Challenges & Advances in Face Recognition

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SWISSCOM-EURECOM Workshop
Sophia Antipolis
May 29th 2012

Outline

- Introduction
  - Semi supervised, self, co–training Face Recognition (FR);
  - Robustness of FR techniques in presence of occlusions;
  - FR from video;
  - 3DFR;
  - Security of FR technologies against spoofing;
  - Soft biometrics: gender, ethnicity, age, etc.;

- Conclusion
Security

Seven types of authentication:

✓ Something you know (1)
  ✓ e.g. PIN code, mother’s maiden name, birthday
✓ Something you have (2)
  ✓ e.g. Card, key
✓ Something you know + something you have (3)
  ✓ e.g. ATM card + PIN
✓ Something you are – Biometrics (4)
  ✓ no PIN to remember, no PIN to forget
✓ Something you have + something you are (5)
  ✓ Smart Card
✓ Something you know + something you are (6)
✓ Something you know + something you have + something you are (7)

Is there a universal biometric identifier?

There are many biometric identifiers:

✓ Fingerprint
✓ Voice
✓ Image
✓ Hand geometry
✓ Retina
✓ Iris
✓ Signature
✓ Keystroke dynamics
✓ Gait
✓ DNA (deoxyribonucleic acid)
✓ Wrist/hand veins
✓ Body odor
✓ Brain activity

In theory many of these biometric identifiers should be universal. However, in practice this is not the case.

Ideally, a biometric identifier should be universal, unique, permanent and measurable. However, in practice each biometric identifier depends on factors such as users’ attitudes, personality, operational environment, etc.
Each biometric identifier has its strengths and weaknesses

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Fingerprints</th>
<th>Hand Geometry</th>
<th>Retina</th>
<th>Iris</th>
<th>Face</th>
<th>Signature</th>
<th>Voice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time to use</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>Medium</td>
<td>Medium</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Snow incidence</td>
<td>Low</td>
<td>High</td>
<td>Hand injury, age</td>
<td>Glasses</td>
<td>Poor Lighting</td>
<td>Light, age, glasses, hair</td>
<td>High, Noise, Cold, weather</td>
</tr>
<tr>
<td>Accuracy</td>
<td>High</td>
<td>High</td>
<td>Very high</td>
<td>Very high</td>
<td>High</td>
<td>High</td>
<td>Medium</td>
</tr>
<tr>
<td>Cost</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
</tr>
<tr>
<td>User acceptance</td>
<td>Medium</td>
<td>Medium</td>
<td>High</td>
<td>Very high</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
</tr>
<tr>
<td>Required security level</td>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>Very high</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
</tr>
<tr>
<td>Long-term stability</td>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
</tr>
<tr>
<td>Template size (bits)</td>
<td>2048</td>
<td>9</td>
<td>96</td>
<td>512</td>
<td>64</td>
<td>35</td>
<td>580</td>
</tr>
</tbody>
</table>
Pattern classification

- Given:
  - a set of observations
  - a set of classes
  - assign each observation to one class

- Main challenge of pattern classification: distinguish between
  - intra-class variability
  - inter-class variability

Face recognition is very challenging due to variations in:
- facial expression
- pose
- illumination conditions
- presence / absence of eyeglasses and facial hair
- aging, etc.

Basic problem:
Are these pictures representing the same person?...
Intra-class
Or they images of different persons?
Inter-class

Test 1


- Is this person in the array?
- If they are present match the person.
Test 1 (Cont.)

- Is this person in the array?
- If they are present match the person.

Test 1 (end)

- When target was present in the array. 12% picked wrong person and 18% said they were not present (overall only 70% correct).
- When target was not present in the array 70% still matched the target to someone in the array.
Face: frontal face recognition

Face is well accepted, with no contact, used in day-life by humans,… but less accurate than fingerprints, iris… … palms

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- Soft biometrics: gender, ethnicity, age, etc.;
- Conclusion

Zhao, Xuran; Evans, Nicholas W D; Dugelay, Jean-Luc;
Semi-supervised face recognition with LDA self-training
Zhao, Xuran; Evans, Nicholas W D; Dugelay, Jean-Luc
A co-training approach to automatic face recognition
Semi-supervised Face Recognition

- A large pool of unlabelled data sometimes can be acquired easily and contain important information:
  - Video surveillance;
  - Digital album;
- *Semi-supervised* face recognition: Using both labeled and unlabeled data.

