A Shape Consistency Measure for Improving the Generalized Hough Transform

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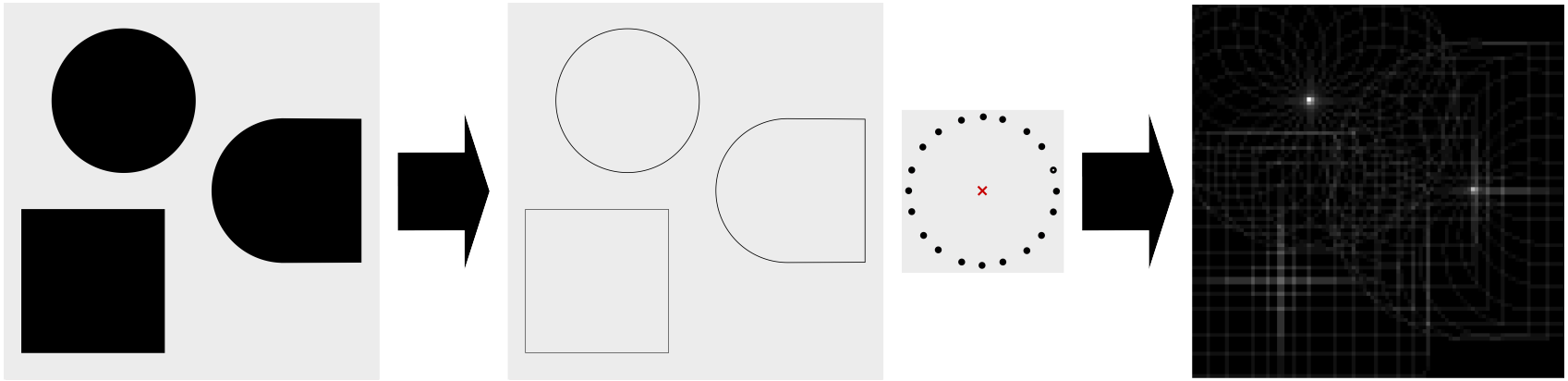
Introduction

- **Task:** General object localization
- **Method:** Discriminative Generalized Hough Transform
  - Based on the Generalized Hough Transform (GHT)
  - Discriminative training of GHT shape model
  - Capable of modeling medium object variability
- **Problem:** Joint support of localization hypotheses by mutually exclusive variations
  - General problem of voting-based methods, like GHT
  - Results in high false-positive rates
- **Solution:** Assessment of complete voting pattern
  $\rightarrow$ Shape Consistency Measure (SCM)

Generalized Hough Transform (GHT)



