# Automated Classification of Erosions in MRI Sequences of Patients with Rheumatoid Arthritis

Final Presentation

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December 18, 2015
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# Outline

- Motivation & State of the Art
- Related Work
- Data
- Pipeline
  - Initialization
  - Model Training
  - Model Fitting
  - Bone Classification
- Conclusion & Discussion
- Outlook

# Motivation & State of the Art

# What is Rheumatoid Arthritis?

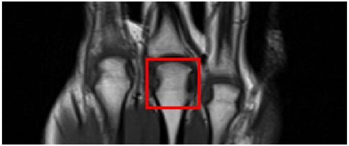
- Autoimmune disorder
- Primarily affects joints
- Characterized by 3 symptoms
    - Synovitis
    - Bone edema
    - Erosions

# Erosion

# State of the Art

## Classification using the EULAR-OMERACT system

- Assessment of 3 symptoms for each bone
- Scoring of 1 cm of bone from the joint for long bones
- Scoring of the whole bone for wrist bones
- Proportion between ideally healthy bone and unhealthy structure
- Erosion graduation in 10% steps



Region of interest for scoring

# Purpose of the Project

## Focus on erosion detection and classification

- Reduce interobserver variability
- Increase the graduation of assessment
- Reduce time for diagnosis
- Reduce time during follow up
- Create an automated tool for erosion detection

# Related Work

# Related Work

## Segmentation of the wrist bones with marginal space learning[1]

- 100 manually segmented training samples
- Only for wrist bones
- Higher quality data with a voxel spacing of $0.365 \times 0.365 \times 0.734$ mm
- Accuracy of $83.2 \pm 10.6\%$

[1] Koch M, Schwing A, Comaniciu D, Pollefeys M. "Fully automatic segmentation of wrist bones for arthritis patients", Proceedings of the ISBI, 2011.

# Related Work

## The BoneXpert method for automated determination of skeletal maturity[2]

- Detection of 15 bones in radiography images
- Model based bone detection
- Texture based age assessment
- Trained with 1559 images

[2] Thodberg H, Kreiborg S, Juul A, Pedersen K. "The BoneXpert method for auto- mated determination of skeletal maturity" in TMI, 2009.

# Data

# Given Training Data

10 MRI sequences

- T1 weighted sequences with turbo spin echo
- Right hands only
- Similar relaxed hand position
- Voxel spacing of $0.5 \times 0.5 \times$ **2.75 mm**
- Manual segmentation required

# Challenges

- Inter-slice gap of 2.75 mm
- Similarity between erosions and cysts
- The head of the bone can completely disappear by an erosion
- Bones can be displaced
- Not the whole bone is visible in MRI

Slices of 2.75 mm

# Difference CT vs MRI

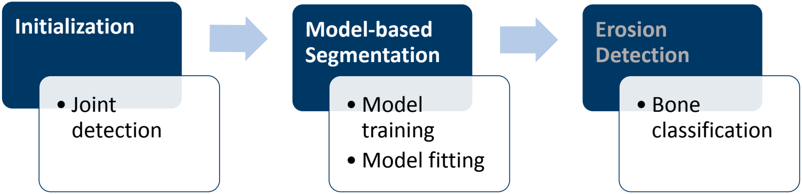
CT

MRI

The bright white cortical bone in the CT image stays black in the MRI image

# Pipeline

# Pipeline


Initialization
• Joint detection
Model-based Segmentation
• Model training
• Model fitting
Erosion Detection
• Bone classification

# Strategy

- Project volume into 2D
- Train a classifier to detect joints in 2D
- Propagate position of the joints into 3D

# Finding the Joints

## Training

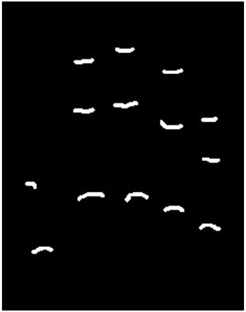
1. Calculation of parallel-beam forward projection

$$\boldsymbol{v}(x, y) = \frac{1}{Z} \sum_{z} \boldsymbol{u}(x, y, z)$$

2. Label joints manually
3. Train a classifier

# Parallel-Beam Forward Projection

Forward Projection



Manually labeled joints

# Feature

- **Gaussian blur**
  intensity feature
- **Sobel filter**
  edge detection
- **Hessian matrix**
  orientation
- **Difference of Gaussians**
  blob detection
- **Membrane projection**
  line detection

# Membrane Projection

- Developed to detect cell membranes
- 30 different kernels
- Each shows a straight line at a distinct slope
- Images are z-projected into one single image

