Sensing Meets Mobile Social Networks: The Design, Implementation and Evaluation of the CenceMe Application

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Ronald Peterson, Hong Lu, Mirco Musolesi
Shane B. Eisenman, Xiao Zheng, Andrew T. Campbell

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what’s the application?
what’s the application?

people-centric sensing
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people-centric sensing

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what’s the application?

people-centric sensing
within people-centric sensing
some things change....

- problem space?
  - MACs
  - multi-hop

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within people-centric sensing some things change....

- problem space?
  - MACs
  - multi-hop

- problem space?
  - sensor-data inference
  - privacy w/ verifiability

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within people-centric sensing but some things stay the same....

- problem space?
- energy
- computation & memory
- calibration
Presence sharing is a rudimentary form of people-centric sensing

- Twitter: 3 million manual ‘tweets’ sent per day
- Facebook: 100+ million users
- Skype: 100+ million users

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contributions

• implementation of CenceMe using COTs mobile phones and already popular social networks

• evaluation within a long lived large scale experiment

• user study of a sensor presence sharing application
sensing with the Nokia N95 mobile phone

- camera
- microphone
- accelerometer
- GPS
- bluetooth radio
  (proximity)

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Inference with sensor data

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cencing with cenceme

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sensor data

inference

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supported inferences:

activity
supported inferences:

- activity
- social context

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supported inferences:

activity

social context

significant places

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supported inferences:

activity

social context

significant places

behaviour

greeny  nerdy  party animal  cultured  healthy
classifying activity

sitting
classifying activity

(a) Sitting

(b) Standing

(c) Walking
classifying activity

sitting

standing

walking
classifying activity

- sitting
- standing
- walking
- running
classifying conversation

talking

no talking
classifying conversation

talking

no talking

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The classifier's feature vector is composed of the mean and standard deviation of the DFT power. The mean is used because the absence of talking shifts the mean lower. The standard deviation is used because the variation of the power in the spectrum under analysis is larger when talking. The equation of the dashed line in Figure 5 is used by the activity classifier to calculate the mean, standard deviation, and number of peaks per unit time. Given these observations, we find that the mean, standard deviation, and the number of peaks are accurate feature vector components, with the running case having a slightly larger mean because typically people tend to rock a bit while standing. The peaks in the walking and running traces are slightly larger because typically people tend to rock a bit while standing.
by operating in the
we use a simple features extraction technique which prove
the computational and memory constraints of mobile phones,
accelerometer data from the phone's local storage (see Fig-
gation component and extracts features (i.e., attributes). Gi
processor and the classifier itself.
Activity classifier.

The activity classifier fetches the raw
samples from over twenty people, and a set of audio sam-
of discriminant analysis. As part of the training set for the
The classifier's feature vector is composed of the mean
Power
1500
2000
2500
3000
1000
1500
3000
3500
4000
4500
5000

Figure 4
Frequency (KHz)
0
500
1000
1500
2000

Figure 6 shows the clus-
tion, and the number of peaks for the accelerometer data across
similarities in the behavior of the mean, standard deviation,
Figure 6 for other people. However, we observe strong sim-
running case than walking. Given these observations, we
runs a larger number of peaks per second is registered than
when people walk. The standard deviation is larger for the
is slightly larger because typically people tend to rock a bi
during the use of the accelerometer.

Power
1500
2000
2500
3000
1000
1500
3000
3500
4000
4500
5000

Figure 5: Discriminant analysis clustering. The dashed lin
tuning the system is critical

- sensor/classifier units have different energy costs
  - (gps, location) is 10 times the cost of (accel, activity)
- duty cycle: \( \{bt, gps\} = 300 \text{ sec} \quad \{accel, audio\} = 30 \text{ sec} \)
- but tuning is more than energy, we must balance the following classifier tradeoffs:
  - fidelity
  - responsiveness
  - energy cost
balancing fidelity against responsiveness
balancing fidelity against responsiveness

![Graph showing ROC curves with different window sizes](image)

- window size = 5
- window size = 10
- window size = 30

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balancing fidelity against responsiveness

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## Impact on Phone Battery Life

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<th>Duration</th>
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<tr>
<td>Talk Time</td>
<td>4 hrs</td>
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<td>Cenceme</td>
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<td>Idle</td>
<td>2%</td>
<td>34.0 mb</td>
</tr>
<tr>
<td>Audio sampling + classifier</td>
<td>60%</td>
<td>34.6 mb</td>
</tr>
<tr>
<td>Accel sampling + classifier</td>
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inferencing robust to phone context

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<tr>
<td>activity</td>
<td>78.5%</td>
</tr>
<tr>
<td>transport mode</td>
<td>82.4%</td>
</tr>
<tr>
<td>conversation</td>
<td>73.5%</td>
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inferences robust to:
- location
- body position

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the user study: an amazing data set
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observations from the user study

• willingness to share sensitive presence information with friends when ‘sensor off’ button is clearly available

• valued access to presence information from the phone

• enjoyed comparing themselves with friends and the population

  • “CenceMe made me realize I’m lazier than I thought and encouraged me to exercise a bit more”
lessons learnt

- symbian gripe I: low level component control was not sufficient (i.e., sensors, radio)

- symbian gripe II: security model cumbersome and too restrictive (i.e., key press simulation required)

- the { audio, location, accel } sensor combination powerful for people-centric inferences
iphone edition

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cheers!
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www.cenceme.org

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