Mobility Monitoring with the Independent LifeStyle Assistant™ (I.L.S.A.)

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Agenda

- I.L.S.A. Introduction
- Mobility Monitoring Design
- Installation
- Results
- Conclusions

I.L.S.A. Overview

Program Objective

Develop an intelligent home automation system with situation awareness and decision-making capability based on integration of diverse sensors, devices, and appliances to support caregivers and enable elderly users to live independently at home.

- Program duration November 2000 ñ July 2003
- Phase I & Phase II research until May 2002
- Field test development May 2002-December 2002
- Field tested with seniors January 2003-July 2003
  - 7 independent living apartments
  - 4 homes

Mobility Monitoring Design

- Used four six-hour periods per day for assessment and reporting to clients and caregivers to accommodate normal fluctuations in daily living patterns.

Morning: 6AM ñ NOON
Afternoon: NOON ñ 6PM
Evening: 6PM ñ MIDNIGHT
Night: MIDNIGHT ñ 6AM

- Initial configuration based on client interview
- Activity ratings
  - Activity levels were rated High, Normal or Low based on comparison to a static model for each client
  - Last registered active period (15 minute resolution) was also reported.
- Alerts, not Alarms
  - Manual panic button activation = Alarm
  - Passive sensor data (or lack thereof) = Alert

❖ A lack of affordable means to identify individuals required us to limit this test to elders living alone.

Mobility Design Cont.

- Alerts for ìNo Mobilityî
  - No mobility was defined by the complete lack of sensor events (from all sensors in the home) for a configurable duration. (e.g., 3 hours) during waking hours.
- Alerts for short-term significant change in pattern
  - A significant change was described as a 50% increase or decrease sustained for three days, as compared to the previous seven days.
- Up-at-Night Notification
  - Sensor readings during the time when the client was normally asleep (static settings for wake/sleep) resulted in notifications of nighttime activity.
- Communication
  - Alerts were issued via telephone to caregiver, and listed on the web site.
  - Notifications appeared on the web site only.
  - Caregivers could access web site or telephone status reports on demand.

