Impact of Cosmetics on Face Recognition

[Work done with Cunjian Chen and Antitza Dantcheva]

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Outline of Talk

• Impact of cosmetics on face recognition
• Automatic facial makeup detector
• Adaptive face recognition
Face Recognition

- Goal: deploying **reliable** face recognition systems in diverse applications

- Challenges:
  - Makeup:
    - Simple, low-cost, non-permanent and socially acceptable alteration that can impact the appearance of a face

Variations due to Pose, Illumination, Expression, Plastic Surgery, Aging...

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Transformation via Makeup

BEFORE MAKEUP

AFTER MAKEUP
Makeup Products
Cosmetic Alterations

- alter the perceived **facial shape** by accentuating contouring,
- alter the perceived **nose shape and size** by contouring techniques,
- enhance or reduce the perceived size of the **mouth**,
- alter the appearance and contrast of the **mouth** by adding color,
- alter the perceived form and color of **eyebrows**,
- alter the perceived shape, size and contrast of the **eyes**,
- conceal dark circles underneath the **eyes**,
- alter the perceived **skin quality and color**, and
- **camouflage** wrinkles, birth moles, scars and tattoos
Makeup Datasets

• **YMU: YouTube makeup dataset**
  • 151 female subjects, 2 makeup, 2 no-make-up shots
  • Variations in expression and pose

• **MIW: Makeup in the wild dataset**
  • 154 WWW images, 77 makeup, 77 no makeup

• **Available at**
  • http://www.antitza.com/makeup-datasets.html
MIW Dataset

BEFORE  AFTER  BEFORE  AFTER

BEFORE  AFTER  BEFORE  AFTER
### YMU Dataset: EER (%)

- **N**: Before makeup
- **M**: After makeup

<table>
<thead>
<tr>
<th></th>
<th>N vs N</th>
<th>M vs M</th>
<th>N vs M</th>
</tr>
</thead>
<tbody>
<tr>
<td>COTS-1</td>
<td>3.84</td>
<td>7.07</td>
<td>12.04</td>
</tr>
<tr>
<td>COTS-2</td>
<td>0.69</td>
<td>1.32</td>
<td>7.69</td>
</tr>
<tr>
<td>COTS-3</td>
<td>0.11</td>
<td>3.29</td>
<td>9.17</td>
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<tr>
<td>OpenBR</td>
<td>6.87</td>
<td>16.44</td>
<td>25.2</td>
</tr>
<tr>
<td>LGBP</td>
<td>5.34</td>
<td>8.77</td>
<td>19.71</td>
</tr>
<tr>
<td>LGGP</td>
<td>5.35</td>
<td>8.01</td>
<td>19.7</td>
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<tr>
<td>HMBP</td>
<td>6.25</td>
<td>10.87</td>
<td>21.54</td>
</tr>
</tbody>
</table>

Note the increase in EER after application of makeup
Observations

- The degree of makeup applied by the subjects in the dataset is not extreme
  - Typical makeup routine

- Alterations due to cosmetic facial makeup are predominantly color-based, but affect the performance of face matchers based on grayscale images

- The impact due to the application of eye makeup is observed to be the most pronounced

- Can we detect makeup in face images?
Facial Makeup Detection

Input Image → Face Detection → Landmark Localization

Makeup vs. No-makeup Classification

Feature Extraction: shape, texture, color

Regions of Interest (ROI)

Normalization
HSV Color Space

Red

Green

Blue

Hue

Saturation

Value
• Geometrically normalize the face images in order to remove the variations in scale and pose.

• Three ROIs are localized according to predefined rectangle locations
  • Left eye ROI: 52 * 52
  • Right eye ROI: 54 * 53
  • Mouth ROI: 56 * 62
Feature: Color

- Used color space: **HSV**
- Tessellation of each ROI into 5x5 blocks
- Computation of **color moments** within blocks
- Color moments

\[
\begin{align*}
\rho &= \sum_{x,y} \frac{1}{N} I_{x,y} \\
\sigma &= \sqrt{\frac{1}{N} \sum_{x,y} (I_{x,y} - \rho)^2} \\
\gamma &= \sqrt[3]{\frac{1}{N} \sum_{x,y} (I_{x,y} - \rho)^3}
\end{align*}
\]

- Features extracted from ROIs in all 3 channels
  \(\rightarrow\) 225-dimensional feature vector
- Face: 9 blocks
  \(\rightarrow\) 81 dimensional feature vector
• **Gabor wavelets** – Gabor kernel of size 64x64
  • Convolution of face with set of Gabor filters: 40 image outputs
  • Computation of mean, variance, skewness for each output: 120 features

