Classification of Voting Patterns to Improve the Generalized Hough Transform for Epiphyses Localization

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San Diego – 28.02.2016

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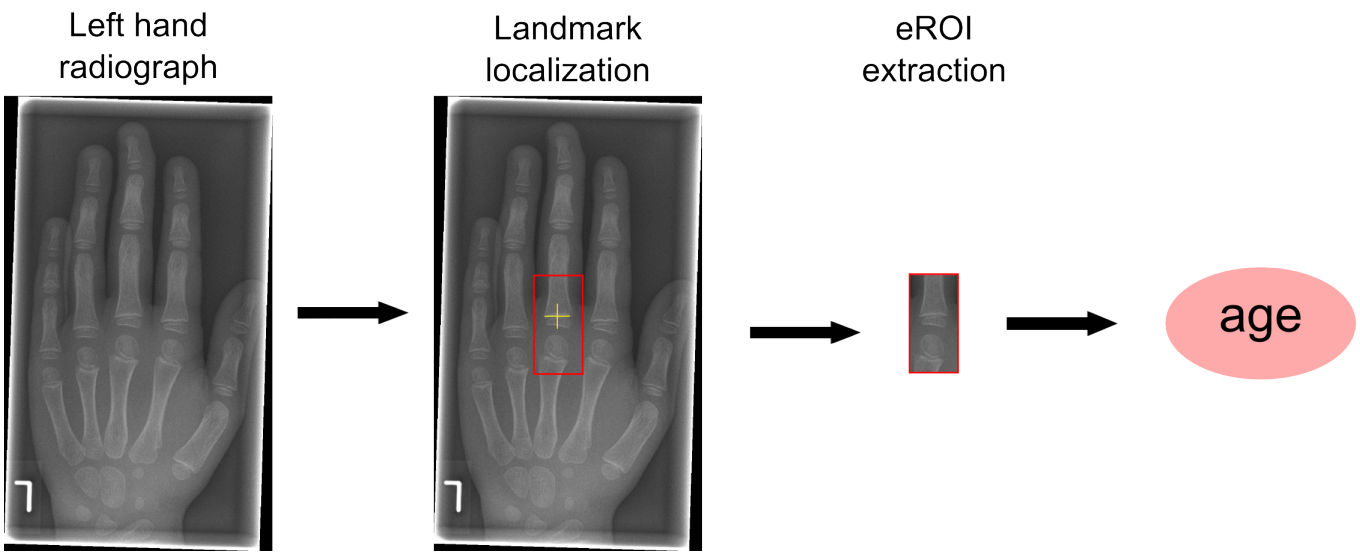
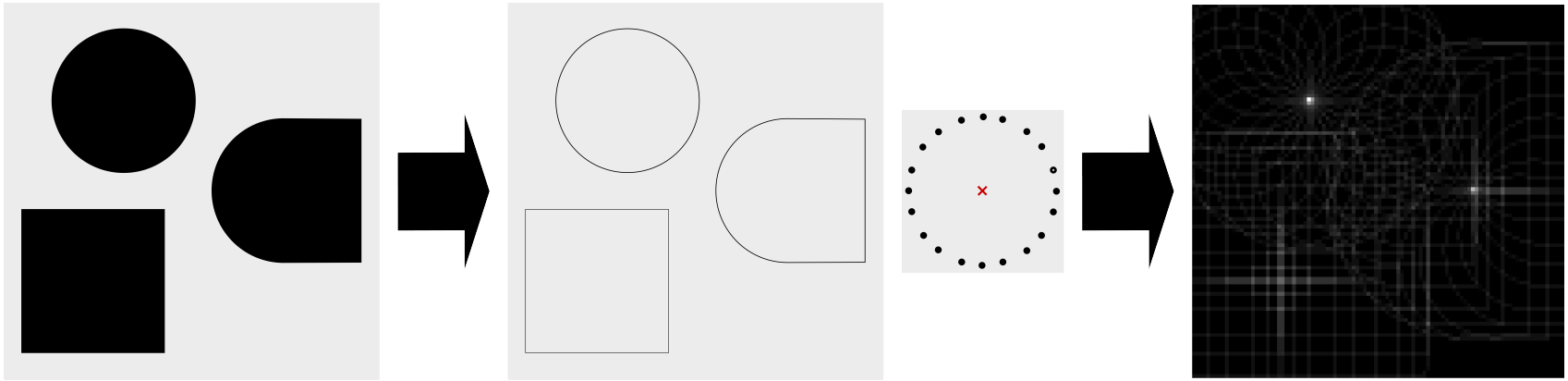
Introduction

- **Motivation:** Epiphyses Localization for automatic Bone Age Assessment
- **General Object Localization Framework**
  - Discriminative Generalized Hough Transform (DGHT)
  - Based on Generalized Hough Transform (GHT)



Generalized Hough Transform (GHT)



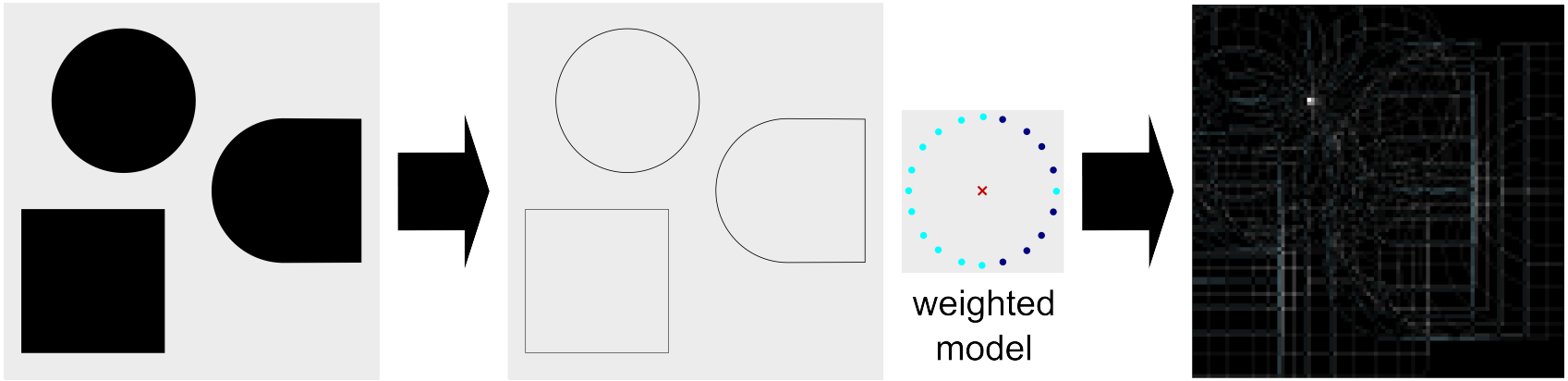
Hough cell $\mathbf{c}_i$ $\widehat{=}$ localization hypothesis

Hough space $H(\mathbf{c}_i)$ $\widehat{=}$ degree of matching

Most likely target point location:

$$\tilde{\mathbf{c}} = \arg\max_{\mathbf{c}_i} H(\mathbf{c}_i)$$

Discriminative Generalized Hough Transform (DGHT)



