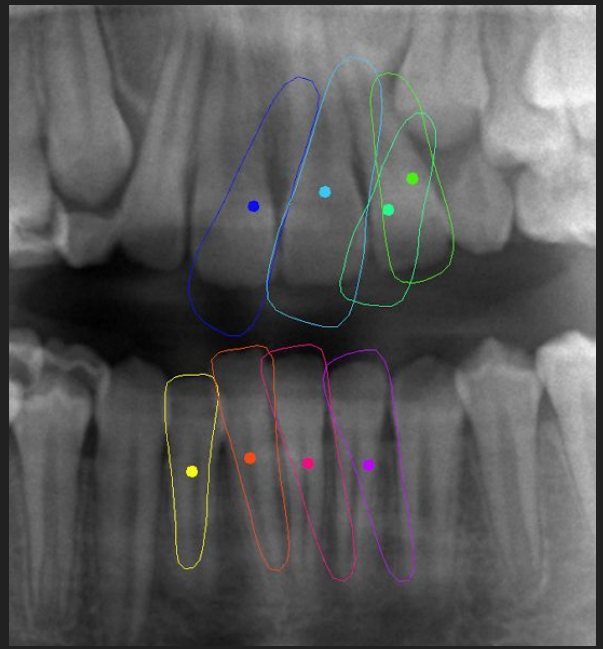


Manual initialization

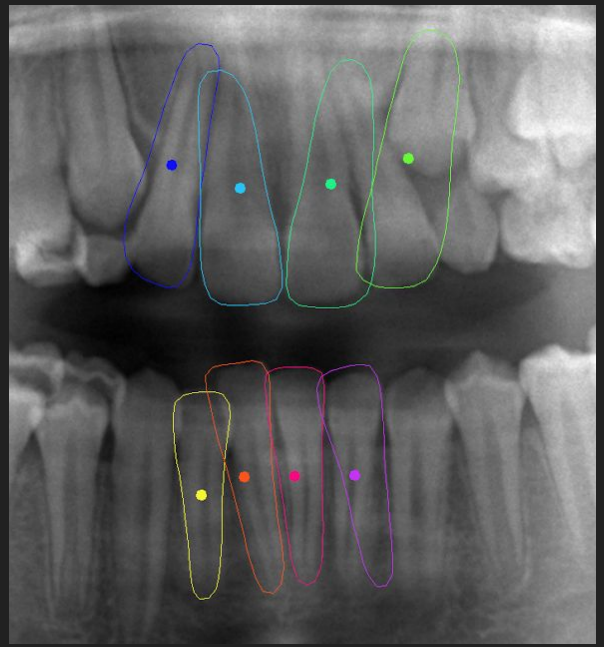


# Results: *Radiograph13*

Automatic initialization

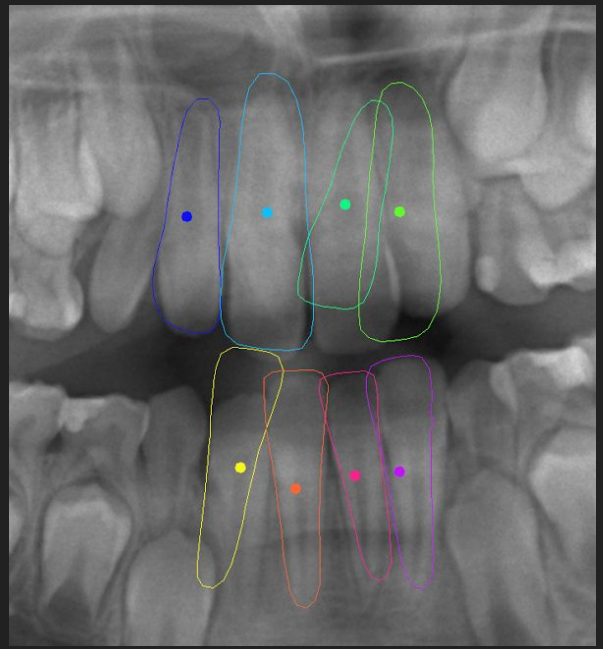


Manual initialization



# Results: *Radiograph14*

Automatic initialization



Manual initialization