Self-training Methods

- Idea: A LDA classifier is used to label unlabelled data and use the most confident results to iteratively updating itself.

Results on ORL Database

<table>
<thead>
<tr>
<th>Method</th>
<th>Unlabeled Acc</th>
<th>Test Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenface [8]</td>
<td>25.3±1.7</td>
<td>25.3±1.6</td>
</tr>
<tr>
<td>Laplacianface [12]</td>
<td>56.1±2.3</td>
<td>56.8±2.4</td>
</tr>
<tr>
<td>Consistency [10]</td>
<td>52.0±1.8</td>
<td>--</td>
</tr>
<tr>
<td>LapSVM [14]</td>
<td>56.5±1.6</td>
<td>56.9±2.6</td>
</tr>
<tr>
<td>LapRLS [14]</td>
<td>57.5±1.6</td>
<td>57.9±2.6</td>
</tr>
<tr>
<td>SDA [7]</td>
<td>59.0±2.0</td>
<td>29.5±2.7</td>
</tr>
<tr>
<td>LDA self-training</td>
<td>84.5±9.5</td>
<td>71.3±8.5</td>
</tr>
</tbody>
</table>
Co-training Method

- Idea: build two classifiers on two distinct facial features, each helps to update the other;

**Fisherface**
- Based on Linear Discriminant Analysis (LDA);
- Supervised method;
- Good performance when labelled training data is sufficient.
- One of the most well-know subspace projection method, reflect global information.

**Local Binary Pattern (LBP)**
- A powerful local feature in face recognition;
- Reflect local features;

![Diagram of LBP](image)

Algorithm

- **Given**: A labeled set $D_l$ and an unlabeled set $D_u$.
- **Initialization**: Learn LDA transform with $D_l$, create a template for each subject by the projected mean of the same class; Create a template for each subject as the mean of LBP vectors of the same class;
- **Iterative co-training**: LDA recognition: Project $D_u$ into LDA space, for each class, find the nearest sample to the template, remove it from $D_u$ and add to $D_l$.
  - LBP recognition: In $D_u$, for each class, find the nearest sample to the template, remove it from $D_u$ and add it to $D_l$.
  - LDA updating: Re-training the LDA projection matrix with the new $D_l$, and re-create the templates;
  - LBP updating: Re-create the templates.
  - Iterate until the $D_u$ is empty;

![Diagram of Co-training Method](image)
Results

- Starting from 2 labeled examples per subject
- The improvement of accuracy as a function of iteration

![Graph showing the improvement of accuracy as a function of iteration.]

### Two features v.s. Single feature

<table>
<thead>
<tr>
<th></th>
<th>$l = 2$</th>
<th>$l = 3$</th>
<th>$l = 4$</th>
<th>$l = 5$</th>
<th>$l = 6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline LBP</td>
<td>63%</td>
<td>70%</td>
<td>72%</td>
<td>78%</td>
<td>80%</td>
</tr>
<tr>
<td>Baseline LDA</td>
<td>30%</td>
<td>57%</td>
<td>67%</td>
<td>78%</td>
<td>84%</td>
</tr>
<tr>
<td>LBP self-training</td>
<td>72%</td>
<td>73%</td>
<td>75%</td>
<td>76%</td>
<td>78%</td>
</tr>
<tr>
<td>LDA self-training</td>
<td>78%</td>
<td>88%</td>
<td>92%</td>
<td>93%</td>
<td>94%</td>
</tr>
<tr>
<td>LBP co-training</td>
<td>80%</td>
<td>82%</td>
<td>84%</td>
<td>85%</td>
<td>85%</td>
</tr>
<tr>
<td>LDA co-training</td>
<td>86%</td>
<td>91%</td>
<td>93%</td>
<td>95%</td>
<td>95%</td>
</tr>
</tbody>
</table>
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Min, Rui; D’angelo, Angela; Dugelay, Jean-Luc;
Efficient scarf detection prior to face recognition

Min, Rui; Hadid, Abdenour; Dugelay, Jean-Luc;
Improving the recognition of faces occluded by facial accessories