# Finding the Joints

## Prediction

1. Calculate probability map and threshold
   $\rightarrow$ get a prediction of the position
2. Use morphological thinning to get center points of the joints
3. Find the hand above the detected joints by threshold
4. Z coordinate is mean of the hand

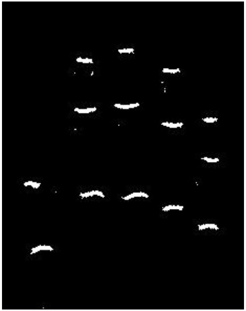
# Experiment

## Evaluate joint prediction

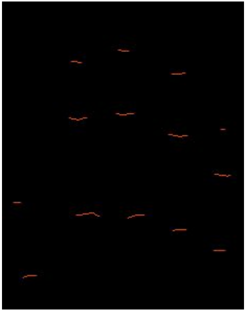
- Leave one out cross validation
- Spatial overlap between manually labeled set and prediction
  $\rightarrow$ Calculation of Dice score

## Results

- Dice score: $67 \pm 5.6\%$



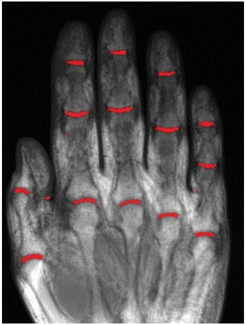
Prediction after threshold



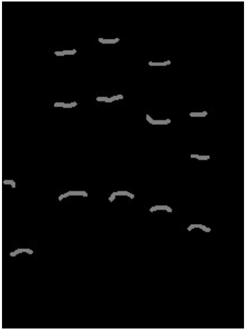
Skeletons

# Discussion

- Interested in position
- No need for exact volumetric segmentation
- Ground truth not an exact segmentation either



Forward Projection



Manually labeled joints

# Pipeline

**Initialization** → **Model-based Segmentation** → **Erosion Detection**

**Initialization**
- Joint detection

**Model-based Segmentation**
- Model training
- Model fitting

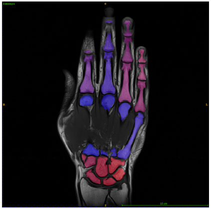
**Erosion Detection**
- Bone classification

# Strategy

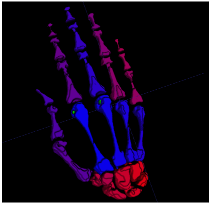
- Create a model of the hand and each bone
- Initialize hand model using the joints
- Optimize bone models

# Creating the Models

1. Manually label MRI sequences
2. Triangulation yielding surface meshes
3. Smoothing of the meshes
4. Establish point correspondence



Manually labeled data



3D representation

# Statistical Shape Model

- Describing an anatomical variation among subjects
- Necessary to have point correspondences
- Solve the Eigenvalue problem of the covariance matrix $S$

$$S\boldsymbol{\Phi}_k = \lambda_k \boldsymbol{\Phi}_k$$

with

$$S = \frac{1}{m}\sum_{i=1}^{m}\left(\boldsymbol{x}_i - \bar{\boldsymbol{x}}\right)\left(\boldsymbol{x}_i - \bar{\boldsymbol{x}}\right)^T$$

# Statistical Shape Model

- Shapes can be expressed by linear combination of

$$\boldsymbol{y} = \bar{\boldsymbol{x}} + \boldsymbol{\Phi}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

- Getting Principal Components $\boldsymbol{\beta}$ by projecting shape on $\boldsymbol{\Phi}$

$$\boldsymbol{\beta}_i = \boldsymbol{\Phi}^T (\boldsymbol{x}_i - \bar{\boldsymbol{x}})$$

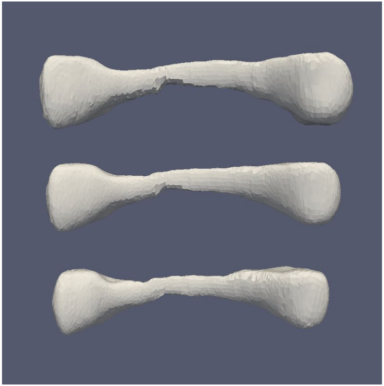
# Statistical Shape Model

## Different types of SSM

One for ...