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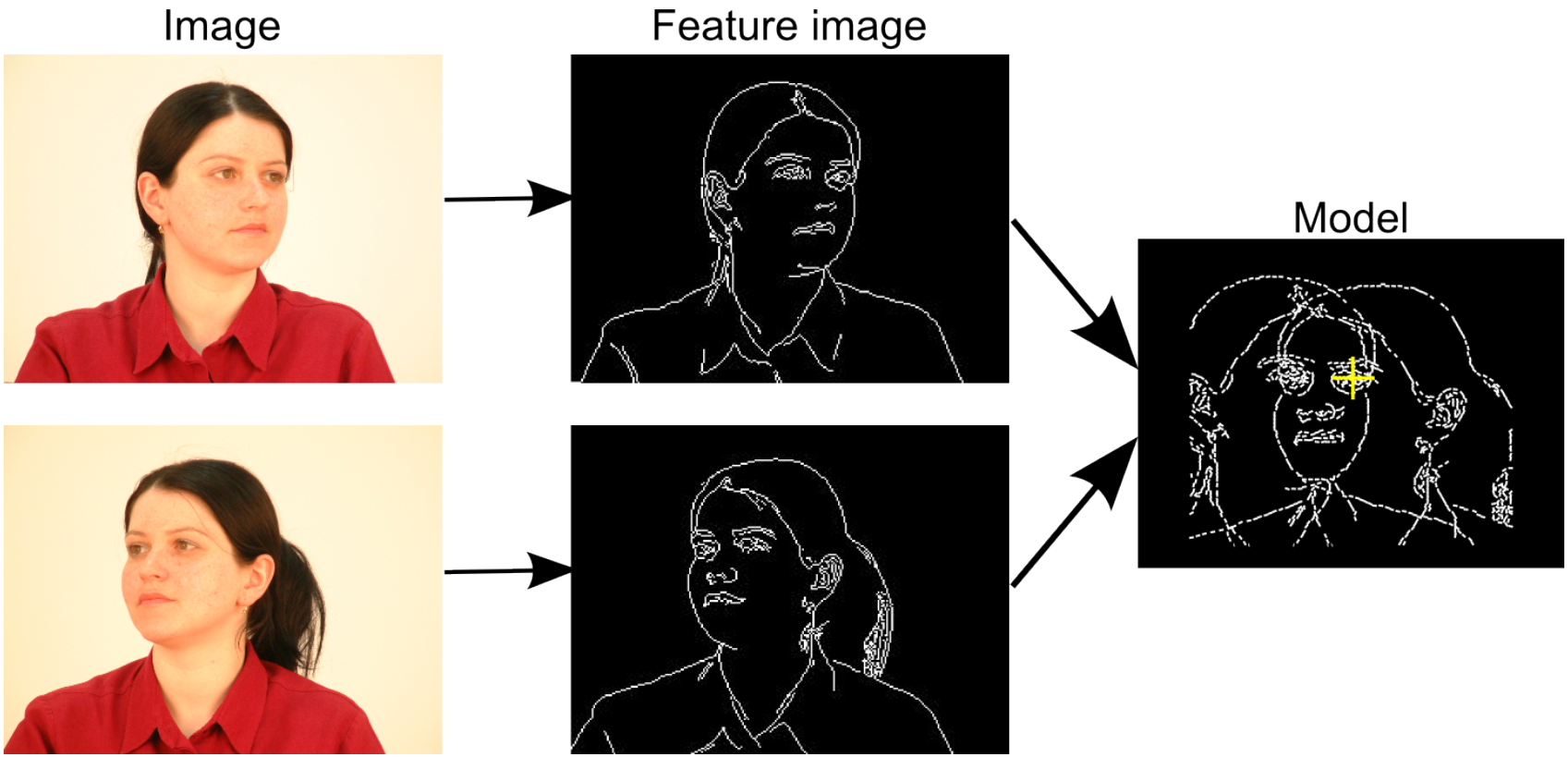
Most likely target point location:

$$\tilde{\mathbf{c}} = \arg\max_{\mathbf{c}_i} H(\mathbf{c}_i)$$

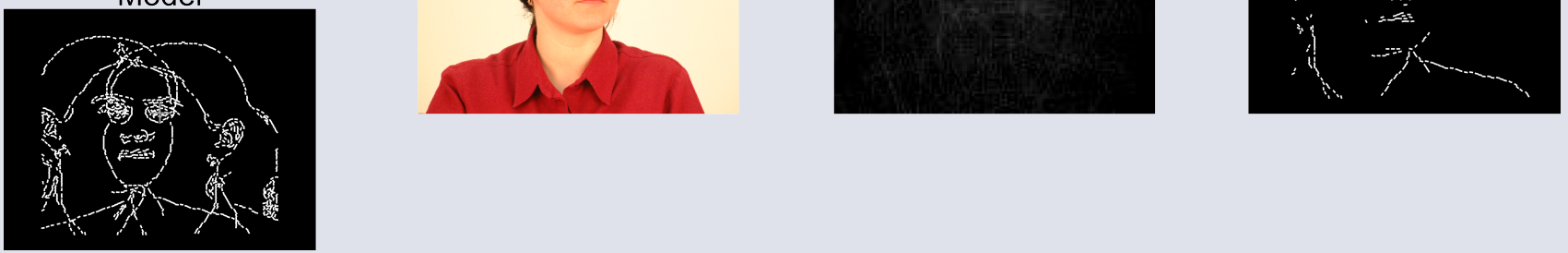
Model generation

Model generation is often initialized
by overlaying training images w.r.t reference point



