Age Classification from Hand Vein Patterns

Yusuf Yilmaz 2009700303
Seniha Köksal 2008700195

Problem

- Automatic Age Estimation from Biological Features of Humans.
- Application Areas:
  - HCI Systems
  - Security Applications
  - Forensics
  - etc.

Our Goal

- Age Estimation from Hand Vein Patterns
- Data To Be Used:
  - Hand Vein Image Data of 30 Persons mixed gender.
  - Age classes are as follows.
    - (15-20) 5 People, (20-25) 5 People, (25-30) 5 People, (30-35) 5 People,
      (35-45) 5 People, (45+) 5 People.

Work Done So Far

- So far the following biometrics are used for age classification
  - Face
  - Speech
  - Chat Messages

Face> The First Published Work

- The main idea is to exploit
  - Craniofacial growth during childhood
  - Loosening of the skin, as we get older
- Age Groups to be classified are Baby, Young Adult and Senior Adult
- Algorithm is as follows:
  - Compute facial feature ratios.
  - Decide whether baby or not.
  - If not baby look for wrinkles on local parts of the face.
  - Decide whether young adult or senior adult.

FACE> Extracting Age Information From Local Spatially Flexible Patches [4]

- Two contribution to the age estimation problem:
  - Present a new feature descriptor for face representation. (They characterized a face image as an ensemble of spatially flexible patches, which encode the local appearance and relative position information simultaneously.)
  - Using the Gaussian Mixture Model (GMM) for characterizing the distribution of their new feature.
FACE> Extracting Age Information From Local Spatially Flexible Patches [4]

- They give a summary of the information on database size, age precision and main features used for different age estimation algorithms.
- GR: geometric relationship between different facial parts
- Wk: wrinkle features

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Faces</th>
<th>Subjects</th>
<th>Precision</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kowal [7]</td>
<td>47</td>
<td>-</td>
<td>Three groups</td>
<td>GR+Wk</td>
</tr>
<tr>
<td>Hayashi [6]</td>
<td>300</td>
<td>-</td>
<td>5y/group</td>
<td>GR+Wk</td>
</tr>
<tr>
<td>Lam/hs [8]</td>
<td>400</td>
<td>40</td>
<td>0-35y</td>
<td>Appearance</td>
</tr>
<tr>
<td>Yan [12]</td>
<td>8,000</td>
<td>1,600</td>
<td>0-93y</td>
<td>Raw Image</td>
</tr>
</tbody>
</table>

FACE> Face Age Estimation Using Patch-based Hidden Markov Model Supervectors[5]

- Authors proposed using a hidden Markov model (HMM) supervector to represent face image patches for age estimation.
- HMM outperforms patch-based Gaussian Mixture Model (GMM) approaches because of:
  - capturing the spatial structure of human faces
  - loosening the assumption of identical face patch distribution within a face image.
- Their face age (age range: 0 and 93) dataset containing two subsets:
  - 4000 images of 800 males
  - 4000 images of 800 females.

FACE> Age Estimation from Facial Aging Patterns

- Appearance Model is used for feature extraction.
- Algorithm is as follows:
  - From samples build model for aging patterns. (EM-like algorithm since highly incomplete dataset)
  - Calculate feature vector for the test input.
  - Fit it into all locations in the aging pattern model
  - Select best fit which makes reconstruction error the least.
  - Since we don’t match the test image on to each aging pattern, but also at each possible point, we already have the face image at the right place in the selected pattern.

FACE> Result of AGES Algorithm

FACE> Age Estimation with AAM and SVR

- Algorithm is as follows:
  - Feature Extraction using AAM.
  - Active Shape Models for Facial Structure and Texture Models for Skin Patches.
  - Binary classification using SVM. (Youth 0-20 years /Adult 21+)
  - Two different aging functions for youth and adults.
  - SVR with images 0-20 ages and the feature vector is used for Growth-and-Development Function.
  - SVR with images 21+ ages and the feature vector is used for Adult Aging Function.

FACE> Results of AAM with SVR
**FACE>kNN with Dimensionality Reduction**

- kNN with \( k=16 \). Mean of the 16 neighbours is used as result.
- 4 different dimensionality reduction techniques are compared.
  - PCA and LPP (standard algorithms)
  - LPP with Local Scaling (LPP-LS) – newly proposed
  - Class Distance Weighted LPP (CDLPP) – newly proposed

**Main Idea**
- Consider classes while doing dimensionality reduction.
- LPP-LS: Only samples with close class labels are assigned.
- CDLPP: Class distance is considered. Weights of two samples with close ages are larger.

