Automated Assessment of Naturally Occurring Conversations

AutoSense respiration sensor on the body

Respiration signals captured by AutoSense

Conversation Status

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NATIONAL INSTITUTES OF HEALTH

NSF
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- Kenzie Preston, NIDA (PI for Drug User Field Study)
- Annie Umbricht, Johns Hopkins (PI for Residential Drug User Study)
AutoSense Wearable Sensor Suite

Ten wireless sensors in two wearable units

Used in 3 studies (n=60) for automated modeling of stress, conversation

Long lifetime (10+ days)

Being used in 4 ongoing studies (n=85, 1-4 weeks of field wearing) for automated modeling of smoking, drinking, drug usage, and craving

(Ertin, et. al., ACM SenSys 2011)
AutoSense in Action

Sony X8

Sensor pairing with phone via UI

Lab session administration via customizable UI

Self-report items and trigger mechanisms are customizable
Monitoring and Improving Compliance

Sensor Connection Status

Review Data Quality & Quantity

Live signal visualization

Select a sensor
- Respiration
- GSR on RPECG mote
- Chestband Accelerometer X value
- Chestband Accelerometer Y value
- Chestband Accelerometer Z value
- Alcohol Consumption

Interview break from 03/22/12
04:07 pm until 03/22/12 05:07 pm

Data collection ends at 03/22/12
11:30 pm, begins again at 03/23/12
10:08 am

So far, you've earned:
$16.25

Field Report Page

Field Study Starts from:
Mar 19, 2012 4:23 PM

Change Start Date  Change Start Time

Back  Save
Stress Modeling with AutoSense

- We conducted a study with a validated stress protocol
  - 21 participants, 2 hour lab study,
    - Public speaking – psychosocial stress
    - Mental arithmetic – mental load
    - Cold pressor – physical stress
  - 2 day field study
    - 10-14 hours in the field (20 self-reports per day)

- Developed two new self-calibrating stress models
  - Physiological stress model (binary: stressed or not)
    - To measure adverse physiological effects of stress
  - Perceived Stress Model (continuous rating)
    - To measure perception of stress in mind as accumulation & decay process
    - Predict self-reported stress rating (Plarre, et. al., ACM IPSN 2011)
Identified 22 Features from Respiration

Basic Features
- Inhalation Duration
- Exhalation Duration
- Respiration Duration
- Insp./Exp. Ratio
- Stretch
- Breathing Rate
- Minute Ventilation

Statistical Features
- Mean
- Median
- 80th Percentile
- Quartile Deviation
Computed 13 Features from ECG

**Basic Features**
- RR Intervals
- RSA

**Statistical Features**
- Variance
- Power in low/medium/high frequency bands
- Ratio of low frequency/high power
- Mean
- Median
- 80th Percentile
- Quartile Deviation
Evaluation of the Physiological Stress Model on Lab Data

<table>
<thead>
<tr>
<th>Stressors</th>
<th>All</th>
<th>Instruction</th>
<th>Speaking</th>
<th>Mental Arithmetic (Standing)</th>
<th>Mental Arithmetic (Seated)</th>
<th>Cold Pressor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classification Accuracy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Selected(S)</td>
<td>S A R E</td>
<td></td>
<td>S A</td>
<td>S A R E</td>
<td>S A R E</td>
<td>S A R E</td>
</tr>
<tr>
<td>All(A)</td>
<td>S A</td>
<td>S A</td>
<td>S A</td>
<td>S A R E</td>
<td>S A R E</td>
<td>S A R E</td>
</tr>
<tr>
<td>RIP(R)</td>
<td>R E</td>
<td></td>
<td>R E</td>
<td>R E</td>
<td>R E</td>
<td>R E</td>
</tr>
<tr>
<td>ECG(E)</td>
<td>E</td>
<td>E</td>
<td>E</td>
<td>E</td>
<td>E</td>
<td>E</td>
</tr>
</tbody>
</table>

Overall Prediction Accuracy = 90%
Evaluation of the Perceived Stress Model

Lab Session

Median Correlation = 0.72
n=21

Field Session (2 days)

PDF(ρ)

Perceived Stress (from the model)

Self-reported Stress

R=0.71
Detecting Smoking from Respiration

- **Smoking:** 161 puffs from 10 daily smokers
  - Conversation, stress, running data for confounding events
- **Evaluation:** Each puff detected by
  - Supervised SVM with 84.5% accuracy
  - Semi-supervised SVM with 86.7% accuracy
- **Research:** Need to develop models for detecting entire smoking episodes reliably

(Ali, et. al., ACM IPSN, 2012)