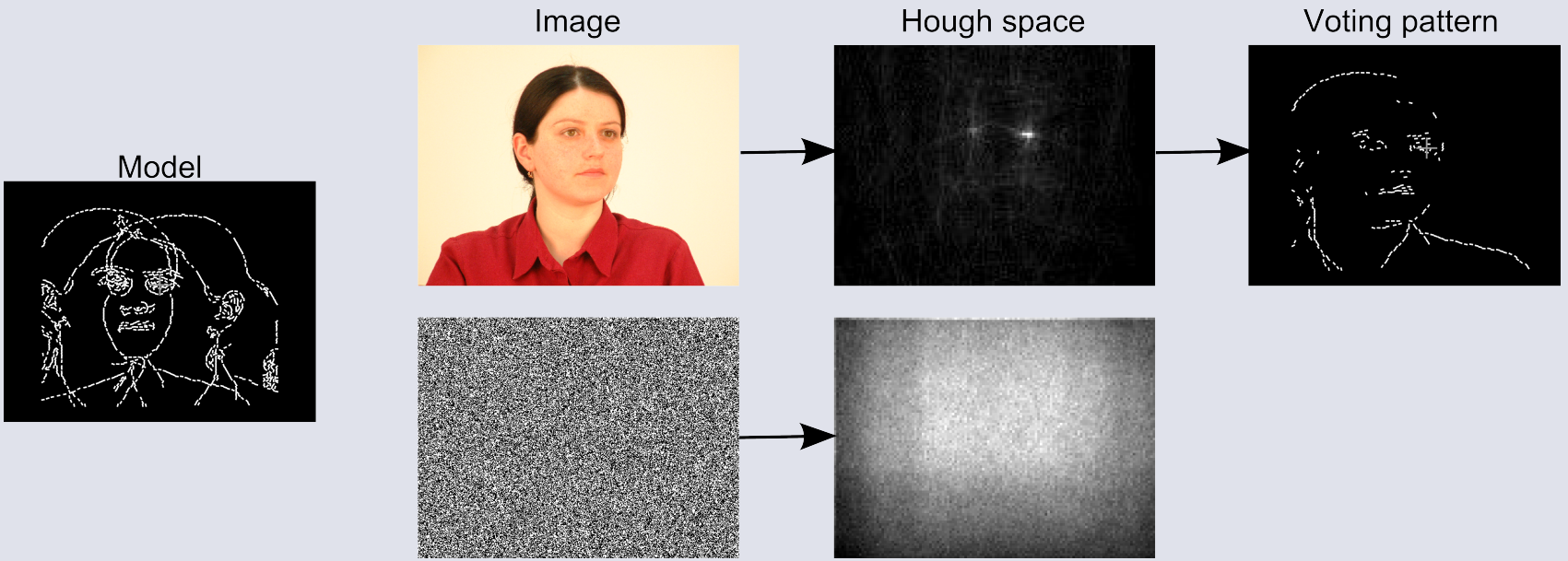
Independent model point voting

Independent model point voting



Lack of inter-dependence of model point voting

Mixed voting from different variations



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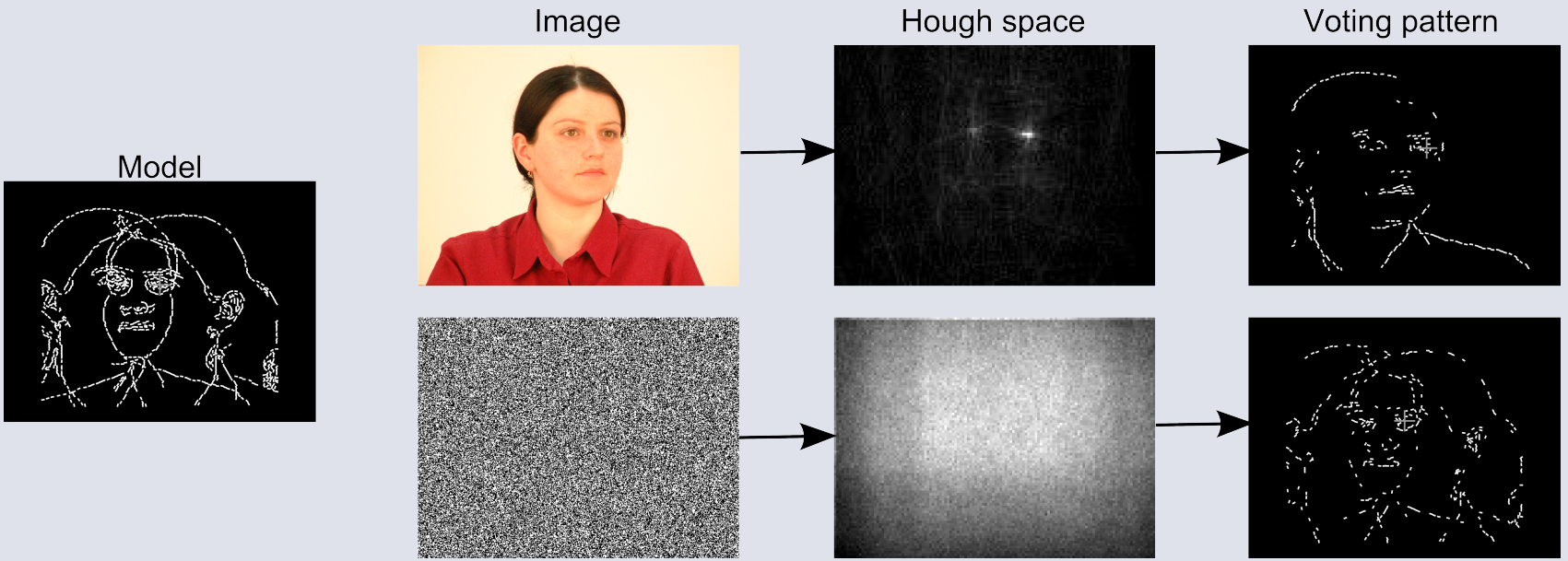
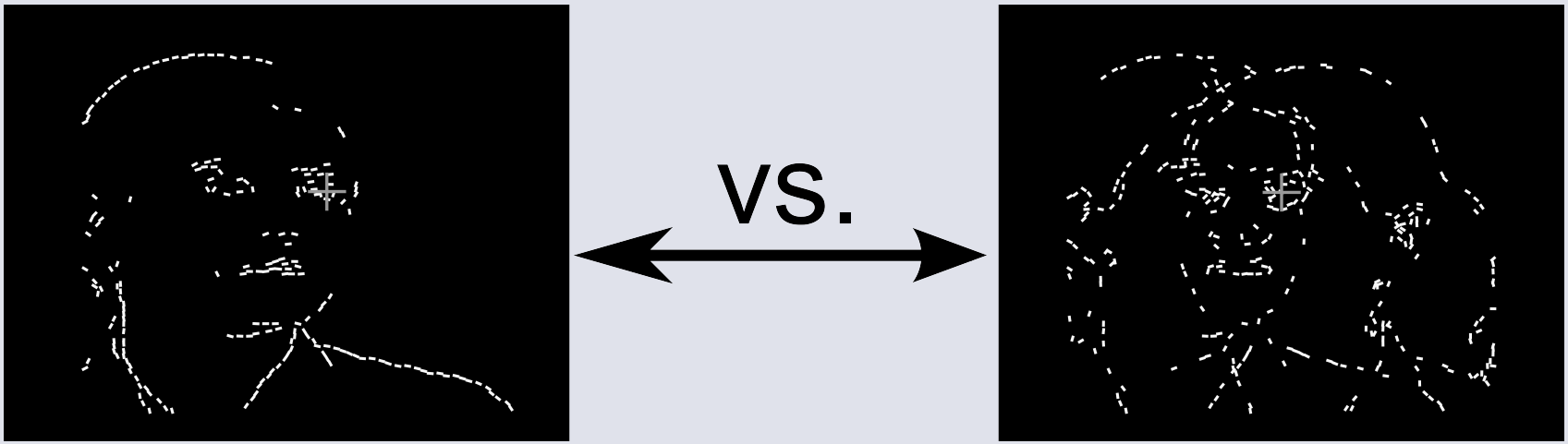


Shape Consistency Measure

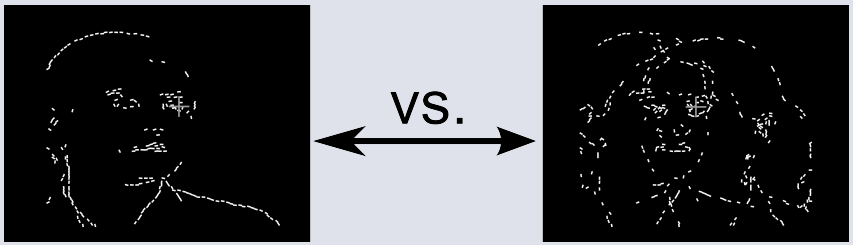
Discrimination:



$p(\text{“Regular Shape”}|\langle\text{Voting pattern}\rangle)$

Shape Consistency Measure

Discrimination:

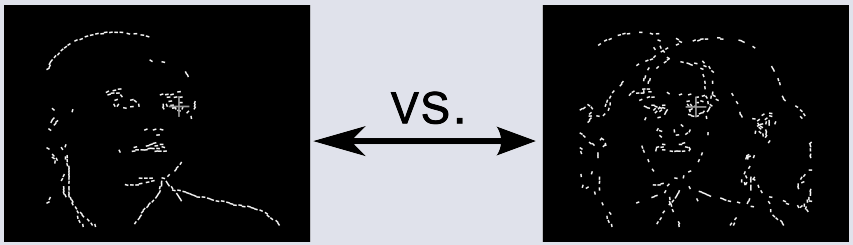


$p(\text{“Regular Shape”}|\langle\text{Voting pattern}\rangle)$

- Definition of “Regular Shape” based on localization error
- Localization hypotheses
  - with small error $\rightarrow$ “Regular Shape”
  - with large error $\rightarrow$ “Irregular Shape”

Shape Consistency Measure

Discrimination:



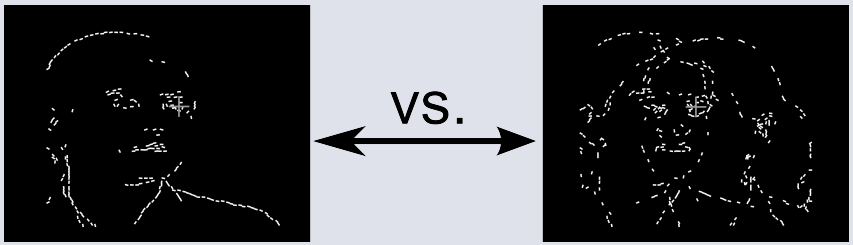
p(“Regular Shape”|<Voting pattern>)

- Classification approach based on Random Forest
- Trained on two classes
  - “Regular Shape”
  - “Irregular Shape”

  on localization hypotheses from training images
- Determination of a-posteriori probability

Shape Consistency Measure

Discrimination:



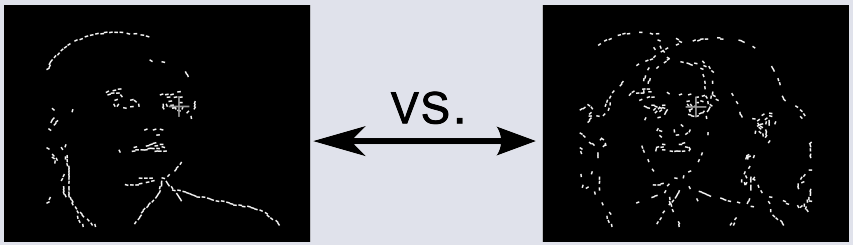
p("Regular Shape"|<Voting pattern>)