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

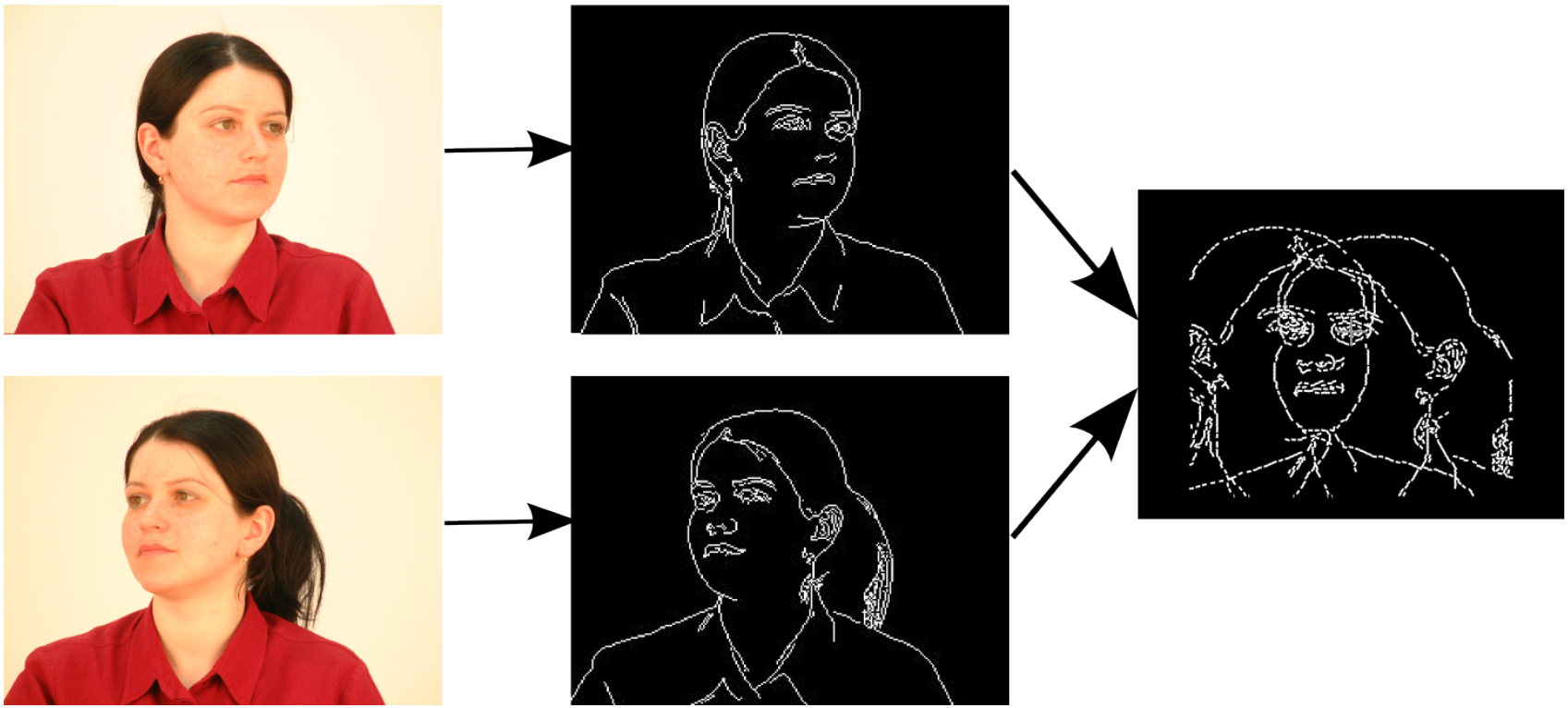
Hough space votes $H(\mathbf{c}_i)$ $\widehat{=}$ Number of corresponding model-feature-point combinations

Localization task (Bayes classifer):

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

Model generation

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



Independent model point voting

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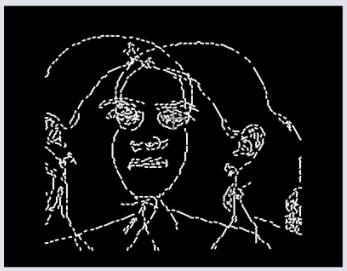