**SPEECH>Age and Gender Classification for a Home-Robot Service [1]**

- They describe a method to recognize the age and gender of a user through human speech.
- They claim that by using this information, service applications for robots can meet their users need more efficiently by offering services adaptive to the special needs of specific user groups like adults and children as well as females and males.
- The Mel Frequency Cepstral coefficients (MFCCs) is used as voice source characteristics.
- Gaussian Mixture Model (GMM) technique is applied to discover the age, gender.

**SPEECH>Comparison of Speech Algorithms for Age Classification**

- Used Data:
  - SpeechDat ll: 4000 calls, native German speakers
  - SD_short: only short utterances from SpeechDat ll
  - SD_long: only long sentences from SpeechDat ll
  - VoiceClass: 660 native German Speakers 5-30 sec.
- Compared Systems:
  - Parallel Phoneme Recognizer (PPR) using Continuous Densities HMM (CDHMM)
  - Dynamic Bayesian Network
  - Linear Prediction Analysis
  - Gaussian Mixture Models based on Mel Frequency Cepstral Coefficients (MFCC) for separate recognition of age and gender.
  - Human

**SPEECH>Comparison Results of Speech Systems**

<table>
<thead>
<tr>
<th>System</th>
<th>SpeechDat ll</th>
<th>SD_short</th>
<th>SD_long</th>
<th>VoiceClass</th>
</tr>
</thead>
<tbody>
<tr>
<td>System A</td>
<td>54%</td>
<td>45%</td>
<td>61%</td>
<td>61%</td>
</tr>
<tr>
<td>System B</td>
<td>40%</td>
<td>35%</td>
<td>52%</td>
<td>42%</td>
</tr>
<tr>
<td>System C</td>
<td>27%</td>
<td>50%</td>
<td>26%</td>
<td>31%</td>
</tr>
<tr>
<td>System D</td>
<td>42%</td>
<td>48%</td>
<td>34%</td>
<td>45%</td>
</tr>
</tbody>
</table>

**SPEECH>Comparison of Speech Algorithms for Age Classification**

- They formulate three tests:
  - an age test: adult or child,
  - a gender test: male or female
  - an age-gender test: male-adult, female-adult, and child. (They assumed that gender characteristics are generally came up after the teenager period.)
- Results that show prediction accuracy of MFCC [1]
Chat Data> Age Detection in Chat [2]

- Presents machine learning techniques to contribute toward building an automatic recognition system of adults conversing with youths.
- They used two classifiers which are Naïve Bayes Classifier and Support Vector Machine.
- Word-based features were used: unigrams, bigrams, trigrams, character trigrams, and word meta-data features.
- They claimed that both models demonstrated that they have the capability to distinguish an author’s age group.

Their training sets and test sets

<table>
<thead>
<tr>
<th>Category</th>
<th>Training Set</th>
<th>Test Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Teen (13-18)</td>
<td>465</td>
<td>116</td>
</tr>
<tr>
<td>Teen (19-24)</td>
<td>608</td>
<td>172</td>
</tr>
<tr>
<td>Teen (25-30)</td>
<td>208</td>
<td>63</td>
</tr>
<tr>
<td>Adult (31-40)</td>
<td>236</td>
<td>30</td>
</tr>
<tr>
<td>Adult (41-50)</td>
<td>60</td>
<td>20</td>
</tr>
<tr>
<td>Adult (51+)</td>
<td>1263</td>
<td>716</td>
</tr>
</tbody>
</table>

Things To Decide

- Features
  - Categories as age range.
    - 15-20, 20-25, 25-30, 30-35, 35-45, 45+ (according to Data)
- Classifiers methodology.
- Measurements to evaluate results.

References

- [1] Age and Gender Classification for a Home—Robot Service: Hye-Jin Kim, Kyungsuk Bae, Ho-Sub Yoon
- [2] Age Detection in Chat: Jenny Tam and Craig H. Martell
- [4] Extracting Age Information From Local Spatially Flexible Patches: Shuicheng Yan, Ming Liu, and Thomas S. Huang
- [6] Age Classification from Facial Images: Young Ho Kwont, Niels da Vitoria Lobo
- [8] Automatic Age Estimation Based on Facial Aging Patterns: Xin Gen g, Zhi-Hao Zhou, Kate Smith—Miles
- [9] Class Distance Weighted Locality Preserving Projection for Automatic Age Estimation: Kazuya Ueki, Masakazu Miya, Tetsuya Ogawa and Tetsunori Kobayashi
- [10] Comparison of Four Approaches to Age and Gender Recognition for Telephone Applications: Florian Metze, Tobias Räimann, Raman Eingert, Ulozub, Felix Burkhardt, Joachim Stegmann, Christian Museler, Richard Huber, Bernt Andrassy, Josef G. Bauer, Bernhard Littel

References Cont.

Thank You.

Questions