Biometrics with Physical Exercise
Using Laser Doppler Vibrometry
Measurements of the Carotid Pulse

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Outline

• LDV Pulse Signal as A Biometric
• Issues with Physical Exercise
• Signal Acquisition Protocol
• Biometric Framework
  – Signal basics for different states
  – Approaches and performance
• Results
  – Log-normal model achieves EER < 2.8% inter-state test
  – 100% Recognition after resting for several minutes
• Conclusions
Laser Doppler Vibrometry Measurements at the Surface of the Skin
Advantages of LDV-Based Biometrics

• Remote: signal acquired at distances up to at least 15 meters
• Non-invasive: non-contact, with potential for invisible laser beam
• Hard to mimic: LDV cardiovascular signal is associated with intrinsic body activities
• Potential for broad assessment of health as well as biometric recognition
• Richly informative: LDV cardiovascular signal is complicated, encoding multiple incident and reflected waves in the individual’s arterial system
LDV Pulse Signal

- LDV Pulse Signal
  - Velocity signal
  - Sampling rate at 1000Hz
  - Aligned at the maximum velocity peak
  - 700 ms per pulse signal

- LDV Acceleration Signal
  - Derivative of the velocity signal
  - Left ventricular ejection time (LVET) is time between peaks
  - Time location of the second peak corresponds to the incisura
LDV Biometrics System

Comments:
• Separate training and testing data sets
• Performance for many different models
• Previous: different training/testing sessions
• This work: same session, different states
General Biometric Evaluation

- Waveform Decomposition with PCA
  - Intra-Session EER: 0.5%; Inter-Session EER: 22.5%
- Asymmetric Dynamic Time Warping
  - Intra-Session EER: 2.6%; Inter-Session EER: 19.3%
- Statistical Models with Informative Component Extraction
  - Exponential Distribution:
    Intra-Session EER: 3.5%; Inter-Session EER: 21.3%
  - Log-normal:
    Intra-Session EER: 1.0%; Inter-Session EER: 10.8% and 13.1%
- Biometric Fusion with Log-Normal Model of Spectrogram
  - Data Fusion with Inter-Session EER: 9.0%
  - Information Fusion with Inter-Session EER: 8.8% [SPIE, 09]
- Nonparametric Density Estimation with Informative and Stable Component Selection
  - Inter-Session EER: 8.2% [BSYM, 08]
- Two Aligned Segments with Spectrogram Based Log-Normal Model
  - Intra-Session EER: 0.5%; Inter-Session EER: 6.3% [IEEE Trans, 09]
Issues with Physical Exercise

• Physical Exercise with Changes
  – Heat rate
  – Blood pressure
  – LDV pulse signal

• Biometrics with Respect to
  – Biometric consistency during and after physical exercise
  – Recovery level and speed following exercise
  – Verification Performance
  – Recognition Performance
Signal Acquisition Protocol

• 21 Individuals
  – Age range: 19-31
  – Gender: 12 female and 9 male
  – Normal blood pressure and normal rest heart rate

• Sitting and Pedaling a Bicycle
  – Initial 3 min rest sitting
  – Pedaling to increase heart rate
  – Heart rate is raised to 55% of the age-adjusted theoretical maximum heart rate (220 – age)
  – 1 min rest to reduce heart rate
  – Repeat pedaling and resting cycle 8 times
  – Finally 5 min rest
Definition of States

- **Rest1**: initial 3 min of resting (150 LDV pulse signals)
- **Pedmax**: 8 distinct high heart rate periods (50 LDV pulse signals)
- **Pedmin**: 8 distinct 1 min resting periods following the *pedmax* (100 LDV pulse signals)
- **Rest2**: the ending rest period of 3 minutes (150 LDV pulse signals)
Signals in Different States

- Observed Changes
  - Heart rate changes during and after exercise
  - Amplitude of main peak changes, especially for state $\text{pedmax}$
  - Time location of the incisura changes: 30 ms early in state $\text{pedmax}$ than other 3 states
Approaches for Biometric Evaluation

- Spectrogram based Log-normal Model with Informative Component Extraction
  - Large EER of inter-state test
  - Intra-individual variability associated with Informative components
- Resampling LDV Pulse Signal
  - Short-term variability due to heart rate change
  - Resampling with LVET
- Two Aligned Segments with Spectrogram based Log-normal Model
- Biometric Recognition
Spectrogram

• Time-Frequency Decomposition
  – Short time Fourier transform
  – Time shifts of 16ms with 80ms overlap
  – 96ms Hamming window applied