Feature vector: $R(\mathbf{c}_i) = \{r_1(\mathbf{c}_i), r_2(\mathbf{c}_i), \cdots, r_J(\mathbf{c}_i)\}$ with

$$r_j(\mathbf{c}_i) = \begin{cases} 1, & \text{if model point } \mathbf{m}_j \text{ voted for Hough cell } \mathbf{c}_i \\ 0, & \text{otherwise} \end{cases}$$

Shape Consistency Measure

Discrimination:

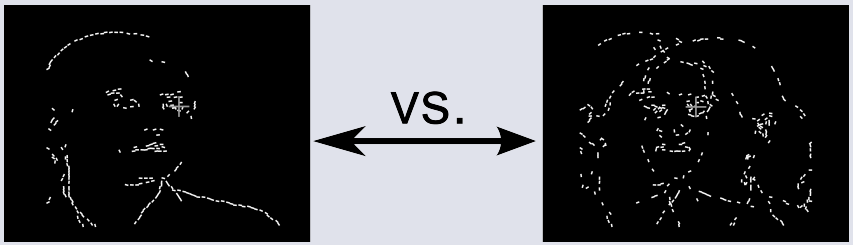


$p(\text{“Regular Shape”} | R(\mathbf{c}_i))$

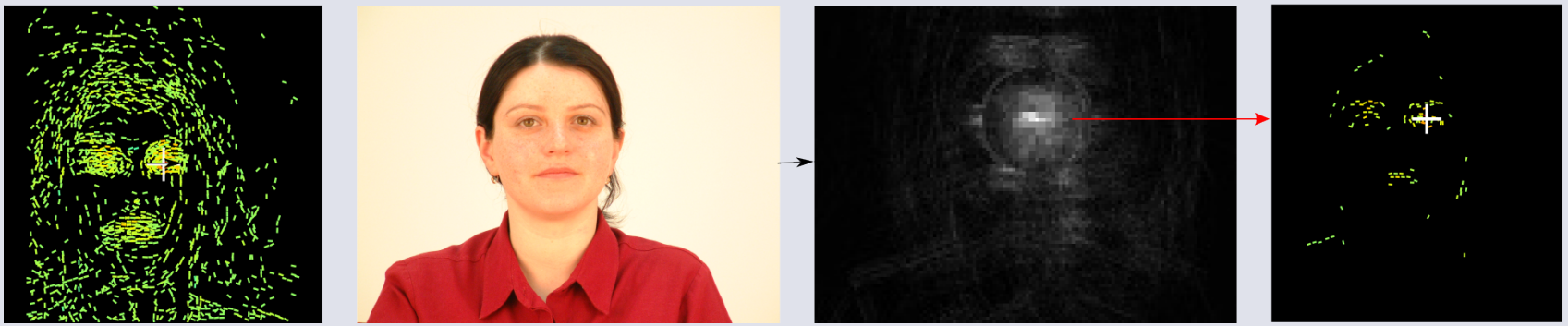


Shape Consistency Measure

Discrimination:

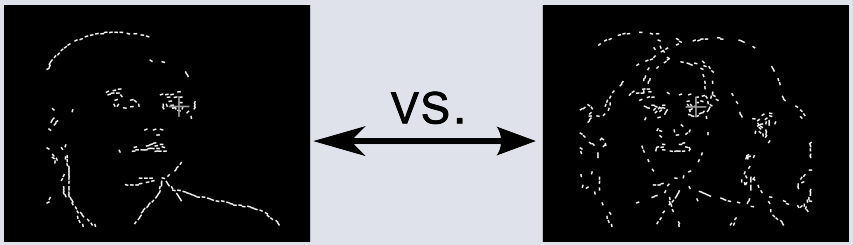


$p(\text{“Regular Shape”} | R(\mathbf{c}_i))$



Shape Consistency Measure

Discrimination:



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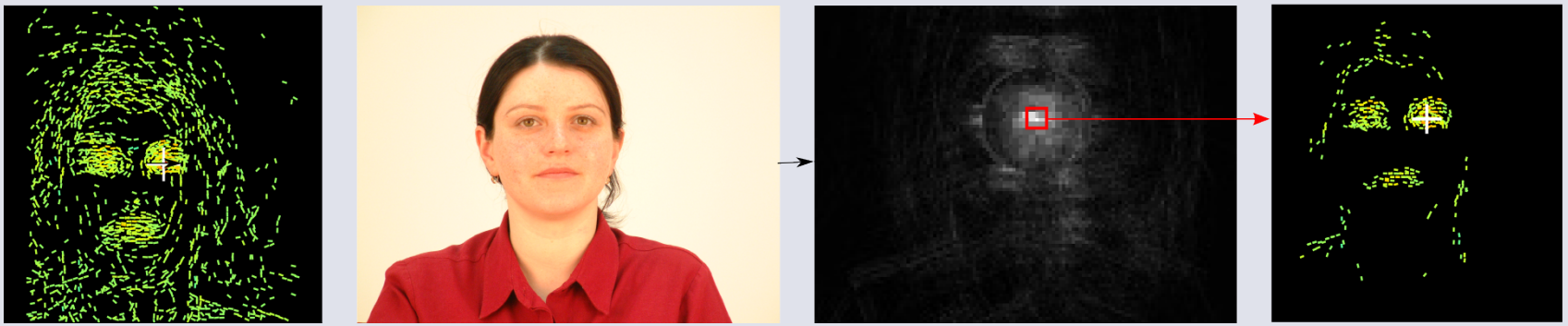

Shape Consistency Measure

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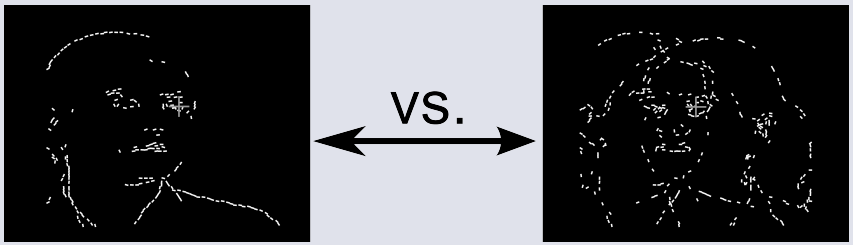
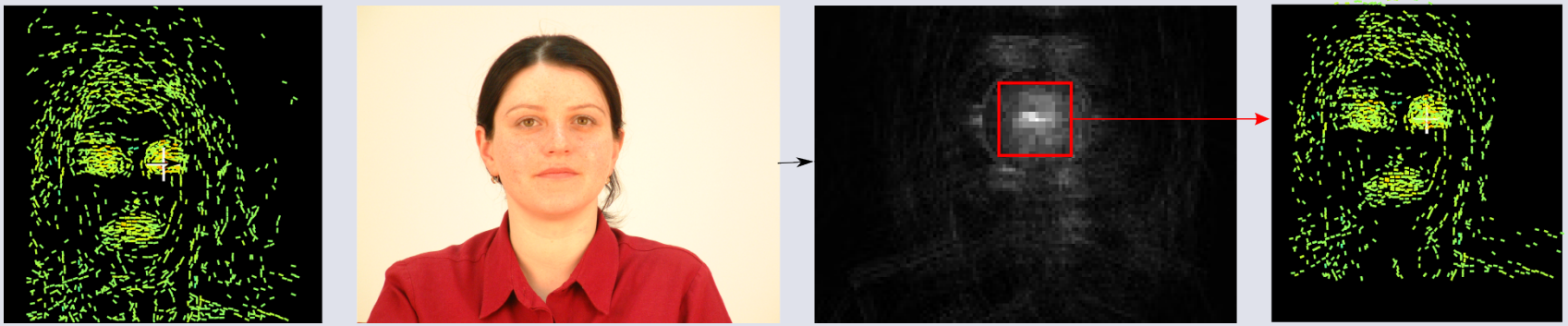
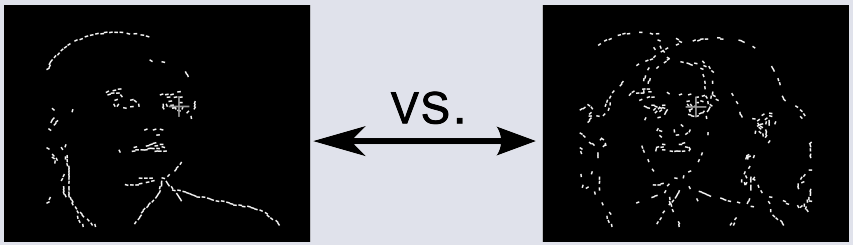


