Fall Detection for Older Adults with Wearables

Chenyang Lu
Internet of Medical Things

- **Wearables**: wristbands, smart watches…
  - Continuous monitoring
  - Sensing: activity, heart rate, sleep, (pulse-ox, glucose…)

- **Connectivity**: Bluetooth, WiFi, cellular…
  - Real-time monitoring and intervention

- **Cloud**: scalable computing and storage.

**Continuous monitoring of patients inside and outside hospitals**
Roadmap

Goals
- Expand monitoring: ICU → General Hospital Wards → Outpatients
- Leverage machine learning to predict patient outcomes

Recent projects
- Early warning system for patients in general-hospital wards
- Predict readmissions of heart failure patients after hospital discharge.
- Wearables for health monitoring and intervention
Falls: Serious Problem!

- Falls can cause severe injury for older adults.

- **One in four** older adults has at least one fall per year\(^1\).

- **2.5 million** older adults are treated in emergency departments, and **250,000** are hospitalized, because of falls.
  - 40% of those older adults do not return to independent living.
  - 25% die within the same year.
  - Fewer than half of fallers report falls to their doctors.

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\(^1\) *US. Health, United States, 2014: with special feature on adults aged 55-64*, National Center for Health Statistics. 2015.
Fall Detection Needed

- Fall detection could reduce the likelihood of severe consequences by alerting medical services.

- No reliable fall detection system or device in use.

- Current methods of fall studies face challenges.
Challenge 1: Insufficient Fall Data for Training

- Fall detection relies on sufficient fall data to train classifiers.

- No standard open fall data set exists.

- Falls are rare events\(^2\).
  - 2.6 falls vs. 31.5 million activities of daily living (ADL).
  - Highly skewed data, making it difficult to develop generalizable classifiers.

\(^2\) The Center for Disease Control and Prevention.
Challenge 2: Inaccurate Ground Truth

- Training classifiers needs ground truth (labeled fall data).
- Fall journal (“gold standard”): error-prone.

<table>
<thead>
<tr>
<th>Data</th>
<th>Did you fall?</th>
<th>If yes, what time?</th>
</tr>
</thead>
<tbody>
<tr>
<td>12/4/2012</td>
<td>Yes</td>
<td>1) 3:45 am -- fell from bed to knees.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2) 4:15 am -- used bathroom and fell to knees.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3) 4:48 am -- fell out of bed and landed in praying position.</td>
</tr>
<tr>
<td>12/11/2012</td>
<td>Yes</td>
<td>1) 3:12 am -- Near fall, going to the bathroom and lost balance,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>but caught self on bathroom commode.</td>
</tr>
</tbody>
</table>

- Using camera: privacy concerns.
- Real-time confirmation?
Challenge 3: Using Artificial Falls

- Use artificial falls instead?
  - Artificial falls: falls simulated in controlled laboratory settings.
  - Around 94% of studies\(^3\) use artificial falls to develop their detection algorithms.

- Assumption: artificial falls are representative of actual falls.
  - The complexity of real-world settings?
  - The variety in the causes of falls?

Are artificial falls representative of actual falls?

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Contributions

- Clinical study on community-dwelling older adults.

- Analysis of real-world fall data of older adults.
  - Differences between actual falls and artificial falls.
  - Accuracy of classifiers trained on artificial falls.

- Lessons learned from clinical study.
Clinical Study

- Older adults: 65 years or older.
  - Mean age 74 years (min 69, max 82).
  - 3 male, 2 female
  - Two participants were frequent fallers

- Collaboration with the Program in Occupational Therapy at Washington University School of Medicine.

- Study started in 12/2012 and ended in 5/2015.
  - 14 days of data collection per participant.
Data Collection System

- Objective: capture longitudinal data from older adults.

- Shimmer sensor platform.
  - Local storage (micro-SD, no networking)

- Fall Journals (ground truth).

- Obtained data of 20 falls.
  - Participants reported 24 falls, 2 near falls.
  - 2 falls reported but not captured by Shimmer, because participants were on the way to the shower, or in it.
  - 2 falls data is missing, due to collection system bug.

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Artificial vs. actual falls

- Time series of Signal Magnitude Vector (SMV)

  Much smaller value change.

  Significant value change.

