Where Communication Meets Healthcare

Wade Trappe
trappe@winlab.rutgers.edu
Why is a Wireless Center Talking About Healthcare?

- Communications is essential to health at many levels:
  - Individual patient data is needed for managed care
  - Realtime multimodal and multipatient data is needed for smart health
  - Lifestyle management will play an increasing role in addressing diseases
  - Many diseases are the result of breakdown in biological communication pathways

- Smart Health needs 5G:
  - The patient will be mobile!
    - Preventative and sustained, personalized care
    - It will take a village: there is knowledge in the village!
    - Deep learning will lead to better predictions and recommendations
  - The communication fabric will be the infrastructure across which data will be delivered to the cloud and deep analytics!

- The patient needs better communications analysis
  - There are networks and communication pathways within the patient
  - Communication tools will be valuable to gaining new knowledge that complements current medical research
WHAT DO YOU THINK OF WHEN YOU HEAR “INTERNET OF MEDICAL THINGS”?
Fitbit
Zeo – sleep manager

Sunday, January 15, 2012
Total Sleep 8:18  ZQ 90

Wake 0:07  (1%)
REM Sleep 3:10  (37%)
Light Sleep 4:25  (54%)
Deep Sleep 0:43  (8%)

Monday, January 23, 2012
Total Sleep 4:38  ZQ 47

Wake 0:14  (4%)
REM Sleep 1:17  (26%)
Light Sleep 2:52  (60%)
Deep Sleep 0:30  (10%)
Medical Robots and Assisted Surgery
Smartphone, laptop, tablet
Low-end devices: RFID tags, small sensors ...
The IoMT and Smarth Health is really about "DATA"

- Smart healthcare is about the DATA and closing the loop!!!
  Many communications challenges: latency, ubiquity and volume!

Needs…

And…
WINLAB has collaborated with industry to develop medical sensing, inference, and active monitoring technologies.

**Sensing Layer**
- **PHYSICAL SENSORS**
  - <bodytemp: 98.6°F>
  - <bloodpressure: high>
  - <insulin: bad>
  - <hydration: low>
  - <Tcell Assay: CD8+, CD4+>
  - <other: location, voice, etc...>

- **EXTERNAL EVENTS**
  - <weather>
  - <schedule>

- **SOCIAL FEEDS**
  - <family events>

- **WIRELESS LINK SIGNAL**
  - <signal: strength>

**Inference Layer**

**Physical**
- Passive Location/mobility Inference
  - Location: kitchen
  - Speed: 1m/s
  - Activity: eating

**Social**
- Passive Socialization Inference
  - Activity: talking to 3 people
  - Duration: 15 minutes
  - Last time left house: 2 hours ago

**Cognitive**
- Passive Cognitive Level Inference
  - Location: leaving kitchen
  - Stove: on

**Feature/Context Inferences**

**Behavioral/Correlation Inferences**
- Average walking speed? Any recent degradation?
  - Does indoor atmosphere impact her balance?
  - Any leading indicators before she falls?
  - How is hydration correlated with historical data?
  - Does blood analysis suggest increasing diabetic risk?

- Average socialization level?
  - Any recent degradation?
  - Social/not social compared to peers?
  - What factors affect her social interaction?

- How often does she forget? Taken pills lately?
  - Any recent degradation?
  - Does she forget more than peers?
  - What causes her to forget more?

**Assessment**

- Degradation alerts:
  - Walked slower by 30% yesterday!
  - Talked less by 80% last week!
  - Forgot to take her pills last 3 days!