$p(\text{“Regular Shape”}|R(\mathbf{c}_i))$



Shape Consistency Measure

Discrimination:



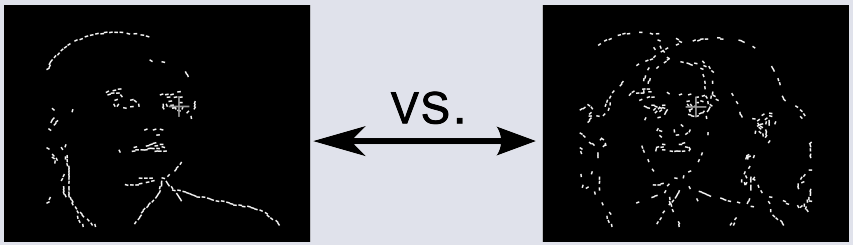
$p(\text{“Regular Shape”}|R(\mathbf{c}_i))$

Feature vector: $R(\mathbf{c}_i) = \{r_1(\mathbf{c}_i), r_2(\mathbf{c}_i), \cdots, r_J(\mathbf{c}_i)\}$ with

$r_j(\mathbf{c}_i) :=$ Minimum neighborhood size around $\mathbf{c}_i$ in which model point $\mathbf{m}_j$ has voted

Shape Consistency Measure

Discrimination:



$$p(\text{“Regular Shape”}|R(\mathbf{c}_i))$$

Usage for localization task

Usage of posterior probability as additional weighting factor:

$$\tilde{\mathbf{c}} = \arg\max_{\mathbf{c}_i}[p(\text{“Regular Shape”}|R(\mathbf{c}_i)) \cdot H(\mathbf{c}_i)]$$

$\tilde{\mathbf{c}}$: Most likely target point location

$H(\mathbf{c}_i)$: Hough space votes

Outline

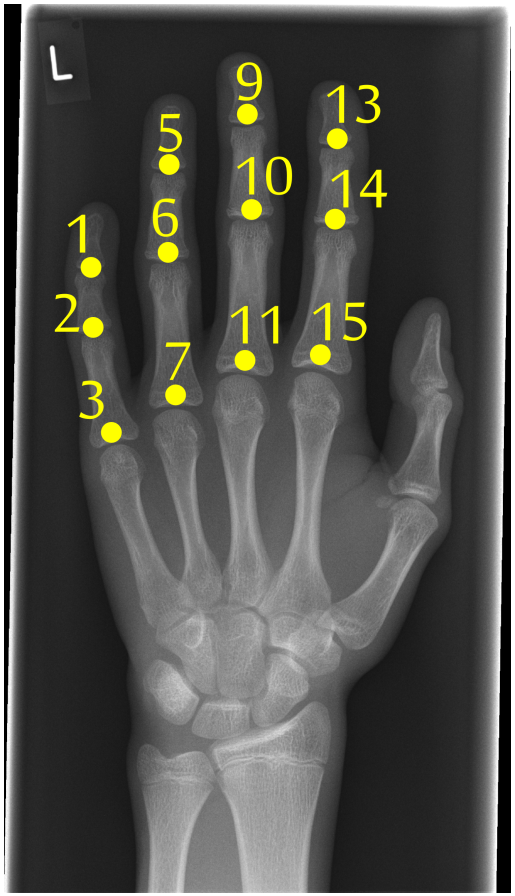
1 Introduction

2 Method

3 Experiments

4 Conclusion

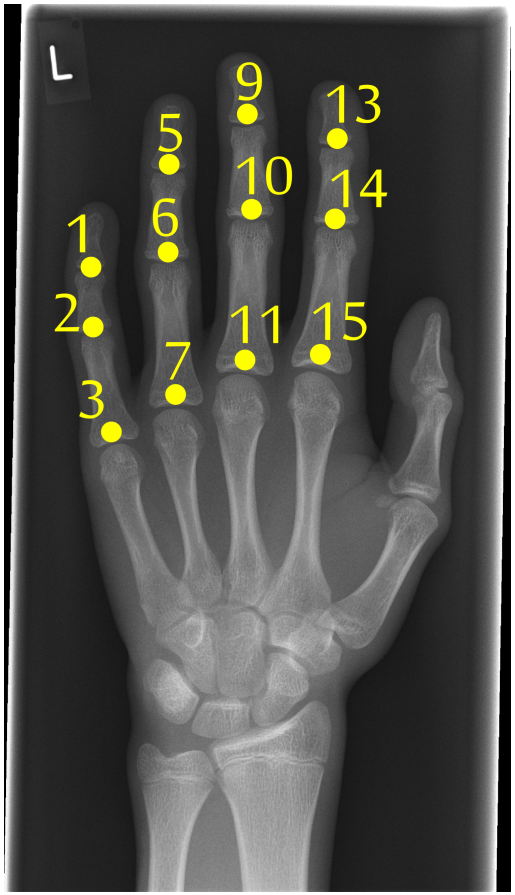
Setup



Data

- Origin: University Hospital Aachen
- 812 unnormalized radiographs
- Age range of subjects:
  3 to 19 years
- Male and female subjects
- Training on
  400 randomly selected images
- Evaluation on
  remaining 412 images

Setup

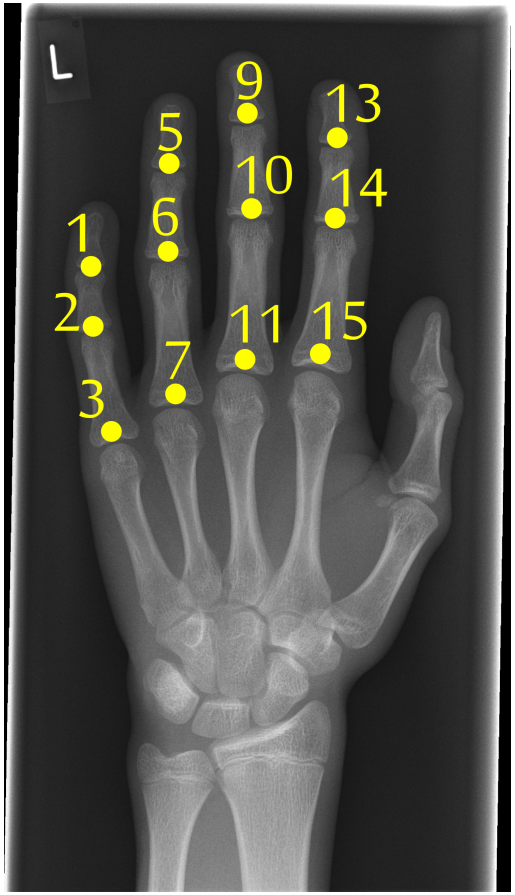


Setup

- Aim: Localization of 12 epiphyses
- Discriminative Generalized Hough Transform (DGHT)
- Shape Consistency Measure (SCM):
  - Random Forest Classifer
  - Number of trees: 500
- Allowed error distance:

$$\frac{6}{256} \cdot \text{<image height>}$$

Results

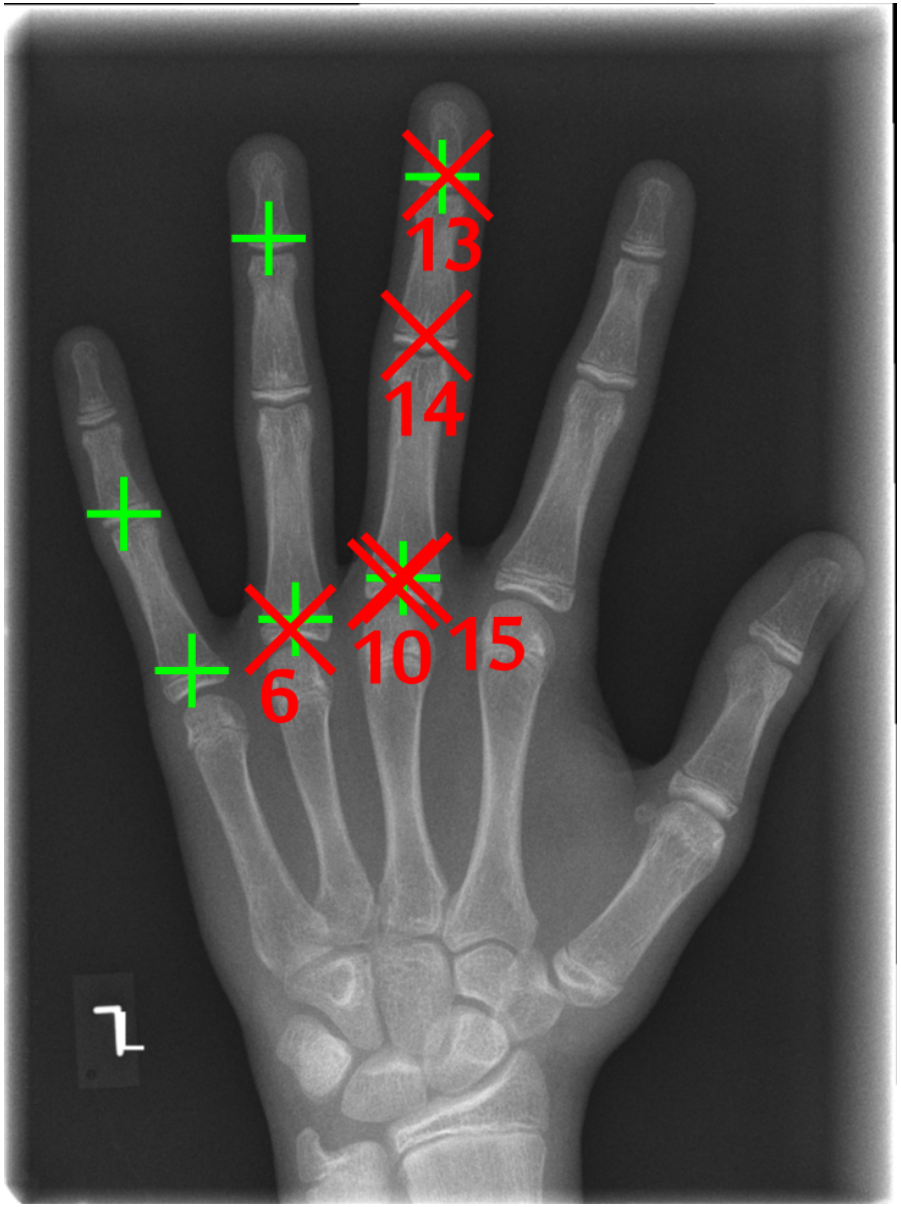


Results

	mean success rate	mean error (pixel)
DGHT	96.5%	14.6
DGHT+SCM	**99.4%**	**6.6**

- 83% of errors were corrected by SCM
- All epiphyses correctly localized: 96.2% of 412 test images
- Worst image: 7 of 12 epiphyses correct

Examples



Conclusion

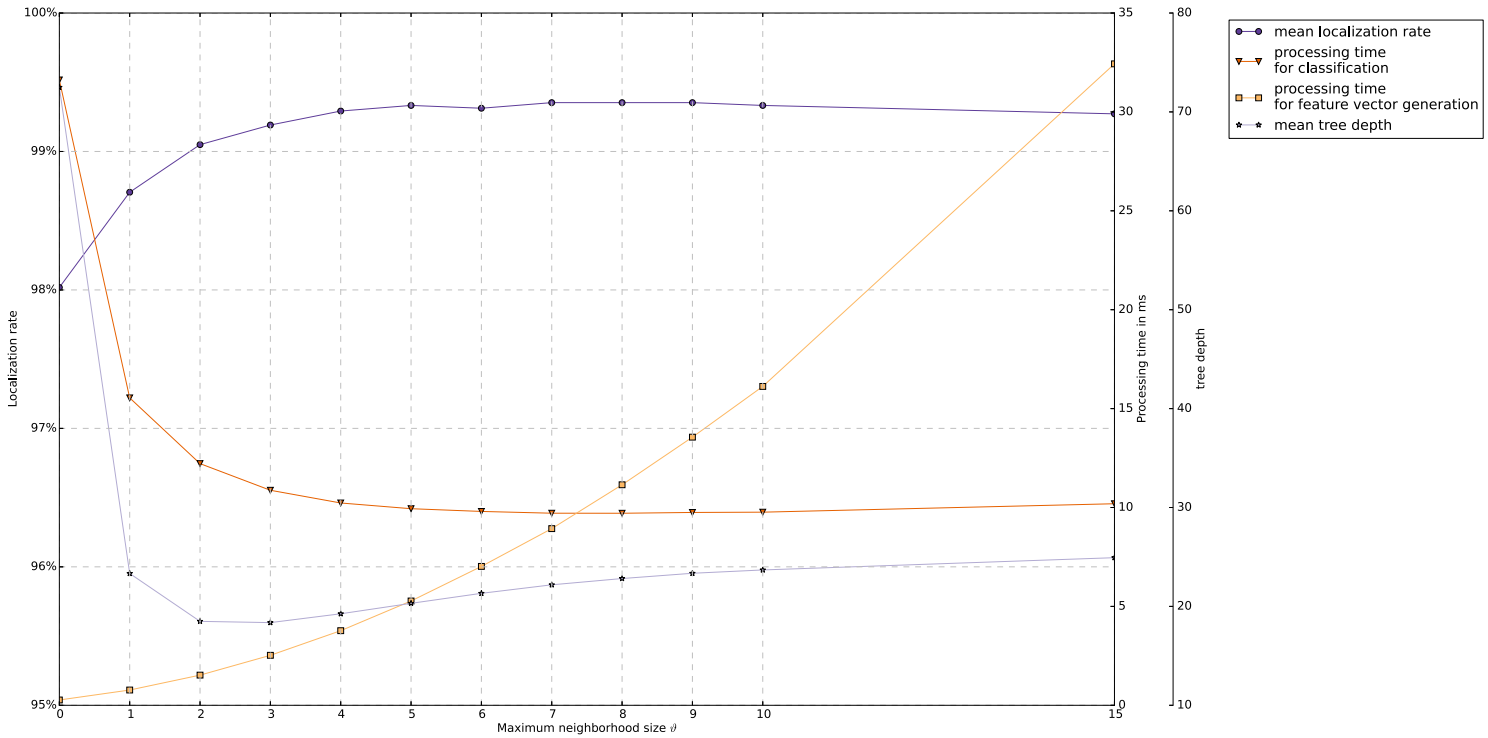
- General Object Localization Framework: Discriminative Generalized Hough Transform
- Shape Consistency Measure improved performance by assessing complete voting pattern
- High epiphyses localization rate
- Automatic framework easily adaptable to other medical and non-medical tasks

Thank you!

