Gender Classification

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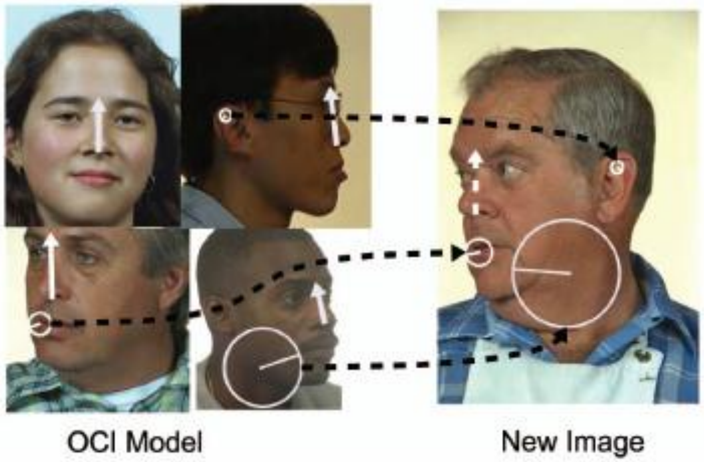
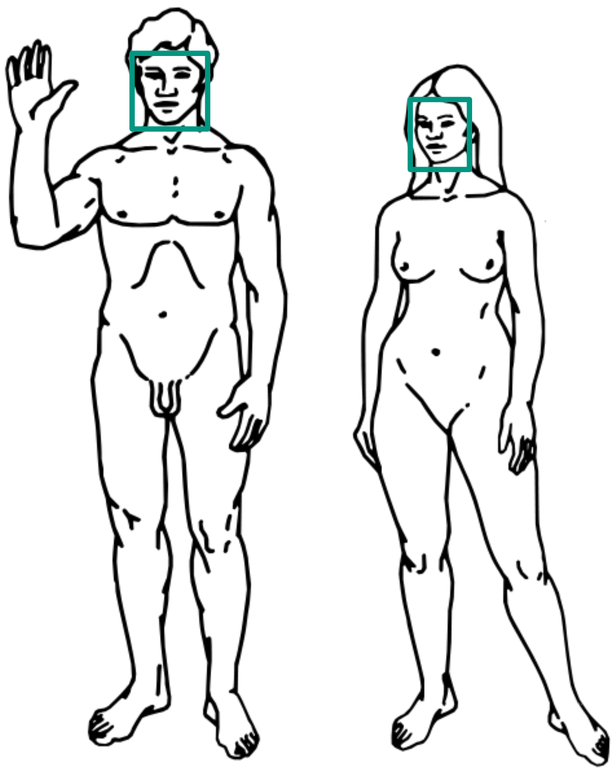


Motivation

- Distinguish between male or female?
  - Body shape
  - Hair style
  - Vocal tone
  - Facial features



Source: http://en.wikipedia.org/wiki/Body_shape

Motivation

- Area of application
  - Directly – only few possibilities
    - demographic data collection
    - gender-based personalized advertising
  - Indirect
    - Pre-processing step in face recognition
      → increase classification accuracy

Sources:
http://en.wikipedia.org/wiki/File:Red_High_Heel_Pumps.jpg
http://www.hoepfner.de/marketing/grafikvorlagen/Kisten_pdf/Pilsner_0,5.pdf