1. ... estimating the hand position out of the joint locations
2. ... each of the 27 bones
3. ... the whole hand containing all vertices of all bones for regularization

# Model of First Hand Bone



Variation of first principal component

# Pipeline

**Initialization**
- Joint detection

→

**Model-based Segmentation**
- Model training
- Model fitting

→

**Erosion Detection**
- Bone classification

# Initialize Models

1. Estimate centers of the bones between the joints
2. Calculate weights for hand model to describe estimated centers best
3. Project SSM for each bone into the volume

# Segmentation

1. Learn a 2D patch at each vertex of each bone

Iterative for each bone

2. Patch based position detection
   - Find optimal position in a 3D cube around the vertices current position
   - Using sum of squared distances as similarity measure
3. Update position and weights of bone model

$$\beta_i = \mathbf{\Phi}^T \left( R^{-1} \left( \boldsymbol{x}_i - T \right) - \bar{\boldsymbol{x}} \right)$$

4. Reinitialize with the model

$$\widetilde{\boldsymbol{x}}_{i+1} = R_i \left( \bar{\boldsymbol{x}} + \mathbf{\Phi} \beta_i \right) + T_i$$

Afterwards

4. Regularization of the hand bones using whole hand model

# Evaluation

## Evaluation of the segmentation accuracy

- Leave one out cross validation
- Mean squared distance between vertices of the segmentation and the ground truth

# Results

| | MSD |
|---|---|
| Bones in between detected joints | $3.19 \pm 1.96$ mm |
| All other bones | $7.93 \pm 1.67$ mm |
| Large bones | $4.05 \pm 1.58$ mm |
| Small bones | $9.91 \pm 2.98$ mm |
| All bones | $5.77 \pm 1.35$ mm |

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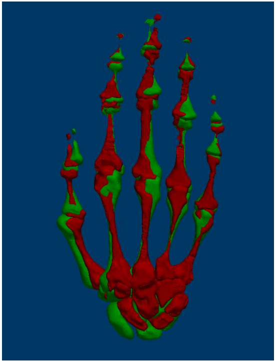
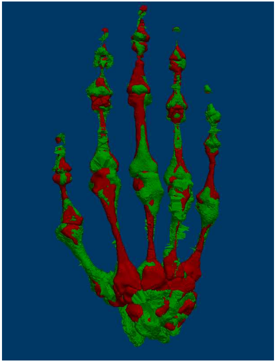
# Results



Initialization



After 4 iterations

ground truth

model

# Discussion

- Bones where the center can be estimated from the joints are much better
- Regularization does not have the expected results yet
- Add wrist joint into initialization to get better guess of the size of the hand

# Pipeline

**Initialization**
- Joint detection

**Model-based Segmentation**
- Model training
- Model fitting

**Erosion Detection**
- Bone classification

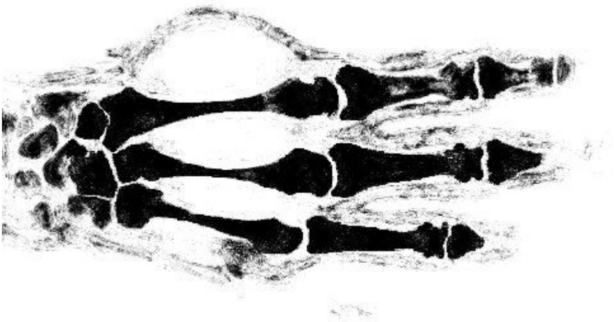
# Erosion Detection

1. Morphological dilation of bone labels as a mask
2. Train a classifier within the mask to detect bone

3. Apply classifier inside bone models
4. Calculate ratio between model bone and bone classified structure
5. Regression of the results with the expert labels after EULAR-OMERACT

# Discussion

- Bone classifier shows promising results
- Did not yet applied to image



# Pipeline

**Initialization**
- Joint detection

→

**Model-based Segmentation**
- Model training
- Model fitting

→

**Erosion Detection**
- Bone classification

# Conclusion & Discussion

# Discussion

- First tests show promising results
- Segmentation of the "easy" bones is already quite good
- Initialization could be improved with adding the wrist joint
- Global optimization of the wrist bones before optimization of the model

# Conclusion

## What did we do?

- Initialization
  - Projected MRI volume into 2D
  - Trained a classifier to detect joints
  - Estimated center points of the joints in 3D
- Model based segmentation
  - Trained different Statistical Shape Models
  - Fitted them into the volume over a patch based optimization
  - Regularization with a Statistical Shape Model
- Bone classification
  - Trained bone classifier

# Outlook

# Outlook

- Apply bone classification inside the segmentation
- Make a regression between calculated ratio and expert labels

- Include T2 weighted MRI sequences to prove detected erosions
- Include synovitis and edema detection and classification
- Speed up and implement as ImageJ plugin

The End