Feature vector: $R(\mathbf{c}_i) = \{r_1(\mathbf{c}_i), r_2(\mathbf{c}_i), \cdots, r_J(\mathbf{c}_i)\}$

$$r_j(\mathbf{c}_i) = \min_{\mathbf{c}_k} \begin{cases} d(\mathbf{c}_i, \mathbf{c}_k), & \text{if model point } \mathbf{m}_j \text{ has voted for} \\ & \text{Hough cell } \mathbf{c}_k \text{ and } d(\mathbf{c}_i, \mathbf{c}_k) < \vartheta \\ \vartheta, & \text{otherwise} \end{cases}$$

$$d(\mathbf{c}_i, \mathbf{c}_k) = max_t |\mathbf{c}_i^t - \mathbf{c}_k^t|$$



Model point weight estimation

- Generation of Hough spaces for training images, using initial GHT model
- Separation of Hough space votes coming from every single model point
- Weighted recombination of model point contributions into Maximum Entropy Distribution
- Optimization of introduced weights λ_j by using a Minimum Classification Error (MCE)

Model point weight estimation

- Generation of Hough spaces for training images, using initial GHT model
- Separation of Hough space votes coming from every single model point

$$f_j(c_i, X_n) = v_{i,j}$$

$v_{i,j}$: Votes of model point m_j in Hough cell c_i
X_n : Features of image n

- Weighted recombination of model point contributions into Maximum Entropy Distribution
- Optimization of introduced weights λ_j by using a Minimum Classification Error (MCE)

Model point weight estimation

- Generation of Hough spaces for training images, using initial GHT model
- Separation of Hough space votes coming from every single model point: $f_j(c_i, X_n)$
- Weighted recombination of model point contributions into Maximum Entropy Distribution

$$p_\Lambda(c_i|X_n) = \frac{\exp\left(\sum_j \lambda_j \cdot f_j(c_i, X_n)\right)}{\sum_k \exp\left(\sum_j \lambda_j \cdot f_j(c_k, X_n)\right)}$$

$\Lambda = [\lambda_1, \lambda_2, ..., \lambda_J]$: Individual model point weights

- Optimization of introduced weights λ_j by using a Minimum Classification Error (MCE)

Model point weight estimation

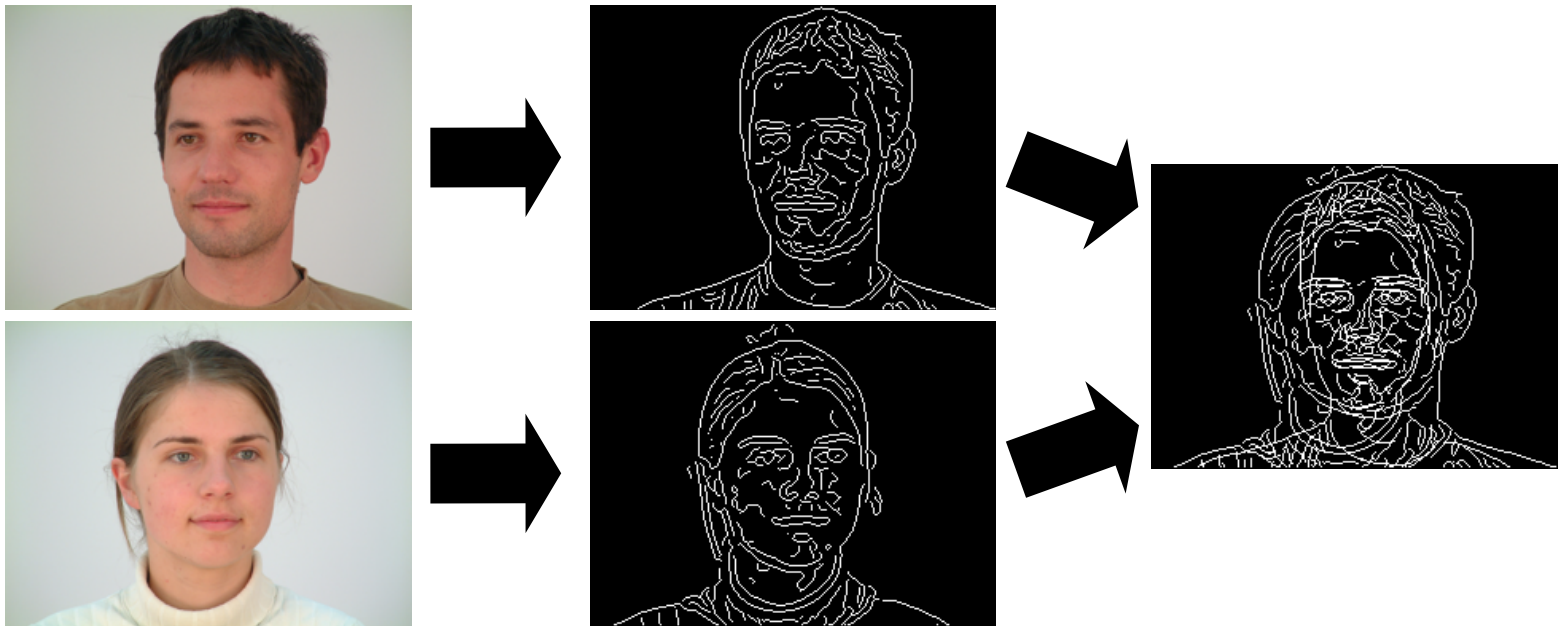
- Generation of Hough spaces for training images, using initial GHT model
- Separation of Hough space votes coming from every single model point: $f_j(c_i, X_n)$
- Weighted recombination of model point contributions into Maximum Entropy Distribution : $p_\Lambda(c_i|X_n)$
- Optimization of introduced weights λ_j by using a Minimum Classification Error (MCE)

$$E(\Lambda) = \sum_{n=1}^{N} \sum_{i=1}^{I} \varepsilon(c_i, \tilde{c}_n) \cdot \frac{p_\Lambda(c_i|X_n)^\eta}{\sum_k p_\Lambda(c_k|X_n)^\eta}.$$

$\varepsilon(c_i, \tilde{c}_n)$:	Error measure (e.g. Euclidean Distance)
$\tilde{c}_n$:	Target cell in Hough space for image X_n
I:	Number of Hough cells
N:	Number of training images

Iterative training

- Initial Model generation
- Discriminative weighting of individual model points
- Model point selection based on absolute weights
- Eye detection on training images using weighted model
- Select images with high localization error & incorporate image structures into model



Iterative training

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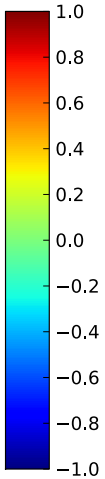
Initial GHT model



Weighted GHT model

$$p_{\lambda}(c_i|X_n) = \frac{\exp\left(\sum_j \lambda_j \cdot f_j(c_i, X_n)\right)}{\sum_k \exp\left(\sum_j \lambda_j \cdot f_j(c_k, X_n)\right)}$$



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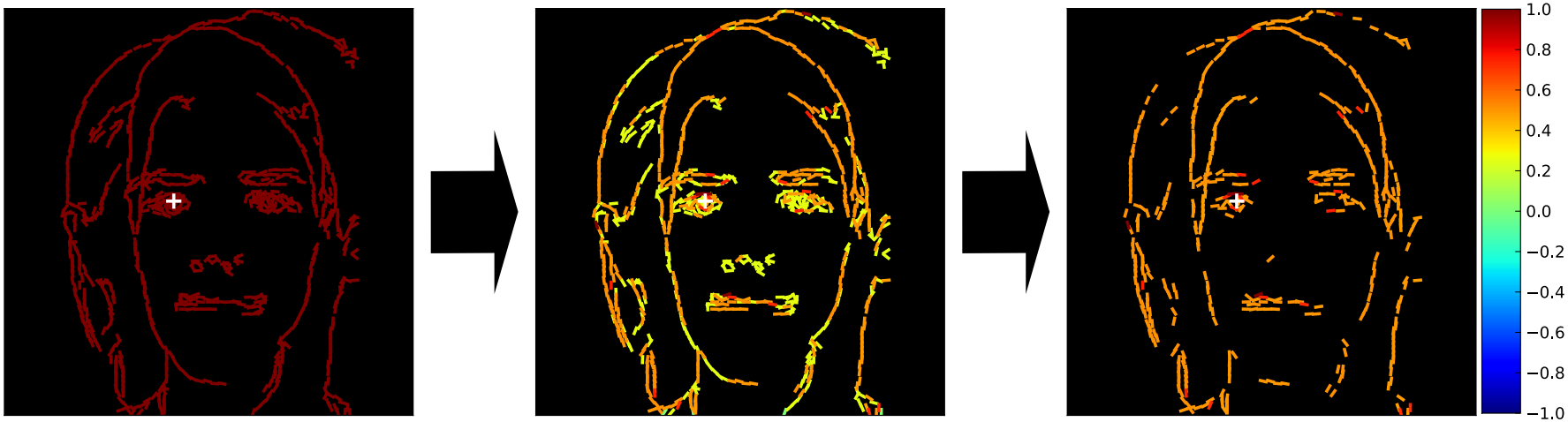