11 Santosh Kumar, University of Memphis 4/12/2012
Measurement of Social Health

- Social health assessment has a variety of uses
  - Mental health screening
  - Tracking common cold
  - Potential moderator for stress, addictive behaviors, obesity
  - Conversations
    - Microphone
    - Respiration measurements
  - Physical Proximity
    - Bluetooth, Wi-Fi, GPS
  - Electronic Communication
    - Emails, SMS
  - Social Network Exposure
    - Facebook, Twitter

(Rabbi, et. al., ACM UbiComp 2011) (Madan et. al., ACM UbiComp 2010)
Measurement of Conversation - Audio

- Body worn microphones are reliable
  - Examples: Sociometer, LENA
  - But, involve subject burden

- Microphone embedded in phones
  - Provide population level scalability
  - But, are prone to microphone occlusion

- Additional issues with microphone
  - Energy drain of microphone sensor
    - Needs high sampling (at 8 KHz) and data processing
  - Privacy concerns due to audio capture
  - May lack speaker specificity
Measurement of Conversation - Respiration

- Respiration measure provides
  - Speaker specificity
  - Privacy preservation
  - Integrated assessment of stress & addictive behavior

Confusion Matrix

<table>
<thead>
<tr>
<th></th>
<th>Quiet</th>
<th>Listening</th>
<th>Speaking</th>
<th>Classified as</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Quiet</strong></td>
<td>0.9005</td>
<td>0.0706</td>
<td>0.0353</td>
<td><strong>Quiet</strong></td>
</tr>
<tr>
<td><strong>Listening</strong></td>
<td>0.1207</td>
<td>0.8275</td>
<td>0.0517</td>
<td><strong>Listening</strong></td>
</tr>
<tr>
<td><strong>Speaking</strong></td>
<td>0.0238</td>
<td>0.0833</td>
<td>0.8929</td>
<td><strong>Speaking</strong></td>
</tr>
</tbody>
</table>

(Rahman, et. al., *ACM Wireless Health*, 2011)
In our pool of 22 participants from college students, we find that conversations are short and frequent.

- Frequency of conversations: 3 per hour
- Avg. duration of a conversation: 3.82 minutes
- Avg. Time between conversations: 13.3 minutes
Ongoing Studies with AutoSense

- **Memphis Study**
  - 40 daily smokers and social drinkers
  - One week of AutoSense wearing in the field
    - Stress, drinking, smoking, and craving for cigarettes are reported

- **National Institute on Drug Abuse (NIDA) Study**
  - 20 drug users undergoing treatment
  - Two lab sessions and 4 weeks of wearing AutoSense in the field
    - Smoking, craving, and stress events are marked in the lab
    - Craving, stress, and drug usage are reported in the field

- **Johns Hopkins Study**
  - 10 drug users in residential treatment
  - Drug self-administration sessions are marked in the lab
## Data Collection Statistics

<table>
<thead>
<tr>
<th>Item</th>
<th>Memphis Study*</th>
<th>NIDA Study+</th>
</tr>
</thead>
<tbody>
<tr>
<td># of participants completed</td>
<td>20</td>
<td>3</td>
</tr>
<tr>
<td># of person days worth of data</td>
<td>140 days</td>
<td>34 days</td>
</tr>
<tr>
<td>Amount of good quality sensor data</td>
<td>76,312 min</td>
<td>22,125 min</td>
</tr>
<tr>
<td># hours worth of data</td>
<td>1,272 hours</td>
<td>369 hours</td>
</tr>
<tr>
<td>Avg data collection per day</td>
<td>9 hours/day</td>
<td>10.8 hours/day</td>
</tr>
<tr>
<td># of EMA received</td>
<td>2145 (or 16/day)</td>
<td>253 (7.5/day)</td>
</tr>
<tr>
<td>% of EMA answered</td>
<td>94%</td>
<td>91.3%</td>
</tr>
<tr>
<td># of smoking self-report</td>
<td>953 (or 6.8/day)</td>
<td>116 (or 3.4/day)</td>
</tr>
<tr>
<td># of drinking self-report</td>
<td>101 (5.6/week)</td>
<td>---</td>
</tr>
<tr>
<td># of craving self-report</td>
<td>---</td>
<td>10</td>
</tr>
<tr>
<td># of drug used self-report</td>
<td>---</td>
<td>6</td>
</tr>
</tbody>
</table>
Conclusions

- AutoSense can be used for long-term data collection of ECG, respiration, GSR, and accelerometer in the field
  - Can obtain continuous assessment of stress level, activity level, conversation status, commuting episodes, and location
  - Can locate smoking puffs in the data stream

- Current and ongoing work
  - Provide dynamic assessment of data quality in a live stream
  - Obtain high data yield without daily meetings with subjects
  - Improve accuracy of detecting stress, smoking, and conversation
  - Automated inference of smoking episode, drug usage, craving
Further Reading


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