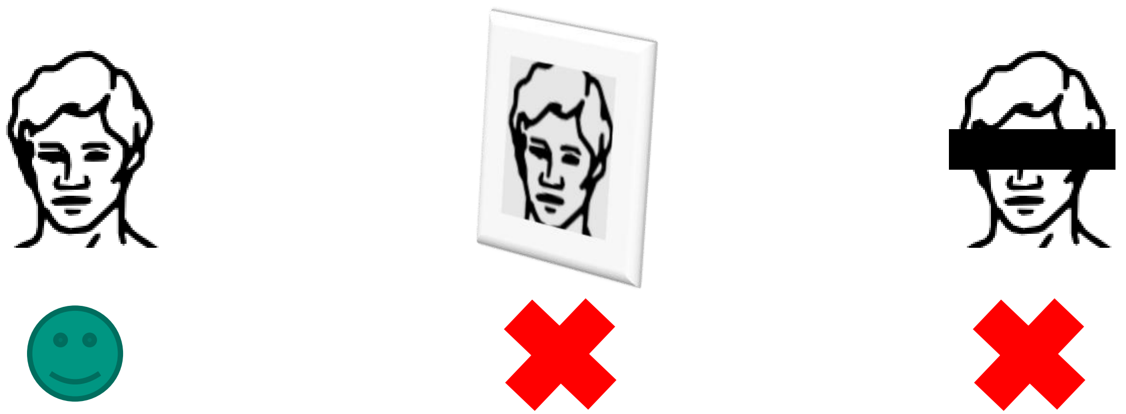
Previous approaches

- Previous approaches in gender classification
  → Combinations of different features and classification algorithms
- Feature input:
  - directly
  - Transformation (e.g. Gabor wavelets)
  - Local features (Local Binary Patterns, SIFT)
- Dimension reduction:
  - Principal Component Analysis
  - Linear Discriminant Analysis
- Classification
  - Support Vector Machines
  - Neural Networks
  - Adaboost

Previous approaches

- Input: frontal faces through preprocessing
- => ideal case results

- No direct classification from arbitrary viewpoints and under occlusions



The quite different approach

- Matthew Toews and Tal Arbel* present:
  - Robust detecting, localizing and classifying in one common framework
  - Classifying different visual traits (e.g. sex, age, brain anatomy)
  - From arbitrary viewpoints
  - Under Occlusion
  - No need for 3D modeling
  - No need for training images from different viewpoints

→ can be used in realistic scenarios

* Paper: Toews, Matthew and Arbel, Tal (2009): Detection and Localization, and Sex Classification of Faces from Arbitrary Viewpoints and under Occlusion

The quite different approach

- General structure of the framework

Feature extracting by SIFT

↓

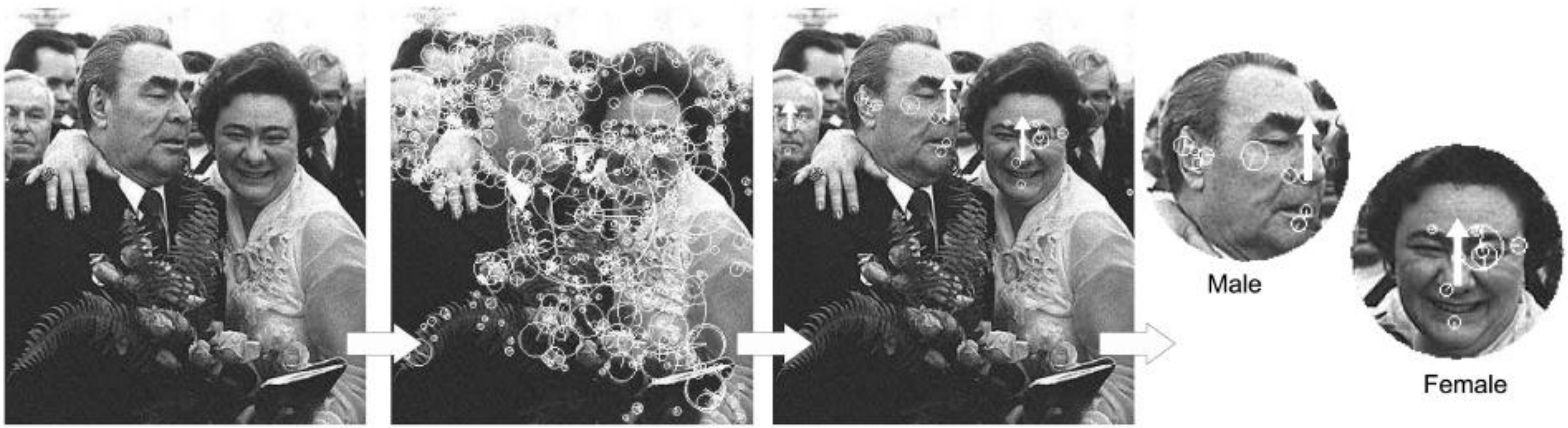
Locating faces with an appearance model represented by an object class invariant (OCI) Model