Initial GHT model | Weighted GHT model | Reduced GHT model

Iterative training

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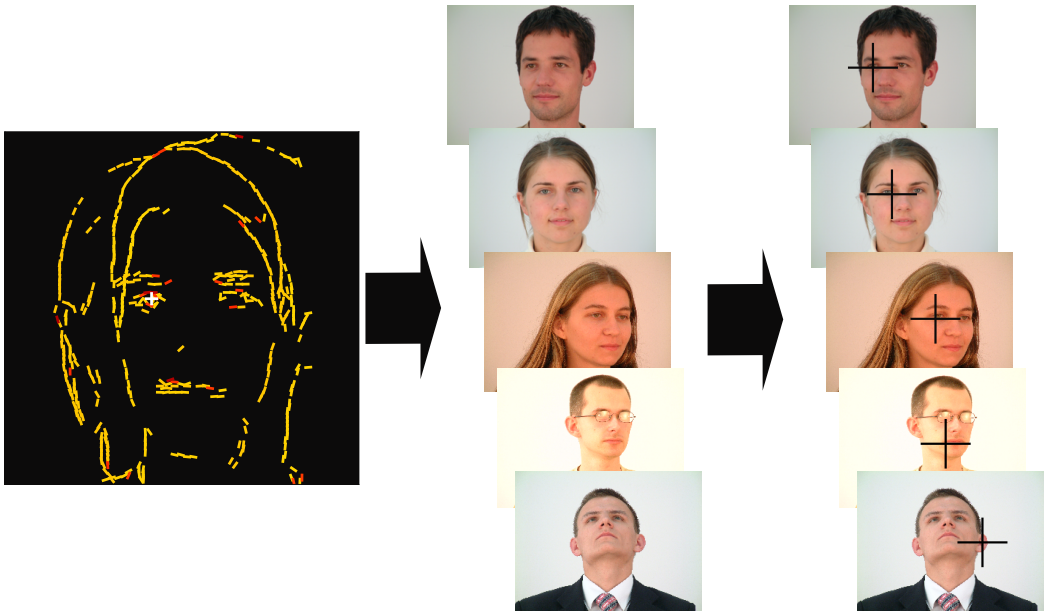

Iterative training

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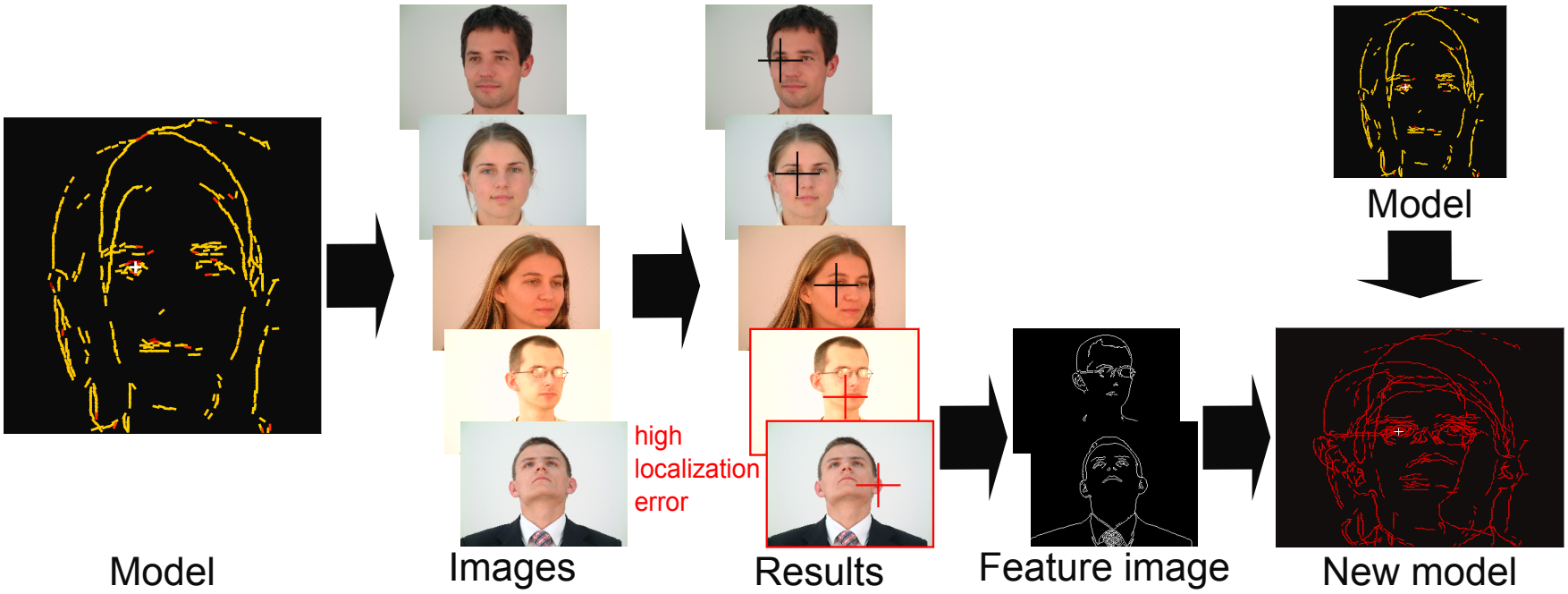
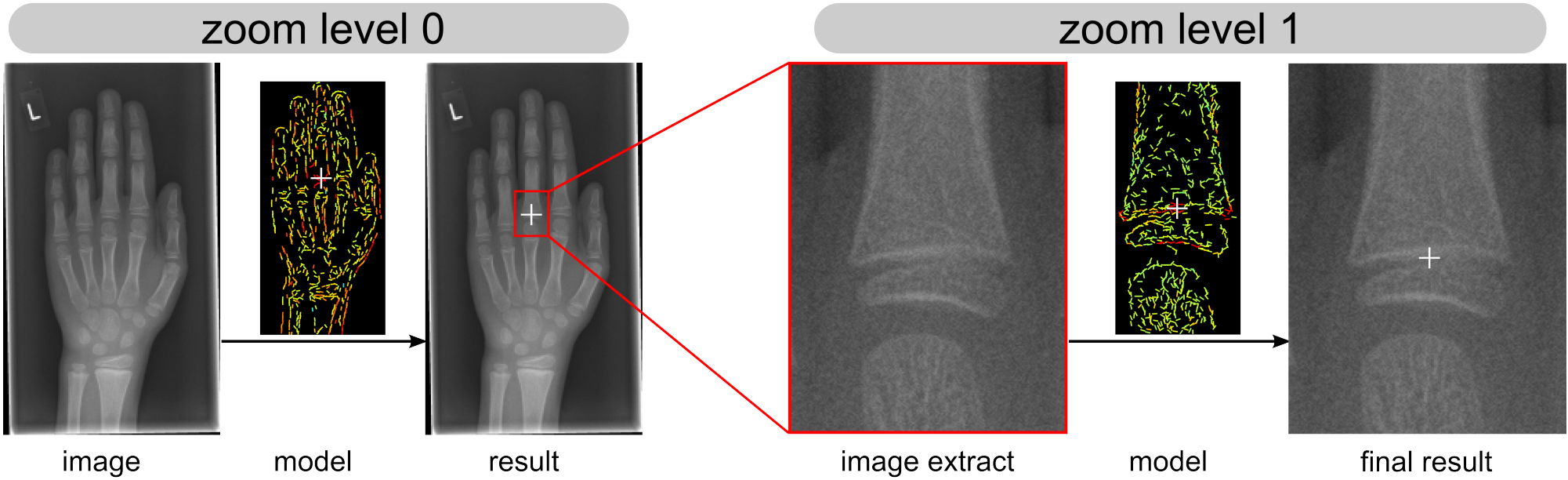


Multi-Level-Approach

- Zooming-in strategy based on Gaussian pyramid
- Stepwise increase image resolution around detected point



- Specifically trained DGHT model on each level
  $\rightarrow$ Capturing of different level-specific details
- Good trade-off between model accuracy and reduced confusion with concurrent objects