Wearable Sensor Data and Medical Records for Clinical Outcome Prediction

Gina Sprint, CS PhD Student
Washington State University
October 14th, 2015
Wearables for Rehabilitation

- Why technology for rehabilitation?
  - Fine-grained, objective data

- Why wearable sensors?
  - Portable, inexpensive, unobtrusive

- Why ecological environments?
  - More representative of abilities
  - Resembles discharge environment
Ambulation Circuit (AC)

Chair Transitions

Linear Rug Walking (2.6 m)

Linear Smooth Surface Walking (6 m)

Shag Rug

Arm Chair

Man Hole Cover

Vehicle Transfer

Vehicle

Curvilinear Smooth Surface Walking (~6.7 m)
AC Study Participants

- N=20 (M=14, F=6)
- 71.55 ± 10.62 years of age
- Stroke, brain injury, debility, cardiac, etc.
- 2 Testing sessions
  - 1 Week apart
Functional Independence Measure (FIM)
  - Measured at admission and discharge
  - 13 Motor tasks
    - Transfers
    - Locomotion
  - 5 Cognitive tasks

Utilize additional patient medical records (N=4936) for training (NAC dataset)

<table>
<thead>
<tr>
<th>Task Type</th>
<th>#</th>
<th>Task</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor</td>
<td>1</td>
<td>Eating</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Grooming</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Bathing</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Upper body dressing</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>Lower body dressing</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>Toileting</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>Bladder management</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Bowel management</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>Bed to chair transfer</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>Toilet transfer</td>
</tr>
<tr>
<td></td>
<td>11</td>
<td>Shower transfer</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>Locomotion (ambulatory or wheelchair level)</td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>Stairs</td>
</tr>
<tr>
<td>Cognitive</td>
<td>14</td>
<td>Cognitive comprehension</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>Expression</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>Social interaction</td>
</tr>
<tr>
<td></td>
<td>17</td>
<td>Problem solving</td>
</tr>
<tr>
<td></td>
<td>18</td>
<td>Memory</td>
</tr>
</tbody>
</table>
Medical Record Features

- Patient characteristics
  - Age
  - Gender
  - Rehabilitation impairment category (RIC)
  - Comorbidity tier
  - Case mix group (accounts for medical complications)

- Admission Functional Independence Measure (FIM)
  - Individual tasks
  - Motor aggregate score
  - Cognitive aggregate score
AC Features

- **Gait**
  - Velocity, cadence, timing, symmetry, smoothness, double support percent, etc.
  - Variability

- **Chair transfer**
  - Root mean square (RMS) duration, range of motion, etc.

- **Vehicle transfer**
  - RMS, duration, peak angular velocity, etc.

[Faruqui, 2010]
AC Change Features

- Percent change
  \[ x_{\Delta \%} = \frac{x_{S2} - x_{S1}}{x_{S1}} \]

- Standardized mean difference effect size for repeated measures
  \[ d_{RM} = \frac{\bar{X}_{post} - \bar{X}_{pre}}{S_D} \] [Viechtbauer, 2007]

  \[ d_{RM} \pm CS \times \hat{\sigma}_d^2 (L1), \hat{\sigma}_d^2 (L1) = \sqrt{\frac{2(1-\hat{\rho})}{n} + \frac{d_{RM}^2}{2(n-1)}} \]
  [Wolff Smith and Beretvas, 2009]
Supervised Models

- Train prediction models $M_1$ (admission), $M_2$ (AC S1), and $M_3$ (AC S2)
- Linear SVM, linear regression, random forest w/100 trees
- Evaluation
  - Mean absolute error (MAE), root mean squared error (RMSE), normalized RMSE, and correlations
Model Approaches

- Cumulative model construction
- Separate model construction
## Discharge FIM Motor Prediction

<table>
<thead>
<tr>
<th>Model</th>
<th>Linear SVM</th>
<th>Linear Regression</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>NRMSE</td>
<td>r</td>
</tr>
<tr>
<td>$M_1$</td>
<td>$M_1$ (w/o NAC)</td>
<td>4.66</td>
<td>11.65%</td>
</tr>
<tr>
<td></td>
<td>$M_1$</td>
<td>7.36</td>
<td>18.41%</td>
</tr>
</tbody>
</table>

### Separate

<table>
<thead>
<tr>
<th>Model</th>
<th>Linear SVM</th>
<th>Linear Regression</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>NRMSE</td>
<td>r</td>
</tr>
<tr>
<td>$M_2$</td>
<td>8.55</td>
<td>21.38%</td>
<td>0.60*</td>
</tr>
<tr>
<td>$M_3$</td>
<td>5.54</td>
<td>13.86%</td>
<td>0.85**</td>
</tr>
<tr>
<td>$M_{avg}$</td>
<td>5.54</td>
<td>13.86%</td>
<td>0.87**</td>
</tr>
<tr>
<td>$M_E$</td>
<td>5.50</td>
<td>13.74%</td>
<td>0.84**</td>
</tr>
</tbody>
</table>