• **GIST**: 
  • Prefiltering to reduce illumination variation
  • Gabor filtering (4 scales, 8 orientations)
  • 4x4 blocks, DFT
  • 4x4x32=512 features

• **Edge information**
  • Canny edge detector
  • Edge orientation histogram (EOH)
Feature: Texture

• Texture
  • LBP texture descriptor
  • Neighborhood size: 8
  • Uniform LBP patterns: 59-bin histogram feature vector

• Overall dimensionality: **1484**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Feature</th>
<th>Face-Dim</th>
<th>ROI-Dim</th>
</tr>
</thead>
<tbody>
<tr>
<td>Color</td>
<td>Moments</td>
<td>81</td>
<td>225x3</td>
</tr>
<tr>
<td>Shape</td>
<td>Gabor</td>
<td>120</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>GIST</td>
<td>512</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>EOH</td>
<td>37</td>
<td>-</td>
</tr>
<tr>
<td>Texture</td>
<td>LBP</td>
<td>59</td>
<td>-</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td><strong>809</strong></td>
<td><strong>675</strong></td>
</tr>
</tbody>
</table>
Makeup Detection Accuracy

- SVM and Adaboost classifiers were used
- SVM gave the best results

- **Train: YMU, Test: YMU**
  - Detection rate: up to 91.2% (at 1% false positive rate)

- **Train: YMU, Test: MIW**
  - Detection rates: up to 93.5% (at 1% false positive rate)

- Overall classification rates of up to 95.45% (SVM)
Makeup Detection Software

- Matlab R2009a on a 32 bit windows operating system with Intel Core i7-2600s CPU at 2.80GHz and 3.16GM RAM

- The makeup detector takes 0.78s for processing an image
Adaptive Face Recognition

- Photometric normalization + blurring operator (smoothens edge-like features induced by makeup)

- Use makeup detector to first determine if images have makeup or not

- If either image is deemed to have makeup: both images photometrically normalized by Multiscale Self Quotient Image (MSQI) technique

- Multi-Scale LBP (MSLBP) used for matching
• 5-fold cross-validation experiment
• Face verification performance (at FAR=1%), before and after applying the face preprocessing scheme (B/A)

<table>
<thead>
<tr>
<th>Trial</th>
<th>M vs N</th>
<th>Increase</th>
<th>M vs M</th>
<th>N vs N</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>56.25/65.55</td>
<td>9.30</td>
<td>92.86/92.86</td>
<td>96.43/96.43</td>
</tr>
<tr>
<td>2</td>
<td>52.75/55.64</td>
<td>2.89</td>
<td>73.44/80.47</td>
<td>87.69/87.76</td>
</tr>
<tr>
<td>3</td>
<td>48.54/54.00</td>
<td>5.46</td>
<td>83.33/83.33</td>
<td>89.29/89.29</td>
</tr>
<tr>
<td>4</td>
<td>45.55/49.23</td>
<td>3.68</td>
<td>80.00/80.00</td>
<td>92.97/95.74</td>
</tr>
<tr>
<td>5</td>
<td>54.34/56.35</td>
<td>2.01</td>
<td>88.46/88.46</td>
<td>95.73/96.15</td>
</tr>
<tr>
<td>Aggregate</td>
<td>48.88/54.10</td>
<td>5.22</td>
<td>84.70/86.05</td>
<td>92.72/92.72</td>
</tr>
</tbody>
</table>

• Application of the preprocessing routine increases the verification performance for M vs N, without impacting the accuracy of M vs M and N vs N
Observations:
- Makeup does have an impact on face recognition
- It is possible to detect facial makeup and account for it during the matching stage

Next steps:
- Quantification of degree of makeup
- Experiments involving both males and females
- Explore possibility of spoofing by makeup
- Impact of makeup on automated gender recognition and age estimation
• Observations:
  • Makeup does have an **impact** on face recognition
  • It is possible to **detect** facial makeup and **account** for it during the matching stage

• Next steps:
  • Quantification of **degree** of makeup
  • Experiments involving **both** males and females
  • Explore possibility of **spoofing** by makeup
  • Impact of makeup on automated **gender** recognition and **age** estimation
[Projects Funded by CITeR]

- A. Dantcheva, A. Ross, C. Chen, Makeup challenges automated face recognition systems, SPIE Newsroom 2013