Occlusions

- General Problems: Illuminations, Facial Expressions, Poses, Occlusions etc.
- Facial Occlusions: Sunglasses, Scarf, Medical Mask, Beards etc.
- Face Recognition in Non-Cooperative Systems (e.g. Video Surveillance)
- Security/Safety Issues:
  - Football Hooligans
  - ATM Criminals
  - Bank/Shop Robbers
  - Etc.
## Static Facial Occlusions Scenario

- **Two Step Algorithm:**
  - Occlusion Detection in Local Patches
  - Face Recognition based on Local Binary Patterns (LBP)
- Recognizing a Probe face
  - Compute the LBP representation
  - Divide the image into local patches
  - Occlusion detection in each patch
  - Non-occluded patches are selected for recognition

### Static Facial Occlusions Scenario – cont.

- **Image Division**
- **Feature Extraction:** Gabor Wavelet filtering
- **Dimensionality Reduction:** Principal Component Analysis (PCA)
- **Classification:** Support Vector Machine (SVM)

### Feature Extraction

- **LBP Code**
  - The LBP code for point \( (x_0,y_0) \) is given by:
  \[
  LBP_{p,r} = \sum_{p=0}^{p-1} s(d_p - \mu_c)^2
  \]

- **Thresholding function:**
  \[
  s(x) = \begin{cases} 
  1 & \text{if } x \geq 0 \\
  0 & \text{otherwise}
  \end{cases}
  \]

- **LBP Histogram**
Static Facial Occlusions Scenario – cont.

Results...

Dynamic Facial Occlusions Scenario

- Time-Invariant occlusions
  - e.g. Scarf, Sunglasses, etc.

- Time-Variant occlusions
  - e.g. Cap of moving people in Entrance Surveillance

- Entrance Surveillance:
  - CCTV cameras mounted at the room ceiling to monitor the entrance of various places (banks, supermarkets, libraries etc.)

- Occlusion vs. Resolution
  - too far: small occlusion, low resolution
  - too close: large occlusion, high resolution

- Detection and Tracking (low resolution, occlusion, rotation, background textures) [solution: scalable Elliptical Head Tracker]

- Non-Homogeneous Occlusion Variations (walking habit, speed, pose, rigid head motion, tracking errors) [solution: DTW]
Biometrics: Novel Facial Biometrics

- Face recognition is a very attractive biometric but yet not as reliable as some other ones like fingerprints...

- Existing solutions in face recognition are still image-based (i.e. appearance only) whereas current sensors are video (i.e. webcam, video surveillance)...

Adding a dimension...

- Face Identification from Video
  - From physical to behavioral biometrics
  - Multimodal: Appearance + motion (pose & expressions)

- Face Identification in 3D

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- Matta, Federico; Dugelay, Jean-Luc
  Tomofaces: eigenfaces extended to videos of speakers

- Matta, Federico; Dugelay, Jean-Luc
  Video face recognition: a physiological and behavioural multimodal approach

- Ouaret, Mourad; Dantcheva, Antitza; Min, Rui; Daniel, Lionel; Dugelay, Jean-Luc
  BIOFACE, a biometric face demonstrator
Face reco. From video: physical & behavioral

Head Motion and facial Mimics
Diagram of the system

Dynamic face (i.e. Tomofaces)

- Contrast enhancement.
  - Histogram equalisation
  - Contrast stretching
- Edge map sequence.
  - Canny edge finding method
- Temporal X-ray transformation.
- Background attenuation.
  - Pixels above a threshold value (>0.66) = Put to black
- Principal Component analysis (PCA).
- Subject models as centroids.
Architecture of the system

Recognition using face fusion results

<table>
<thead>
<tr>
<th>Method</th>
<th>Correct Identification Rate (CIR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple eigenfaces</td>
<td>71.15%</td>
</tr>
<tr>
<td>Tomofaces</td>
<td>78.85%</td>
</tr>
<tr>
<td>Max(max)</td>
<td>77.88%</td>
</tr>
<tr>
<td>Max(mean)</td>
<td>82.69%</td>
</tr>
<tr>
<td>Max(weighted)</td>
<td>81.73%</td>
</tr>
<tr>
<td>Mean(rank)</td>
<td>84.62%</td>
</tr>
<tr>
<td>2nd layer fusion</td>
<td>86.54%</td>
</tr>
<tr>
<td>FA, HM and MM</td>
<td>92.50%</td>
</tr>
</tbody>
</table>
BIOFACE: A Biometric Face Demonstrator