• Spectrogram
  – Matrix whose values are the magnitude square of the Fourier coefficients
  – Column vectors correspond to time frames
  – Row vectors correspond to frequency bins

Typical spectrogram with 32 time bins and 96 frequency bins
Comments:
- Normalization makes LDV pulse signals have constant energy.
- Multiple pulse signals can be used in testing.
- Match can be for recognition or authentication, or other.
- Matching is based on the computation of a score function.
Spectrogram Based Log-Normal Model

- Use Gaussian distribution to model the logarithm of the spectrogram
- Assume independent time-frequency bins
- Maximum likelihood (ML) estimates of the mean and variance for each bin
- Modified distance function
  \[ S_i = \sum_{l=1}^{L} [(Y(l) - M_i(l))^2 - (Y(l) - M_0(l))^2] \]
- Performance is stable in state \( \text{rest2} \) (EER varies less than 1% for each minute data)

<table>
<thead>
<tr>
<th>Testing State</th>
<th>EER of Single Test Pulse</th>
<th>EER of Averaging 4 Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{rest1} )</td>
<td>3.4%</td>
<td>1.1%</td>
</tr>
<tr>
<td>( \text{rest2} )</td>
<td>14.8%</td>
<td>11.0%</td>
</tr>
<tr>
<td>( \text{pedmin} )</td>
<td>17.3%</td>
<td>13.6%</td>
</tr>
<tr>
<td>( \text{pedmax} )</td>
<td>29.8%</td>
<td>25.1%</td>
</tr>
</tbody>
</table>
Informative Components with Variability

- **Informative Components**
  - The nominal model is the average spectrogram
  - Select components whose distance to the nominal model larger than a set $\kappa$
  - Use relative entropy as the distance measure, calculated for each component
  - Applied in high dimension spectrogram matrix to select components
  - Mean relative entropy matrix shows discriminability on average
  - Lightness indicates the information rate

- **Variability Associated with Informative Components**
  - The informative components are around the incisura
  - Short-term variability also around the incisura
  - Need to align the incisura to the maximum velocity peak
Resampling Pulse Signal

• Heart Rate Changes with Short-term Variability
  – Changes occur in Inter-Beat-Interval (IBI) and left ventricular ejection time (LVET) in different states
  – Resampling to align the incisura relative to the maximum velocity peak

• Verification with Resampled Signal
  – Training on \textit{rest1}
  – EERs of intra-state and inter-state tests decrease

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<th>EER of Single Test Pulse</th>
<th>EER of Averaging 4 Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>\textit{rest1}</td>
<td>2.6%</td>
<td>0.9%</td>
</tr>
<tr>
<td>\textit{rest2}</td>
<td>8.4%</td>
<td>4.9%</td>
</tr>
<tr>
<td>\textit{pedmin}</td>
<td>16.7%</td>
<td>12.8%</td>
</tr>
<tr>
<td>\textit{pedmax}</td>
<td>25.8%</td>
<td>21.5%</td>
</tr>
</tbody>
</table>
Two Separate Aligned Segments Model

- Align two segment to the maximum velocity peak and the incisura separately
- 368 ms for each signal
- Spectrogram based log-normal model applied
- Averaging scores of two models
- Intra-state EER 0.3%
- Inter-state EER 2.8%
Recognition Performance

The M-ary hypothesis test is applied

\[ C_i = \arg \max_m L(x_1, x_2, \ldots, x_N \mid \lambda_m) \]

- The test data \( x_1, \ldots, x_N \)
- \( C_i \) is the classification index for the data from subject \( i \)
- \( \lambda_m \) is the model for individual \( m \)
- A correct classification result in \( C_i = i \)
- Two separated segments model applied to calculate the score function

<table>
<thead>
<tr>
<th>Testing State</th>
<th>Number of correctly Recognized</th>
<th>performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>rest1</td>
<td>21/21</td>
<td>100%</td>
</tr>
<tr>
<td>rest2</td>
<td>21/21</td>
<td>100%</td>
</tr>
<tr>
<td>pedmin</td>
<td>19/21</td>
<td>90.5%</td>
</tr>
<tr>
<td>pedmax</td>
<td>13/21</td>
<td>61.9%</td>
</tr>
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</table>
Conclusions

• A Strong Emerging Biometric Marker
  – High verification accuracy for intra-session/intra-state tests
  – Competitive performance for inter-session/inter-state tests
  – Variability during physical exercise
  – Biometric consistency after exercise
  – Signal recovers within minutes
Acknowledgments

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