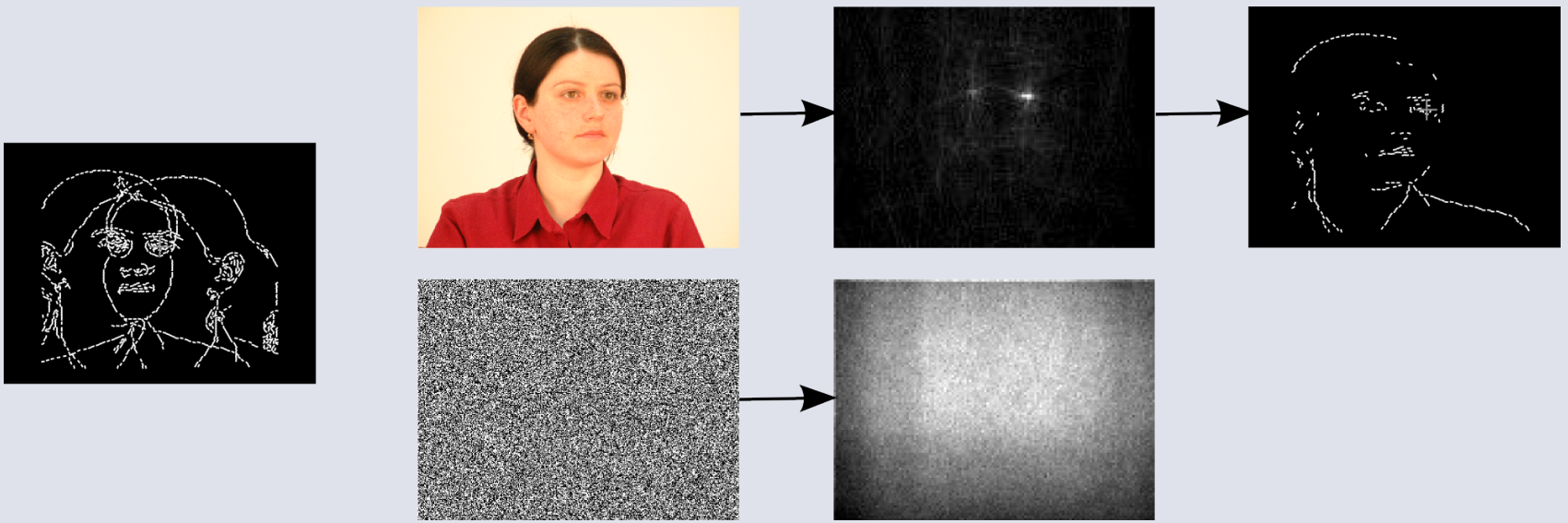






Lack of inter-dependence of model point voting

Mixed voting from different variations



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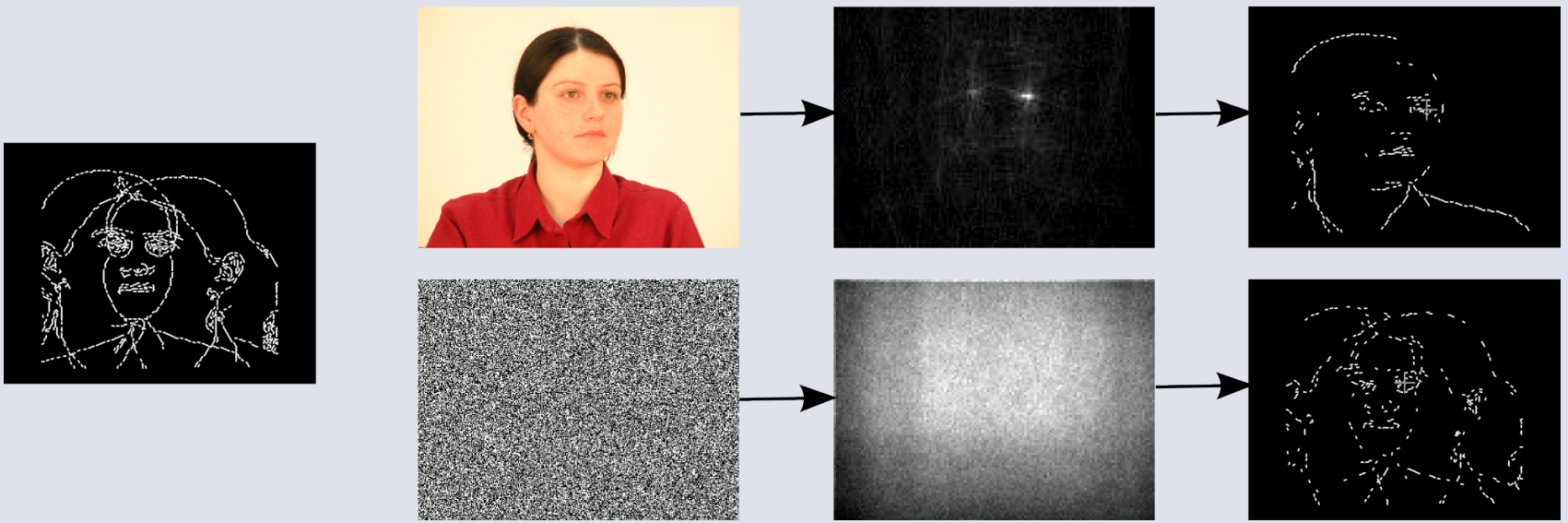
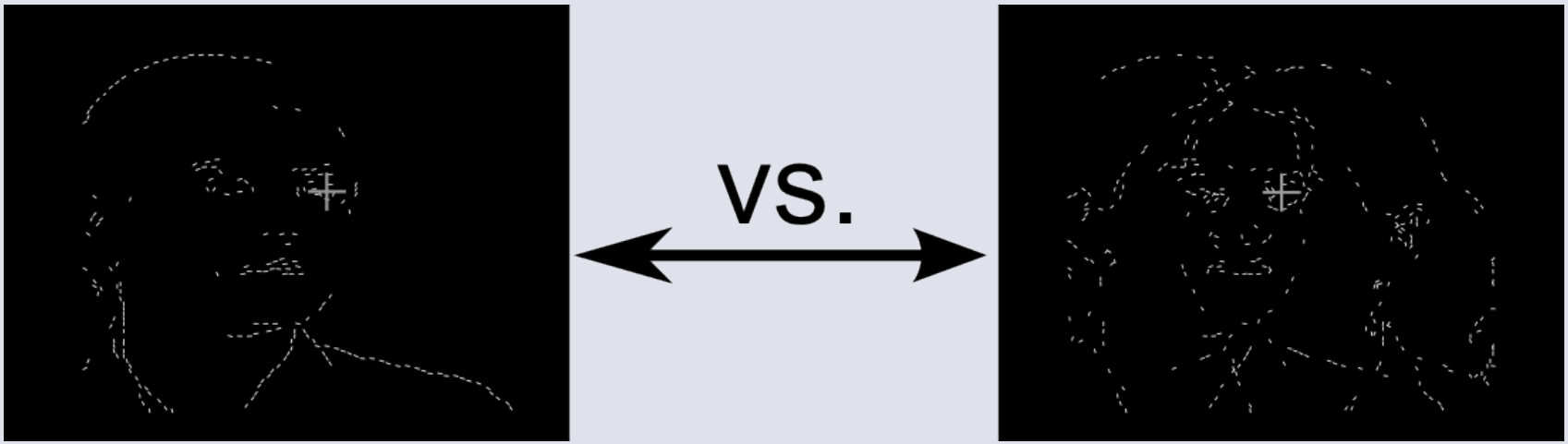