### Cumulative

<table>
<thead>
<tr>
<th>Model</th>
<th>Linear SVM</th>
<th>Linear Regression</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>NRMSE</td>
<td>r</td>
</tr>
<tr>
<td>$M_2$</td>
<td>5.49</td>
<td>13.71%</td>
<td>0.85**</td>
</tr>
<tr>
<td>$M_3$</td>
<td>2.32</td>
<td>5.80%</td>
<td>0.97***†</td>
</tr>
<tr>
<td>$M_{avg}$</td>
<td>4.00</td>
<td>10.01%</td>
<td>0.94***†</td>
</tr>
<tr>
<td>$M_E$</td>
<td>3.41</td>
<td>8.53%</td>
<td>0.95***†</td>
</tr>
</tbody>
</table>

avg = average, $E$ = ensemble, $M$ = model, NAC = non-ambulatory circuit, NRMSE = normalized root mean square error, $r$ = Pearson correlation coefficient, RMSE = root mean square error, SVM = support vector machine, * = $p < 0.05$, ** = $p < 0.01$, † = significantly ($p < 0.05$) improved results from $M_1$. 

---

**ANITA BORG INSTITUTE**

**GRACE HOPPER**

**CELEBRATION OF WOMEN IN COMPUTING**

**2015**

**Association for Computing Machinery**
## Discharge FIM Cognitive Prediction

<table>
<thead>
<tr>
<th>Model</th>
<th>Linear SVM</th>
<th>Linear Regression</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>NRMSE</td>
<td>r</td>
</tr>
<tr>
<td>M₁</td>
<td>2.34 20.19%</td>
<td>0.73**</td>
<td>2.56 21.30%</td>
</tr>
<tr>
<td></td>
<td>2.42 20.19%</td>
<td>0.70**</td>
<td>2.50 20.86%</td>
</tr>
<tr>
<td>M₁ (w/o NAC)</td>
<td>2.42 20.19%</td>
<td>0.70**</td>
<td>2.50 20.86%</td>
</tr>
</tbody>
</table>

### Separate

<table>
<thead>
<tr>
<th>Model</th>
<th>Linear SVM</th>
<th>Linear Regression</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>M₂</td>
<td>3.10 25.82%</td>
<td>0.51*</td>
<td>5.50 45.81%</td>
</tr>
<tr>
<td>M₃</td>
<td>3.74 31.17%</td>
<td>-0.34</td>
<td>3.61 30.11%</td>
</tr>
<tr>
<td>M₅</td>
<td>2.56 21.36%</td>
<td>0.68**</td>
<td>3.06 25.52%</td>
</tr>
<tr>
<td>M₆</td>
<td>2.66 22.14%</td>
<td>0.64**</td>
<td>3.09 25.77%</td>
</tr>
</tbody>
</table>

### Cumulative

<table>
<thead>
<tr>
<th>Model</th>
<th>Linear SVM</th>
<th>Linear Regression</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>M₂</td>
<td>3.44 28.69%</td>
<td>0.19</td>
<td>3.13 26.08%</td>
</tr>
<tr>
<td>M₃</td>
<td>2.42 20.19%</td>
<td>0.70**</td>
<td>2.50 20.86%</td>
</tr>
<tr>
<td>M₅</td>
<td>2.40 20.01%</td>
<td>0.73**</td>
<td>2.32 19.34%</td>
</tr>
<tr>
<td>M₆</td>
<td>2.71 22.59%</td>
<td>0.59*</td>
<td>1.48 12.36%</td>
</tr>
</tbody>
</table>

avg = average, E = ensemble, M = model, NAC = non-ambulatory circuit, NRMSE = normalized root mean square error, r = Pearson correlation coefficient, RMSE = root mean square error, SVM = support vector machine, * = p < 0.05, ** = p < 0.01, † = significantly (p < 0.05) improved results from M₁.
Individual FIM Tasks

All Tasks: Cumulative

Correlation

Task

Eating
Grooming
Bathing
Dressing Upper
Dressing Lower
Toileting
Bladder
Bowel
Bed-Chair Transfer
Toilet Transfer
Tub-Shower Transfer
Walk-Wheelchair
Stairs
Comprehension
Expression
Social Interaction
Problem Solving
Memory

$M_1$
$M_2$
$M_3$
Individual Patient Prediction

010 MAE: Cumulative

015 MAE: Cumulative

FIM Task

(a)

(b)
Clinical Utility of FIM Predictions

- 7 Physical therapists interviewed
- 7/7 are interested in using wearable technologies for their patients
- 6/7 said they would make use of FIM predictions for patients mid-stay
  - “It would be very useful, it could help with discharge planning if we needed to steer one way or another.”
What’s Next?

- Increase sample size
  - Enough participants → condition-specific models
  - Investigate the effects of comorbidities
- Mobile app!
  - Online collection, processing, and prediction
- Advanced machine learning techniques
- Adding sensor-based cognitive features
Thank You!

- Questions?
- Connect with me
  - Gina Sprint
  - Computer Science PhD Student
  - Washington State University
  - gsprint@eecs.wsu.edu
  - www.eecs.wsu.edu/~gsprint
- Related publications
Got Feedback?

★ Rate and Review the session using the GHC Mobile App

To download visit www.gracehopper.org