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Erdogmus, Nesli; Dugelay, Jean-Luc
Automatic extraction of facial interest points based on 2D and 3D data

Erdogmus, Nesli, Ethève, Rémy; Dugelay, Jean-Luc
Realistic and animatable face models for expression simulations in 3D
SPIE 2010, Electronic Imaging Conference on 3D Image Processing (3DIP) and Applications, January 17-21, 2010, San Jose, California | Also published as “SPIE - The International Society for Optical Engineering”, Vol. 7526, 2010
Asymmetrical Approach

- Enrollment in 3D and recognition in 2D
  - By simulating expressions in 3D and generating artificial face images with expressions:
    - It is possible to match the test image and the artificial image
    - It is possible to train the system with many possible expressions for each person to recognize faces with expressions

Introduction

- In our case*:
  - Neutral face scans with closed mouth
  - 3D + texture
  - Constructing an animatable model for each subject

* Neutral face scans with closed mouth, 3D + texture, Constructing an animatable model for each subject
**Motivation**

- **Fully controllable enrollment:**
  - Neutral frontal faces with closed mouth
- **Manual annotation of points**
  - Needs to be automated for a fully automatic system

**Automatic Annotation**

- Face is broken into sub-regions based on a vertical profile analysis.
- Points of interest are detected according to the surface or texture characteristics of the region.
Recognition

- Animating the obtained models of each subject according to the existing facial expression

  ➢ Two examples are as follows:

![Image of original face model, animatable model obtained after warping, obtained model animated to smile, obtained model animated to frown]

Results

- Bosphorus Database
  ➢ Without simulation
  ➢ With simulation
    - Manual annotation
    - Automatic annotation

- FRGC Database
  ➢ Neutral
  ➢ Small expression
  ➢ Large expression
  ➢ Overall
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Benaiss, Abdelaali; Saeed, Usman; Dugelay, Jean-Luc; Jedra, Mohamed
Impostor detection using facial stereoscopic images
Eusipco 2009, 17th European Signal Processing Conference, August 24-28, 2009, Glasgow

Riccio Daniel; Nappi Michele; Dugelay, Jean-Luc;
Moving face spoofing detection via 3D projective invariants
ICB 2012, Delhi.

Attacks, « Liveness » and countermeasure

Impostors may use a fake biometric,
- Replay attack: Photography of a face
  Countermeasure: To use a « liveness » test to check the presence of a “real” biometric, e.g. cardiac activity, heart rate
- Template inversion
- Face mapping / morphing,…
2D/3D Face Spoofing Attacks and Countermeasures

Face Spoofing Attacks:
- masked fake face
- video of the client
- photo of the client
- plastic surgery applied face

Countermeasures for Face Recognition:
- Software based
- Hardware based
- Challenge response based
- Recognition based methods

Examples for Face Spoofing Attack Types

- Mask Attack
  (www.thatsmyface.com)

✓ Only by uploading one frontal and one profile picture of yourself, you can order your mask.
Robustness vs. Security in Biometrics

- **Replay attack**
  
  (basic)

  Impostor detection using facial stereoscopic images

Classification of Captured and Recaptured Images to Detect Photograph Spoofing

**Specifications of NUAA Database**

- publicly available large photo-impostor database containing photo images from 15 subjects which is constructed using a generic cheap webcam.
- collected in three sessions. The place and illumination conditions of each session are different as well.
- for each subject in each session, the webcam is used to capture a series of their face images (with frame rate 20fps and 500 images for each subject).
Classification of Captured and Recaptured Images to Detect Photograph Spoofing

1. NUAA database is used to test our algorithm.
2. LBP variance algorithm with global matching technique is applied to detect spoofing.
3. Aim is to classify captured and recaptured images by texture and contrast analysis.
4. The proposed method is rotation invariant.
5. It is also robust to illumination change.

Almost 88% success on NUAA Database is achieved.

3D Invariants

Fig. Each column contains samples from different sessions. In each row, the left pair is from a live human and the right from a photo.
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Dantcheva, Antitza; Velardo, Carmelo; D’angelo, Angela; Dugelay, Jean-Luc
Bag of soft biometrics for person identification : New trends and challenges

Soft Biometrics?