Study falls based on artificial ones???
Evaluating Fall Detection

Three representative approaches:
- Threshold
- Hidden Markov Model (HMM)
- AdaBoost: designed to reduce false alarms

Training and testing samples
- Training: 66 artificial falls.
- Testing: 26 artificial falls and 20 actual falls.
Evaluation Experiment

<table>
<thead>
<tr>
<th>Approach</th>
<th>Artificial falls</th>
<th>Actual falls</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Threshold-based Approach</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DR</td>
<td>88.46%</td>
<td>0</td>
</tr>
<tr>
<td>FAR</td>
<td>0</td>
<td>0.03%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Approach</th>
<th>Artificial falls</th>
<th>Actual falls</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>HMM-based Approach</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DR</td>
<td>96.15%</td>
<td>44.87%</td>
</tr>
<tr>
<td>FAR</td>
<td>1.41%</td>
<td>11.42%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Approach</th>
<th>Artificial falls</th>
<th>Actual falls</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>AdaBoost-based Approach</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DR</td>
<td>100%</td>
<td>23.08%</td>
</tr>
<tr>
<td>FAR</td>
<td>0.38%</td>
<td>25.19%</td>
</tr>
</tbody>
</table>

Actual falls do not necessarily induce significant signal changes.

HMM trained using artificial falls fails to capture actual falls.

AdaBoost fails to reduce false alarms on real-world data.
Accommodating Timing Inaccuracy

- Fall time recorded in a fall journal may not be precise.

- Unnecessary or unrealistic to report multiple falls within a short time.

- Alarm suppression
  - True Positive (TP): If a window contains a reported fall, a fall alarm at any time within this window is considered a correct detection.
  - False Alarm (FA): If a window does not include a reported fall, at most one false alarm can be raised within this window.
## Accuracy after Alarm Suppression

<table>
<thead>
<tr>
<th>Window size (minutes)</th>
<th>Threshold</th>
<th>HMM</th>
<th>AdaBoost</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DR</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>38.33%</td>
<td>76.92%</td>
<td>35.90%</td>
</tr>
<tr>
<td>20</td>
<td>43.33%</td>
<td>76.92%</td>
<td>39.74%</td>
</tr>
<tr>
<td>30</td>
<td>58.97%</td>
<td>84.62%</td>
<td>43.59%</td>
</tr>
<tr>
<td><strong>False alarms per hour</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.73</td>
<td>2.96</td>
<td>2.05</td>
</tr>
<tr>
<td>20</td>
<td>0.60</td>
<td>1.74</td>
<td>1.14</td>
</tr>
<tr>
<td>30</td>
<td>0.50</td>
<td>1.25</td>
<td>0.77</td>
</tr>
</tbody>
</table>
Lessons Learned

- Co-design annotation methods and fall detection.
  - Data must be annotated with ground truth in real-time.

- Visibility is key.
  - Remote communication with sensors.
  - Visibility into the logs, and inspecting the system.

- Avoid limitations when selecting sensor hardware.
  - ON/OFF switch, accurate wall-clock.

- Plan larger studies.
Conclusion

Contributions
- Clinical study on community-dwelling older adults.
- Artificial falls of younger adults vs. actual falls of older adults.
- Evaluation of three representative approaches.

Insights
- Artificial falls are not representative of actual falls.
- Fall detection algorithms trained with artificial falls suffer significant performance degradation under actual falls.
- Importance of accurate ground truth and more fall data
Next: Smart Watches

- **Open, programmable platform**
  - Android Wear, Apple Research Kit
  - Tailored onboard analytics
  - Shorter Latency

- **Two-way Communication**
  - Push ecological momentary assessments

- **Raw Data**
  - Accelerometer, gyroscope, magnetometer, Heart Rate, GPS...

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Overcome the Challenges?

- Co-design annotation methods and fall detection.
  - Data must be annotated with ground truth in real-time.

- Visibility is key.
  - Remote communication with sensors.
  - Visibility into the logs, and inspecting the system.

- Avoid limitations when selecting sensor hardware.
  - ON/OFF switch, accurate wall-clock.

- Plan larger studies.
Example: Timed Up And Go @ Home

- Remind participants to take the assessment
- Automatically upload the data to the cloud for analysis
- Analyze gait and motion features
- Real-time analytics → feedback to physicians and participants