- Causal alerts:
  - Low air pressure + slow paced walk → high fall likelihood
  - Alone in Holiday → social withdrawal
  - Glucose levels → diabetic shock

- Emergency alerts:
  - Still in shower after 1 hour!!!
Three levels to look for today

**Top Down View**

- **Data Analytics:** Learning and AI
- **Sensors and Data:** Collect and Deliver
- **The Patient:** Fixing Pathways

**Near Horizon:** Immediate Impact

**Far Horizon:** Long Term Impact
Today’s Highlights

- Anand Sarwate, “Collaborative Learning on Private Data: Opportunities in Healthcare Research and Practice”

- Keynote: Dorin Comaniciu, Siemens Medical Solutions, “Shaping the Future through Innovations: Artificial Intelligence for Healthcare”

Today’s Highlights

• Yingying Chen, “Unobtrusive Wellbeing Monitoring and Personalized Fitness Assistance”

• Rich Martin, “Monitoring Laboratory Animals using Wireless Ammonia Sensors”

• Zhenhua Jia, “Monitoring a Person’s Heart Rate and Respiratory Rate on a Shared Bed Using Geophones”
Today’s Highlights

- Laleh Najafizeh, “Brain Function: A Network Perspective”
- Poster Session
Resource Management and Bargaining in Pharmaceutical Dosing

- Pharmaceutical agents are characterized by therapeutic and harmful effects
  - Dilemma how to appropriately tradeoff between “good” and “bad”
  - Traditional pharmacology: population studies to determine population effective and tolerable dosages

- Possible to apply resource management as a framework to address this problem:
  - Analytical dose-response relationships (e.g. Langmuir, Michaelis-Menton)
    \[
    R(x) = \frac{a_{max} x^n}{a + x^n}
    \]
    \[
    S(x) = b_{max} - \frac{b_{max} x^n}{b + x^n}
    \]
  - Nash Bargaining Solution is unique, can be found explicitly, and maximizes the “safe treatment response”

- Framework is modular: swap out cost functions easily (e.g. maximize response while addressing production cost)

- Extension to multi-drug combinations is being explored
  - Chou-Talalay combination index for receptor-based treatments
BioMarkers: Graph Analysis of Brain Connectivity for Neurological Disorder Diagnosis

• Functional Magnetic Resonance Imaging (fMRI) has been used to characterize neural activity
  – Has been used to examine the functional organization of a diseased brain

• Regions of the brain become nodes and interactions between regions as edges in a brain connectivity network
  – Altered neural activity induced by disease pathologies → altered topological properties
  – Temporal variation of functional connectivity is further evidence of neurological disorder

• We have proposed the use of dynamic graph measures, such as the Fiedler value, as a biomarker for Parkinson’s Disease
  – Support Vector Machine classifier built upon graph measures accurately differentiated PD patients from Healthy Control (HC)

<table>
<thead>
<tr>
<th>Graph Measures</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Characteristic path length</td>
<td>59.1%</td>
<td>66.7%</td>
<td>50.0%</td>
</tr>
<tr>
<td>Global efficiency</td>
<td>59.1%</td>
<td>91.7%</td>
<td>20.0%</td>
</tr>
<tr>
<td>Clustering coefficient</td>
<td>54.5%</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>Transitivity</td>
<td>77.3%</td>
<td>91.7%</td>
<td>60.0%</td>
</tr>
<tr>
<td>Modularity</td>
<td>68.2%</td>
<td>83.3%</td>
<td>50.0%</td>
</tr>
<tr>
<td>Assortativity</td>
<td>63.6%</td>
<td>66.7%</td>
<td>60.0%</td>
</tr>
<tr>
<td>Edge density</td>
<td>68.2%</td>
<td>91.7%</td>
<td>40.0%</td>
</tr>
<tr>
<td>Fiedler value</td>
<td>72.7%</td>
<td>75.0%</td>
<td>70.0%</td>
</tr>
<tr>
<td>Synchronizability</td>
<td>68.2%</td>
<td>83.3%</td>
<td>50.0%</td>
</tr>
<tr>
<td>Transitivity + Fiedler value</td>
<td>86.4%</td>
<td>91.7%</td>
<td>80.0%</td>
</tr>
</tbody>
</table>

This work in collaboration with Z. Jane Wang and M. McKeown, University of British Columbia