

# Computer Vision Head pose estimation

Jonas Vanthornhout University of Leuven

June 18, 2012

#### Outline

#### Possible Approaches

Appearance template methods

Detector arrays

Nonlinear regression methods

Manifold embedding methods

Flexible models

Geometric methods

Tracking methods

Hybrid method:

#### Chosen approach

Yaw detection

Pitch detection

#### Conclusion

# Possible approaches [5]

Possible Approaches

Appearance template methods

Detector arrays

Nonlinear regression methods

Manifold embedding methods

Flexible models

Geometric methods

Tracking methods

Hybrid methods

#### Appearance template methods

- 1. Match head with set of heads
- 2. Best match determines pose

#### Appearance template methods

- 1. Match head with set of heads
- 2. Best match determines pose

| Advantages             | Disadvantages                    |
|------------------------|----------------------------------|
| No features needed     | Only discrete poses              |
| Can be easily expanded | Head region must be known        |
|                        | Performance degradation possible |
|                        | Pairwise similarity              |

#### Detector arrays

- 1. Similar to appearance template methods
- 2. Detector for each pose is made
  - $\Rightarrow$  only variation corresponding to pose change is learned
  - $\Rightarrow$  pairwise similarity problem is solved

#### Detector arrays

- 1. Similar to appearance template methods
- 2. Detector for each pose is made
  - ⇒ only variation corresponding to pose change is learned
  - ⇒ pairwise similarity problem is solved

| Advantages                           | Disadvantages                    |  |  |
|--------------------------------------|----------------------------------|--|--|
| No head localization needed          | More difficult training phase    |  |  |
| Learns the correct appearance varia- | Performance degradation possible |  |  |
| tion                                 |                                  |  |  |

# Nonlinear regression methods

- Calculate from each image a value
   Possible to use features to calculate this value
- 2. Use nonlinear regression on these values to estimate the pose

Remark: mostly used in combination with a neural network

## Nonlinear regression methods

- Calculate from each image a value
   Possible to use features to calculate this value
- 2. Use nonlinear regression on these values to estimate the pose

Remark: mostly used in combination with a neural network

| Advantages | Disadvantages         |  |  |
|------------|-----------------------|--|--|
| Fast       | Nontrivial regression |  |  |
| Accurate   | Head locator needed   |  |  |

## Manifold embedding methods

- 1. Reduce the dimensionality of the image
- 2. Uses these dimensions to estimate pose

## Manifold embedding methods

- 1. Reduce the dimensionality of the image
- 2. Uses these dimensions to estimate pose

| Advantages             | Disadvantages                      |  |
|------------------------|------------------------------------|--|
| Uses correct dimension | Difficult to reduce dimensionality |  |

#### Flexible models

- 1. Map a known model to an image
- 2. Compare this mapping to other mappings
- 3. Best match determines the head pose

#### Flexible models

- 1. Map a known model to an image
- 2. Compare this mapping to other mappings
- 3. Best match determines the head pose

| Advantages             | Disadvantages             |  |
|------------------------|---------------------------|--|
| Robust to deformations | Feature detector needed   |  |
|                        | Computationally expensive |  |
|                        | Frontal position needed   |  |

#### Geometric methods

- 1. Based on psychophysical experiments
- 2. Use this knownledge to determine head pose

Remark: a lot of implementations possible

- Features
- Gradients

#### Geometric methods

- 1. Based on psychophysical experiments
- 2. Use this knownledge to determine head pose

Remark: a lot of implementations possible

- Features
- Gradients

| Advantages                       | Disadvantages              |  |  |
|----------------------------------|----------------------------|--|--|
| Simplicity                       | Feature/ detector needed   |  |  |
| Uses information known to humans | Accuracy limited by humans |  |  |

## Tracking methods

- 1. Use information from consecutive images
- 2. "Normal" head pose estimator for first image
- 3. Next images can use previous estimation and the image

Remark: pose estimation of next images

- Feature tracking
- Texture mapping

# Tracking methods

- 1. Use information from consecutive images
- 2. "Normal" head pose estimator for first image
- 3. Next images can use previous estimation and the image

Remark: pose estimation of next images

- Feature tracking
- Texture mapping

| Advantages | Disadvantages             |  |  |
|------------|---------------------------|--|--|
| Robust     | Consecutive images needed |  |  |
|            |                           |  |  |