- Provide (biometrical) information about individual
- Lack distinctiveness and permanence
- Are not “expensive” to compute
- Do not require the cooperation of the individual
- Can be sensed from a distance
- Can be applied to unknown individuals.

- Can increase the system reliability
- Narrowing down the search within a limited group of candidate individuals
Soft biometrics candidates

- Age
- Hair color, Eye color, Skin color
- Height
- Weight
- Gender
- Gait
- Glasses
- Beard, Cloths color, Make up

Eye colors classification: Carlton Coon chart

TEST-2
Normalization

Normalized size of 64x64
• eyes axis = horizontal
• centre of the picture = nose
• distance between eyes = half of the picture

Male or Female?
Male or Female?

Male or Female?
Male or Female?

Male or Female?
Male or Female?

Male or Female?
Soft biometrics for authentication?

- 864 categories:

<table>
<thead>
<tr>
<th>Skin Color</th>
<th>Hair Color</th>
<th>Eye Color</th>
<th>Glasses presence</th>
<th>Beard presence</th>
<th>Moustache presence</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>6</td>
<td>6</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

- Consideration of:
  - Distributions
  - Correlations
- Probability of having 2 subjects in the same category

Extraction

Viola & Jones Face and features detector
- Glasses: line detection between the eyes
- Color face soft biometrics: ROI finding and GMM color classification
- Beard and moustache: comparison of color of ROI’s color with skin and hair color

<table>
<thead>
<tr>
<th>Soft biometric trait</th>
<th>Algorithm</th>
<th>Traits instances</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skin color</td>
<td>Derived from [1]</td>
<td>3</td>
</tr>
<tr>
<td>Hair color</td>
<td>Derived from [2]</td>
<td>5</td>
</tr>
<tr>
<td>Eye color</td>
<td>Own developed</td>
<td>4</td>
</tr>
<tr>
<td>Beard</td>
<td>Own developed</td>
<td>2</td>
</tr>
<tr>
<td>Moustache</td>
<td>Own developed</td>
<td>2</td>
</tr>
<tr>
<td>Eye glasses</td>
<td>Derived from [3]</td>
<td>2</td>
</tr>
</tbody>
</table>

Demographic classification: Do Ethnicity and Gender affect each other?

Some features are discriminative for ethnicity but not for gender

Some features are discriminative for gender but not for ethnicity

Some features are discriminative for both gender and ethnicity

SKIN COLOR

SECONDARY SEXUAL CHARACTERISTICS

FACE GEOMETRY

Average Faces from Different Countries / in 3D
Demographic classification: Do Ethnicity and Gender affect each other?

Results show that, at least for the features tested:

1. Ethnicity does not have any impact on gender classification
2. Gender does not have any impact on ethnicity classification

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Dantcheva, Antitza; Dugelay, Jean-Luc
Female facial aesthetics based on soft biometrics and photo-quality
ICMIE 2011, IEEE International Conference for Multimedia and Expo, July 11-15, 2011, Barcelona, Spain
Soft biometrics for facial aesthetics

- Ratios of facial features and their locations
- Facial color soft biometrics
- Shapes of face and facial features
- Non-permanent traits and
- Expression.

Examples:
- Ratio (eye height / head length) f/a
- Ratio (head width / head length) b/a
- Eye make up
- Face shape
- Eye Brow shape
- Fullness of Lips
- Ratio (from top of head to nose / head length) (d+c)/a
- Presence of glasses
- Lipstick
- Skin goodness
- Hair Length / Style
- Ratio (from top of head to mouth / head length) (d+e+d)/a
- Ratio (from top of head to eye / head length) d/a
- Skin color
- Hair color
- Eye color

Photo quality measures

- Simple and objective aesthetics measures regarding the photograph

Examples:
- Image format
- Image Resolution
- JPEG quality measure [7]
- Illumination
- Zoomfactor
- Angle of face
- BIQI [5], [6]
- Left eye distance to middle of image or to mass point [4]


We used the 37 presented objective facial features \( x_i \) to construct a linear metric for facial aesthetics prediction:

\[
\tilde{\text{MOS}} = \sum_{i=1}^{37} y_i \cdot x_i.
\]