Shape Consistency Measure

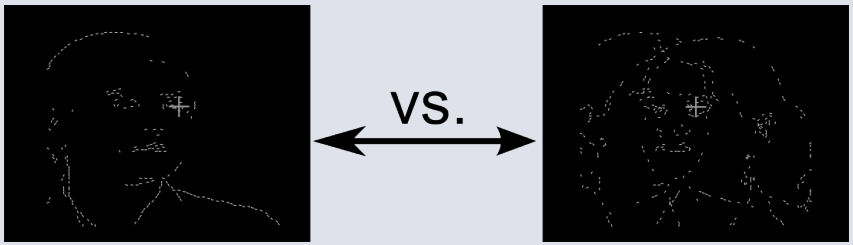
Discrimination:



p(“Regular Shape”|<Voting pattern>)

Shape Consistency Measure

Discrimination:

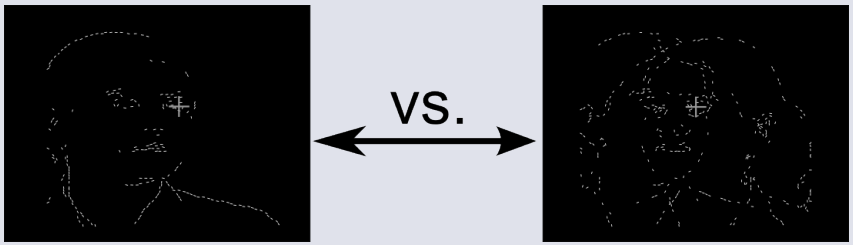


$p(\text{“Regular Shape”}|\langle\text{Voting pattern}\rangle)$

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

Shape Consistency Measure

Discrimination:



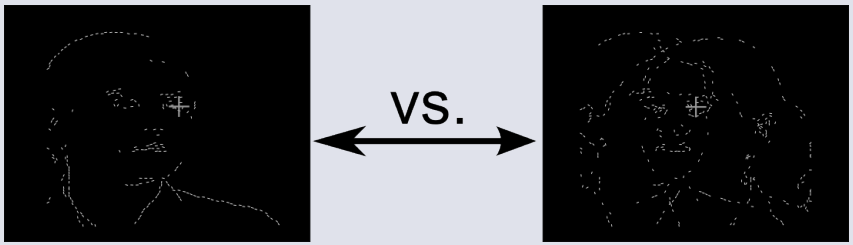
p(“Regular Shape”|<Voting pattern>)

- 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:



$p(\text{“Regular Shape”}|\text{<Voting pattern>})$

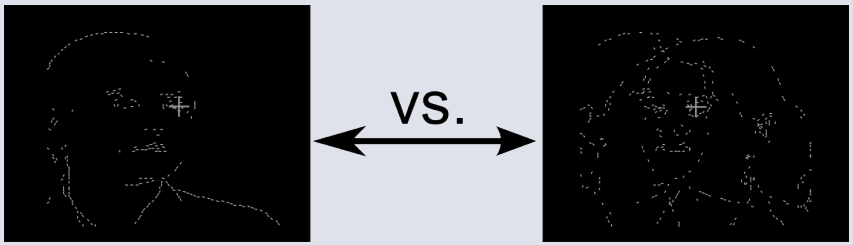
Feature vector: $R(\mathbf{c}_i) = \{r_1(\mathbf{c}_i), r_2(\mathbf{c}_i), \cdots, r_J(\mathbf{c}_i)\}$

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:

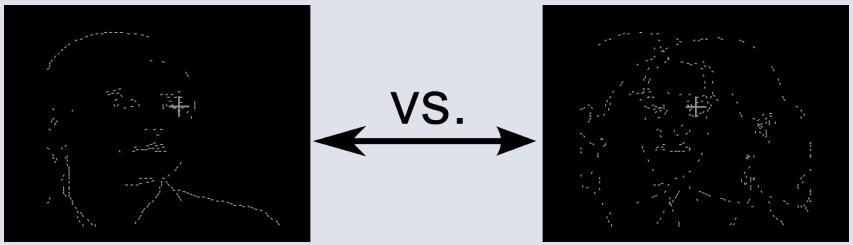


$p(\text{“Regular Shape”} | R(\mathbf{c}_i))$



Shape Consistency Measure

Discrimination:



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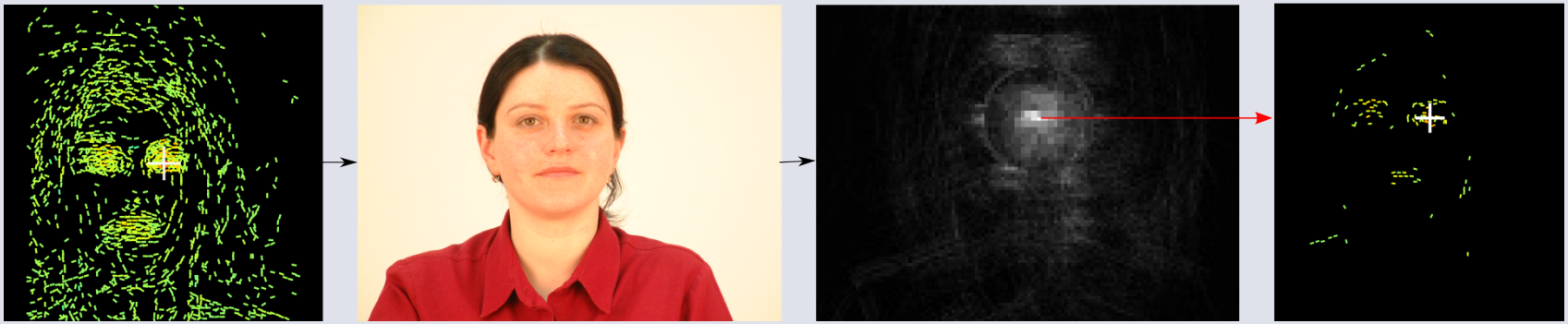
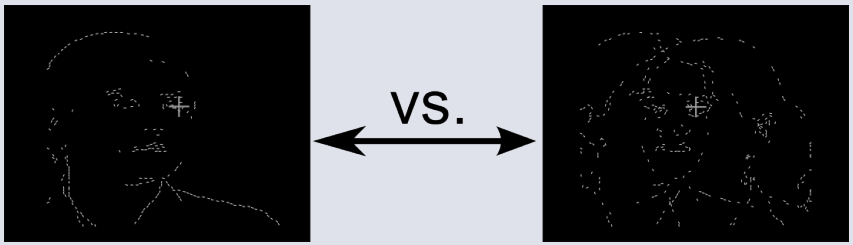


Shape Consistency Measure

Discrimination:



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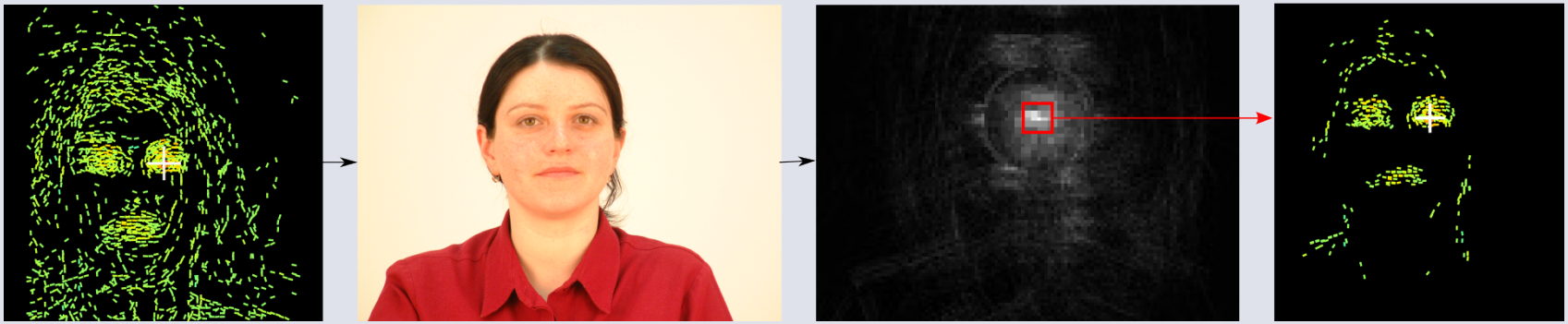
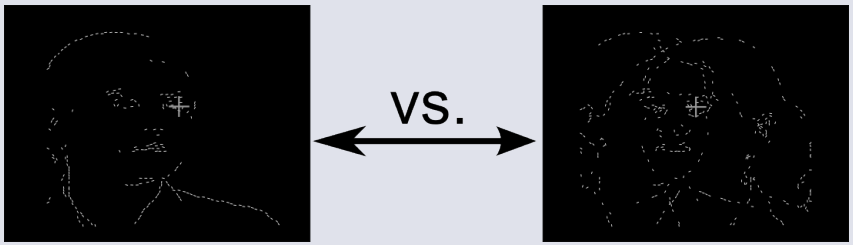


Shape Consistency Measure

Discrimination:



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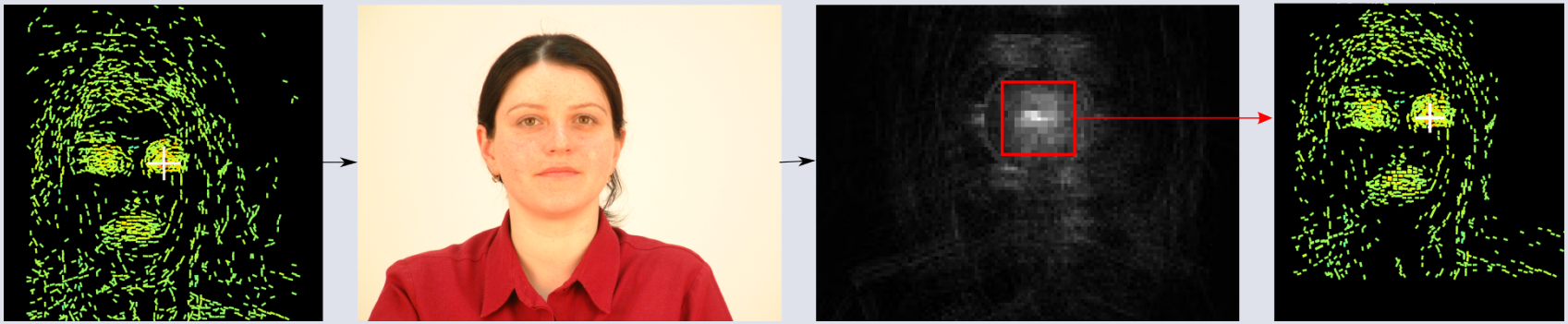

Shape Consistency Measure

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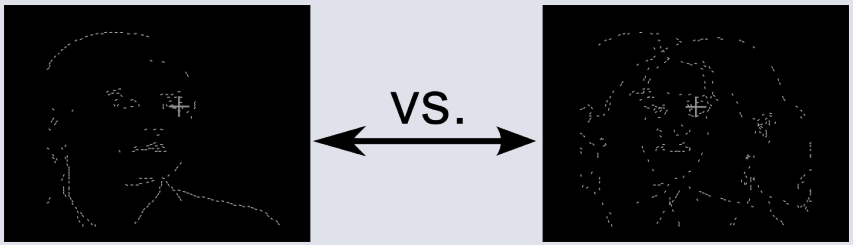