## Hybrid methods

- Combine results to get an average head pose
- Use weights to get best head pose

# Hybrid methods

- Combine results to get an average head pose
- Use weights to get best head pose

| Advantages | Disadvantages              |  |  |
|------------|----------------------------|--|--|
| Robust     | Multiple estimators needed |  |  |
|            | Slower                     |  |  |

# Geometric method [3]

- Based on results of psychophysical experiments
- Uses features
- Perception of head pose

#### Chosen approach

Yaw detection Pitch detection

#### Geometric method

| Advantages | Disadvantages       |  |
|------------|---------------------|--|
| Intuitive  | Noise sensitive     |  |
| Simplicity | Features needed     |  |
| Fast       | Head locator needed |  |

Chosen approach
Yaw detection

Jonas Vanthornhout KUL

## Yaw detection: training

## Yaw detection: training

- 1. Detect eyes Cascade classifier [4] Unable to detect eye  $\rightarrow$  position = (0,0)
- 2. Get relative horizontal positions of eyes

## Yaw detection: testing

- 1. Detect eyes  $(e_1 \& e_2)$
- 2. Calculate average position  $(p_1 = e_1 + e_2)$
- 3. Get score of each image

Calculate average position  $(p_2)$ 

Check if amount of eyes matches, otherwise score = 1,000,000.

No eyes, score = 0.

One eye, different eye, score = 1,000,000

One eye, same eye, score =  $|p_1 - p_2|$ 

Two eyes, score  $=|p_1-p_2|$ 

4. Best score determines the yaw

#### Yaw detection: results

| method              | correct | accuracy | avg. abs. err. | wrong<br>direction | wrong<br>frontal |
|---------------------|---------|----------|----------------|--------------------|------------------|
| detect (sorted)     | 209     | 86.0%    | 6.3            | 4                  | 9                |
| landmarks (sorted)  | 214     | 88.1%    | 8.4            | 15                 | 0                |
| detect              | 211     | 86.8%    | 5.6            | 2                  | 9                |
| landmarks           | 228     | 93.8%    | 0.84           | 0                  | 0                |
| hybrid              | 183     | 75.3%    | 10.3           | 4                  | 13               |
| landmarks (logical) | 212     | 87.2%    | 3.4            | 0                  | 0                |
| hybrid (logical)    | 191     | 78.6%    | 9.3            | 4                  | 13               |

Table 1: 20-fold cross validation on the Bosphorus database [6] with 243 samples

#### Yaw detection: implementation

#### Eyes resize image

raise minimum neighbours till maximum two eyes are found two eves must be at the same height, otherwise delete lowest two eyes overlap → remove biggest eye if no eyes are found, redo with bigger image

- Make the estimator more robust to inconsistencies of the head locator
- Use a more accurate feature detector
- Use a continuous pose instead of a discrete pose
- Use a eye detector that knows which is the left and right eye

- Make the estimator more robust to inconsistencies of the head locator
- Use a more accurate feature detector

- Make the estimator more robust to inconsistencies of the head locator
- Use a more accurate feature detector
- Use a continuous pose instead of a discrete pose
- Use a eye detector that knows which is the left and right eye

- Make the estimator more robust to inconsistencies of the head locator
- Use a more accurate feature detector
- Use a continuous pose instead of a discrete pose
- Use a eye detector that knows which is the left and right eye

Chosen approach

Pitch detection

Jonas Vanthornhout KUL Slide: 21

# Pitch detection: training

1. Detect eyes [4], mouth and nose [2]

Jonas Vanthornhout KUL Slide: 22

## Pitch detection: training

- 1. Detect eyes [4], mouth and nose [2]
- 2. calculate d1 = d(eyes, nose) and d2 = d(nose, mouth)

KUL Slide: 22

## Pitch detection: training

- 1. Detect eyes [4], mouth and nose [2]
- 2. calculate d1 = d(eyes, nose) and d2 = d(nose, mouth)
- 3. calculate  $r = \frac{d1}{d2}$

1. Calculate ratio  $r_{test}$ 

Jonas Vanthornhout KUL Slide: 23

- 1. Calculate ratio  $r_{test}$
- 2. Let every image vote for its pitch Image may vote if  $|r_{train} r_{test}| < threshold$

- 1. Calculate ratio  $r_{test}$
- 2. Let every image vote for its pitch Image may vote if  $|r_{train} - r_{test}| < threshold$
- 3. Pitch with most votes wins