- **Annotation:** \( x_i \) ...facial features
- **\( y_i \)....weights**

\( \text{MOS} \) ... mean opinion score

\( \tilde{\text{MOS}} \) ... estimated MOS

### Results

<table>
<thead>
<tr>
<th>Feature</th>
<th>Pearson's Correlation Coefficient</th>
<th>MOS Model</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_1 ): Ratio (eye height / head length)</td>
<td>0.5111</td>
<td>18.3596</td>
<td>0.7576</td>
</tr>
<tr>
<td>( x_2 ): Ratio (head width / head length)</td>
<td>0.4467</td>
<td>4.5709</td>
<td>0.7053</td>
</tr>
<tr>
<td>( x_3 ): Eye makeup</td>
<td>0.3256</td>
<td>0.3053</td>
<td>0.6006</td>
</tr>
<tr>
<td>( x_4 ): Face shape</td>
<td>0.3251</td>
<td>0.6006</td>
<td>0.3337</td>
</tr>
<tr>
<td>( x_5 ): Eye brow shape</td>
<td>0.2220</td>
<td>0.2019</td>
<td>0.2019</td>
</tr>
<tr>
<td>( x_6 ): Proportion of lips</td>
<td>0.2188</td>
<td>-13.8277</td>
<td>0.2188</td>
</tr>
<tr>
<td>( x_7 ): Glosses</td>
<td>-0.2089</td>
<td>-6.6707</td>
<td>-0.2089</td>
</tr>
<tr>
<td>( x_8 ): Lipstick</td>
<td>0.1967</td>
<td>0.0592</td>
<td>0.1967</td>
</tr>
<tr>
<td>( x_9 ): Skin smoothness</td>
<td>0.3955</td>
<td>0.3955</td>
<td>0.3955</td>
</tr>
<tr>
<td>( x_{10} ): Hair length / style</td>
<td>0.3251</td>
<td>0.8617</td>
<td>0.3251</td>
</tr>
<tr>
<td>( x_{11} ): Ratio (from top of head to mouth / head length)</td>
<td>0.1818</td>
<td>-4.1919</td>
<td>0.1818</td>
</tr>
<tr>
<td>( x_{12} ): Ratio (from top of head to eye / head length)</td>
<td>0.1774</td>
<td>49.9039</td>
<td>0.1774</td>
</tr>
<tr>
<td>( x_{13} ): Lime / Lash</td>
<td>0.1657</td>
<td>0.0853</td>
<td>0.1657</td>
</tr>
<tr>
<td>( x_{14} ): Ratio (eye width / distance between eyes)</td>
<td>0.1556</td>
<td>0.0853</td>
<td>0.1556</td>
</tr>
<tr>
<td>( x_{15} ): Ratio (from nose to chin / eye to nose)</td>
<td>-0.1294</td>
<td>0.0670</td>
<td>-0.1294</td>
</tr>
<tr>
<td>( x_{16} ): Left eye distance to middle of image or to mass point</td>
<td>0.1183</td>
<td>0.4297</td>
<td>0.1183</td>
</tr>
</tbody>
</table>

- \( x_1 \): Ratio of the right eye distance to the middle of the image or to mass point
- \( x_2 \): Ratio of the top of the head to the eye of the mass point
- \( x_3 \): Ratio of the eye to the mass point
- \( x_4 \): Ratio of the eye to the mass point
- \( x_5 \): Ratio of the eye to the mass point
- \( x_6 \): Ratio of the eye to the mass point
- \( x_7 \): Ratio of the eye to the mass point
- \( x_8 \): Ratio of the eye to the mass point
- \( x_9 \): Ratio of the eye to the mass point
- \( x_{10} \): Ratio of the eye to the mass point
- \( x_{11} \): Ratio of the eye to the mass point
- \( x_{12} \): Ratio of the eye to the mass point
- \( x_{13} \): Ratio of the eye to the mass point
- \( x_{14} \): Ratio of the eye to the mass point
- \( x_{15} \): Ratio of the eye to the mass point
- \( x_{16} \): Ratio of the eye to the mass point

\( \text{MOS} \) ... mean opinion score

\( \tilde{\text{MOS}} \) ... estimated MOS
Perspective

- Biometrics in Video surveillance
- Extension of on-going work on 2D to 3D

http://image.eurecom.fr