$p(\text{“Regular Shape”}|R(\mathbf{c}_i))$

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

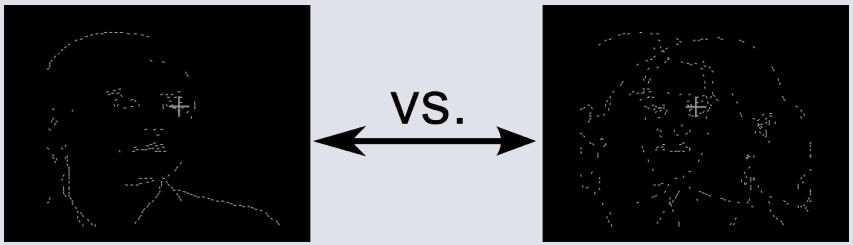
with

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

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

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 Voting-based localization approaches

3 Shape Consistency Measure

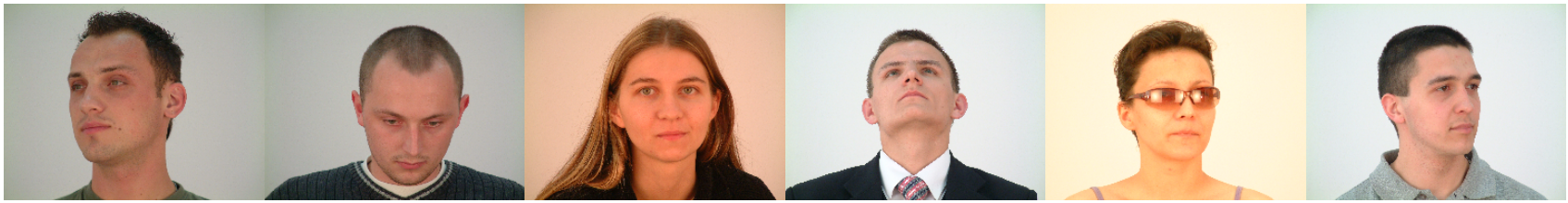
4 Experiments

5 Conclusion

Experimental Setup

Data: PUT Face Database [Kas08]

- 9971 face images of 100 subjects
- Large variations in head pose
- Random separation into training and evaluation subjects
- 600 training images for GHT model generation
- 1200 training images for Random Forest training
- Evaluation on 3830 images from 40 evaluation subjects



[Kas08]: A. Kasinski et al., The PUT face database, Image Processing and Communications 13(3-4), 2008

Experimental Setup

Baseline system

- Discriminative Generalized Hough Transform (DGHT)
- Feature generation: Canny edge detector [Can86]

Shape Consistency Measure

- Random Forest Classifer
- Number of trees: 500
- Training on ~14 000 localization hypotheses
- Weighting of Hough votes of 10 best DGHT localization hypotheses using Shape Consistency Measure

[Can86]: J. Canny, A computational approach to edge detection, Pattern Analysis and Machine Intelligence 8(6), 1986

Results

Successful localization of iris of both eyes:

- Localization success rate: 99.2%
- Shape Consistency Measure:
  - Improvement of 2%
  - Classification rate of Random Forest classifier: 97%

DGHT baseline [HBS13]	97.2%
DGHT with Shape Consistency Measure	**99.2%**
Kasinski et al. [KS10]	94%
DGHT with facial Landmark combination [HBS13]	97.9%

[KS10]: A. Kasinski et al., The architecture and performance of the face and eyes detection system based on the haar cascade classifiers, Pattern Analysis & Applications 13(2), 2010
[HBS13]: F. Hahmann, G. Böer, and H. Schramm. Combination of Facial Landmarks for Robust Eye Localization Using the Discriminative Generalized Hough Transform. In International Conference of the Biometrics Special Interest Group (BIOSIG), 2013.

Conclusion

- Joint voting from mutually exclusive variations results in high false-positive rates
- Pattern of model points voting for same localization hypothesis is a learnable structure
- Random Forest based classification determines "Shape Consistency Measure" (SCM)
- SCM is used for weighting the Hough space
- Iris localization rate improved from 97.2% to 99.2%

Thank you!