ECE 598HH: Advanced Wireless Networks and Sensing Systems

Lecture 14: Wireless Sensing Part 3
Haitham Hassanieh

*Slides Courtesy of Mingmin Zhao*
<table>
<thead>
<tr>
<th>Previous Lectures</th>
<th>This Lecture</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>WiVi</strong>: Sensing humans through walls with WiFi</td>
<td><strong>EQ-Radio</strong>: Detecting emotions from wireless signals</td>
</tr>
<tr>
<td><strong>WiTrack</strong>: Accurately Localizing humans through walls</td>
<td><strong>RF-Sleep</strong>: Detecting sleep stages from wireless signals</td>
</tr>
<tr>
<td><strong>RF-Capture</strong>: Capturing human figure through walls</td>
<td></td>
</tr>
<tr>
<td><strong>Vital Ratio</strong>: Extracting vital signs (Breathing rate and heart rate)</td>
<td></td>
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</tbody>
</table>
Can you tell people’s emotions even if they don’t show up on their faces?

Smart Homes that adapt to our mood

Did I get the Job? .... No

Does my advisor like my work?

Combating Depression

Is the date going well!
Existing approaches measure **vital signs**

- Use ECG to get very accurate heartbeats
Use wireless reflections off the human body
Use wireless reflections off the human body
Wireless device

Solution: Use the phase of the wireless reflection

Wireless wave has a phase:
- Chest Motion changes distance
- Heartbeats also change distance

\[ \phi = 2\pi \frac{\text{distance}}{\text{wavelength}} \]
Emotion recognition using wireless signals
Key challenge: Inter-Beat Interval (IBI)

- Emotion recognition needs accurate measurements of the length of every single heartbeat

We need to extract IBI with accuracy over 99%
Input signal

Wireless reflection of the human body
Inhale
Exhale
Heartbeats

Our signal:

ECG signal:

Input signal
Step 1: Remove breathing signal

- Breathing masks heartbeats
- We use acceleration filter
  - Heartbeat involves rapid contraction of muscle
  - Breathing is slow and steady
Heartbeat signal

- Output of acceleration filter

- ECG signal
Heartbeat signal

- Other typical examples:

How to segment the signal into individual heartbeats?
Step 2: Heartbeat segmentation

- **Intuition**: heartbeat repeats with certain shape (template)

- If we can somehow discover the template, then we can segment into individual heartbeats
Step 2: Heartbeat segmentation

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- **Intuition**: heartbeat repeats with certain shape (template)

Random template:

Segmentation Update

Template Update
Caveat: Shrinking & Expanding

- IBI are not always the same

- Template subject to shrink and expanding
  - Linear warping
Algorithm

Need to recover both segmentation and template

- Joint optimization:
  \[ \min_{S, \mu} \sum_{s_i \in S} \| s_i - \omega(\mu, |s_i|) \|^2 \]

Segmentation Update
\[ S^{l+1} = \arg \min_S \sum_{s_i \in S} \| s_i - \omega(\mu^l, |s_i|) \|^2 \]
(dynamic programming)

Template Update
\[ \mu^{l+1} = \arg \min_{\mu} \sum_{s_i \in S^{l+1}} \| s_i - \omega(\mu, |s_i|) \|^2 \]
(weighted least squares)
Algorithm

Need to recover both segmentation and template

• Joint optimization:

$$\min_{S, \mu} \sum_{s_i \in S} \| s_i - \omega(\mu, |s_i|) \|^2$$

Segmentation Update

$$S^{l+1} = \arg \min_S \sum_{s_i \in S} \| s_i - \omega(\mu^l, |s_i|) \|^2$$
(dynamic programming)

Template Update

$$\mu^{l+1} = \arg \min_{\mu} \sum_{s_i \in S^{l+1}} \| s_i - \omega(\mu, |s_i|) \|^2$$
(weighted least squares)
Example run
Example run

Iteration 1:

<table>
<thead>
<tr>
<th>Template</th>
<th>Segmentation</th>
</tr>
</thead>
</table>

---

[Graphic showing segmentation of a signal with dotted lines indicating segments]
Example run

Iteration 2:

<table>
<thead>
<tr>
<th>Template</th>
<th>Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="example.png" alt="Template Image" /></td>
<td><img src="example.png" alt="Segmentation Graph" /></td>
</tr>
</tbody>
</table>
Example run

Iteration 2:

<table>
<thead>
<tr>
<th>Template</th>
<th>Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Template Image" /></td>
<td><img src="image2.png" alt="Segmentation Image" /></td>
</tr>
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</table>
Example run

Iteration 3:

<table>
<thead>
<tr>
<th>Template</th>
</tr>
</thead>
<tbody>
<tr>
<td>![Template Image]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>![Segmentation Image]</td>
</tr>
</tbody>
</table>
Example run

Iteration 3:

<table>
<thead>
<tr>
<th>Template</th>
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<tbody>
<tr>
<td>![Template Image]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>![Segmentation Graph]</td>
</tr>
</tbody>
</table>
Example run

Iteration 7:

<table>
<thead>
<tr>
<th>Template</th>
<th>Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Template Graph" /></td>
<td><img src="image2" alt="Segmentation Graph" /></td>
</tr>
</tbody>
</table>
Example run

Iteration 7:

<table>
<thead>
<tr>
<th>Template</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Template Graph" /></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Segmentation Graph" /></td>
</tr>
</tbody>
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ECG

![ECG Graph](image)
From vital signs to emotions
Physiological Features for Emotion Recognition

• 37 Features similar to ECG-based methods
  • Variability of IBI
  • Irregularity of breathing
Emotion Classification

- Recognize emotion using physiological features
- Used L1-SVM classifier
  - select features and train classifier at the same time
Emotion Model

- Standard 2D emotion model
- Classify into anger, sadness, pleasure and joy
Does it detect emotion accurately?

- Anger
- Joy
- Sadness
- Pleasure

- High Excitement
- Low Excitement

- Positivity
- Negativity
Person-dependent Classification

- Train and test on the same person

Accuracy: 92.5%
Person-independent Classification

- Train and test on the different person

Accuracy: 72.3%
Comparison with ECG-based system

<table>
<thead>
<tr>
<th>Task</th>
<th>Classification Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Person-dependent</td>
<td>87 (EQ-Radio) 88.2 (ECG-based system)</td>
</tr>
<tr>
<td>Person-independent</td>
<td>72.3 (EQ-Radio) 73.2 (ECG-based system)</td>
</tr>
</tbody>
</table>
Comparison with Image-based system

![Bar chart showing comparison between EQ-Radio (person-independent) and Microsoft Emotion API.](chart)

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Classification Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joy/Pleasure</td>
<td>82</td>
</tr>
<tr>
<td>Sadness</td>
<td>47</td>
</tr>
<tr>
<td>Anger</td>
<td>73</td>
</tr>
<tr>
<td>Neutral</td>
<td>11</td>
</tr>
<tr>
<td>Neutral</td>
<td>75</td>
</tr>
<tr>
<td>Neutral</td>
<td>2</td>
</tr>
<tr>
<td>Neutral</td>
<td>81</td>
</tr>
<tr>
<td>Neutral</td>
<td>98</td>
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</table>
Learning Sleep Stages from Radio Signals
Background
Awake
REM
Light
Deep

Time
Understanding Diseases with Sleep Stages

Sleep Disorders

Depression

Parkinson's Disease

Alzheimer's Disease
But, monitoring sleep stages is difficult ... done in hospital with many electrodes on the body
Can we do it in bedroom without any electrodes?
RF-Based Sleep Staging

New Model
Awake
REM
Light
Deep
Time
RF signals reflect off body and change with physiological signals

Our objective: High accuracy on par with sleep lab, but in one’s bedroom and without electrodes on the body
Key Challenge

RF reflections are highly dependent on the measurement conditions and the individuals.
Need to remove such extraneous information!
Multi-Source Domain Adaptation

domain = measurement condition + individual
Multi-Source Domain Adaptation

domain = measurement condition + individual
**Problem:** Discriminator removes both extraneous and useful information

\[
V(E, F, D) = \mathcal{L}_f(F; E) - \lambda \cdot \mathcal{L}_d(D; E)
\]

- Value function of three-player game:

**Input:** \( x \)

**Encoder:** \( E \)

\( E(x) \)

**Predictor:** \( F \)

Stage prediction

**Discriminator:** \( D \)

Discriminative domain information to be removed

Domain prediction
Conditional Adversary

- **Input** $\mathbf{x}$
- **Encoder** $E$
  - $E(\mathbf{x})$
- **Predictor** $F$
  - Stage prediction
- **Discriminator** $D$
  - Domain prediction
- $P_y(\cdot | \mathbf{x})$
Role of Adversary

Independence

Conditional-Independence

Input $x$

Encoder $E$

$E(x)$

Predictor $F$

stage prediction

Discriminator $D$

domain prediction

$P_y(\cdot|x)$
Does it work?

input $\mathbf{x}$

Encoder $E$

$E(\mathbf{x})$

Predictor $F$

stage prediction

Discriminator $D$

$P_y(\cdot | \mathbf{x})$

domain prediction

Solution: Condition Discriminator on predicted label distribution

Posterior not available when training!
It Works

**Theorem** (informal): Given enough capacity, the encoder at equilibrium discards all extraneous information specific to domains, while retaining the relevant information for the predictive task.
Evaluation

• 25 different bedrooms and 100 nights
• Ground-truth: FDA-approved EEG-based sleep profiler provides sleep stage labels
• ~90k 30-second pairs of RF measurements and corresponding sleep stages
Accuracy of sleep lab
Inter-rater agreement: 83%
Our accuracy 79.8%
(Tested on new subjects not in training, i.e., new domains)

Previous solutions: 64%

Labelling sleep stages is subjective
~83%
Representative Example    Acc = 80%

Ground-truth using EEG

RF-Sleep Prediction
Accuracy for Different Subjects (Domains)

Accuracy for Subjects 1 to 25.
Learning sleep stages from wireless signals