↓

Gender classification with a Bayesian classifier

The quite different approach

Example for classifying sex of persons in a cluttered image:

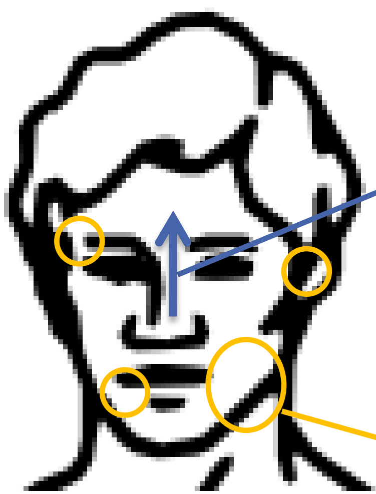


Example image: cluttered scene → Feature extraction by SIFT → Face detection by OCI model → Bayesian classifier determines sex

Source: Toews, Matthew and Arbel, Tal (2009): Detection and Localization, and Sex Classification of Faces from Arbitrary Viewpoints and under Occlusion

The quite different approach

- What is an OCI Model?
  - relates scale-invariant features to an OCI



OCI

- 3D geometrical structure related to an underlying 3D object class
- maintains consistence across different viewpoints

Model feature

- Scale-invariant features are automatically extracted from training images
- Identifying clusters of features which then present a model feature relating to OCI

The quite different approach

- Bayesian classifier for gender classification

$$\log \psi(c) = \underbrace{\log \frac{p(c)}{p(\bar{c})}}_{(1)} + \sum_{i}^{M} \underbrace{\log \frac{p(f_i|c)}{p(f_i|\bar{c})}}_{(2)}$$

- (1) Ratio of trait value presence c versus absence
- (2) Likelihood ratio of trait presence c versus absence coinciding with observed features f_i

→ Optimal Bayesian classifier by choosing c which maximizes the term
→ Threshold ψ^* decides if male or female

Evaluation

- Classification results for the framework

Classification results from framework based on three different sets of training data, remaining images are used for testing:

Training test size	classification EER
100	28%
200	21%
300	19%
400	18.5%
500	16.3%

Classification results from framework based on three ranges of face viewpoints with 500 training images:

Viewpoint range	mean EER
$0° - 22°$	11.9%
$22° - 67°$	15.6%
$67° - 90°$	19.9%

Source: Toews, Matthew and Arbel, Tal (2009): Detection and Localization, and Sex Classification of Faces from Arbitrary Viewpoints and under Occlusion

Evaluation

- Comparison to other approaches (based on FERET images)

Classification results from other approaches for FERET images with normalization when a separate set of FERET images was used for training.

Method	Average EER %
Neural network	8.99
SVM	14.55
Threshold Adaboost	16.66
LUT Adaboost	8.99
Mean Adaboost	10.83
LBP + SVM	13.72
Average	11.43

Classification results from new framework based on three ranges of face viewpoints with 500 training images:

Viewpoint range	mean EER
$0° - 22°$	11.9%
$22° - 67°$	15.6%
$67° - 90°$	19.9%

Left image: Mäkinen (2008), Erno and Raisamo, Roope, An experimental comparison of gender classification methods
Right image: Toews, Matthew and Arbel, Tal (2009): Detection and Localization, and Sex Classification of Faces from Arbitrary Viewpoints and under Occlusion

Evaluation

- Advantages of the novel approach
  - Detecting, localizing, classifying in one common framework
  - From arbitrary viewpoints
  - Under occlusion
  - No 3D modelling or images from multiple viewpoints in training needed
  - Used for other visual traits (e.g. Age, brain anatomy)

- Disadvantages
  - No overhead or underhead views
  - Exploits symmetry of faces
  - Identifying instances of the same class
    but not : between different instances of the same object

Conclusion

- Lessons learned:
  - Why do we need gender classification?
  - What are previous approaches in this research field?
  - What is the new approach from Toews and Arbel?
  - How are the classification results?

Discussion

- Questions?

- Other equivalent approaches comes in mind?
- Are there following papers from Toewn and Arbel? Content?
- Is manually labelling OCI practicable?
- Using body shape for classification?

Thanks for your attention!