Fine tuning: threshold

- 1. good initial value?
- 2. decrease threshold when tie  $\rightarrow$  more specific wins
- 3. increase threshold when tie  $\rightarrow$  more general wins

#### Pitch detection: results

| method                    | correct | accuracy | avg. abs. err. | wrong<br>direction | wrong<br>neutral |
|---------------------------|---------|----------|----------------|--------------------|------------------|
| detect                    | 71      | 68.3%    | 0.35           | 0                  | 20               |
| landmarks                 | 71      | 68.3%    | 0.35           | 1                  | 16               |
| facial normal [1]         | 51      | 49.0%    | 1.1            | 27                 | 22               |
| facial normal (corr.) [1] | 74      | 71.2%    | 0.29           | 0                  | 14               |

Table 2: The obtained results of the pitch detector

#### Pitch detection: ratios

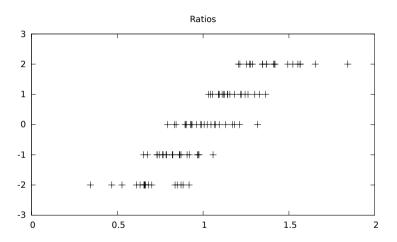


Figure 1: The ratios (x-axis) for the pitches (y-axis) using the cascade classifier.

#### Pitch detection: ratios

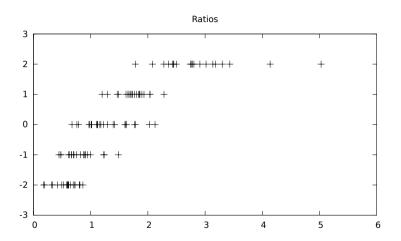


Figure 2: The ratios (x-axis) for the pitches (y-axis) using the landmarks.

#### Pitch detection: ratios

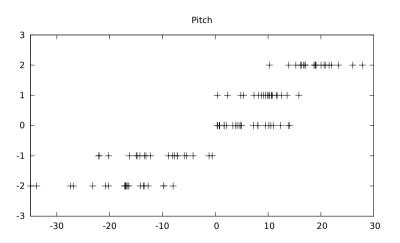


Figure 3: The ratios (x-axis) for the pitches (y-axis) using the facial normal.

### Pitch detection: implementation

Eyes see yaw detection

Nose resize image raise minimum neighbours till maximum one nose is found if no nose is found, redo with bigger image

Mouth resize image

delete every mouth that doesn't have a point in the lower quarter two mouths overlap  $\rightarrow$  delete smallest too many eyes → increase minimum neighbours, redo too few eyes  $\rightarrow$ , redo with bigger image

### Pitch detection: futher improvements

- Normalize the ratios  $\rightarrow$  deviation head length needed

### Pitch detection: futher improvements

- lacktriangle Normalize the ratios o deviation head length needed
- $\blacksquare$  We can conclude we've reached the limits of the method  $\rightarrow$  new method

KUL Slide: 30

#### Conclusion

- Yaw detection is far mor easier than pitch detection
- Yaw detector better feature detector  $\rightarrow$  better results
- Pitch detector: inherently difficult

### Bibliography I

[1] Oljira Dejene Boru.

Head pose estimation using opency.

http://mmlab.disi.unitn.it/wiki/index.php/Head\_Pose\_Estimation\_using\_OpenCV

[2] M. Castrillón Santana, O. Déniz Suárez, M. Hernández Tejera, and C. Guerra Artal.

Encara2: Real-time detection of multiple faces at different resolutions in video streams.

Journal of Visual Communication and Image Representation, pages 130–140, April 2007.

[3] A. H. Gee and R. Cipolla.

Determining the gaze of faces in images.

Image and Vision Computing, 12:639–647, 1994.

## Bibliography II

- [4] Shameem Hameed.
  http://www-personal.umich.edu/~shameem/haarcascade\_eye.html.
- [5] E. Murphy-Chutorian and M. Trivedi. Head pose estimation in computer vision: A survey. IEEE Transactions on Pattern Analysis and Machine Intelligence, 31 Issue 4(Pages 607-626), 2009.
- [6] A. Savran, N. Alyz, H. Dibekliolu, O. eliktutan, B. Gkberk, B. Sankur, and L. Akarun.

Bosphorus database for 3d face analysis.

In The First COST 2101 Workshop on Biometrics and Identity Management (BIOID 2008), May 2008.