Installation

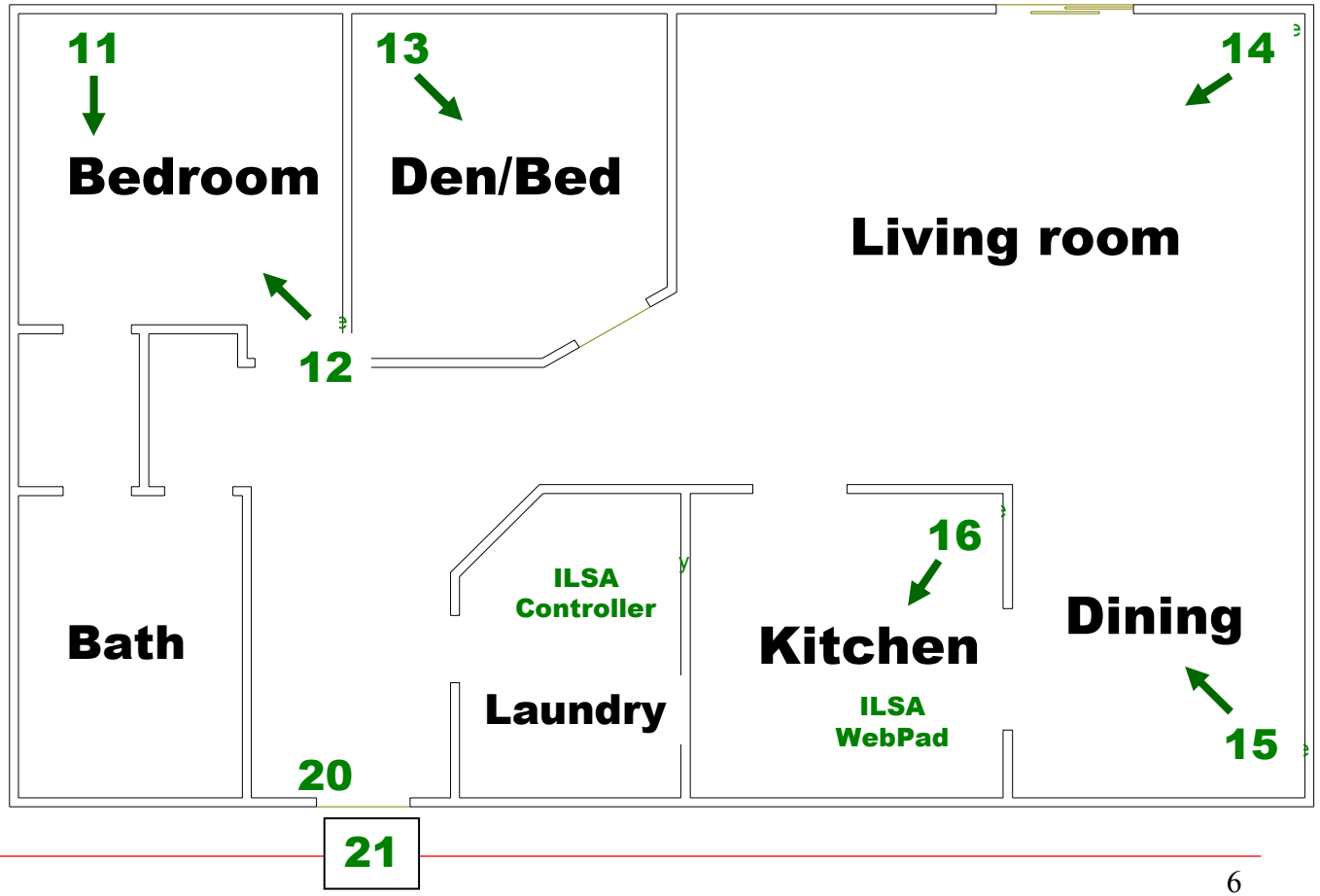
Example apartment layout with sensor locations

ïZones 11-16
IR motion
detectors

ïZone 20
Entry Door
contact switch

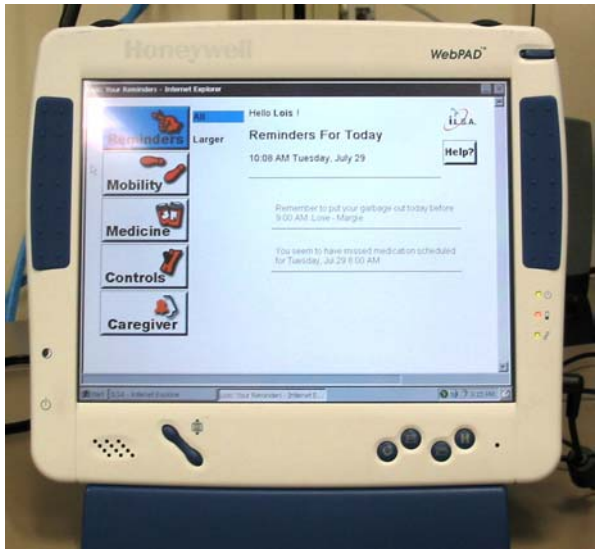
ïZone 21
Hallway
Pressure Mat

ïZone 10
med caddy
contact switch



Installation Cont.

- Data was collected via standard Honeywell home control and security products.
- I.L.S.A. relied upon near real-time data transmission via broadband to a central server.
- I.L.S.A. equipment required professional installation
- Clients interacted with I.LS.A. via the Honeywell WebPadô tablet PC with touchscreen.



Results – Sensor Placement

ï Sensor Placement

- ï Placement of bedroom sensors picked up motion in bed and required modification of up-at-night evaluation.
- ï In small apartments, where zones may overlap, few assumptions can be made about location of activity.
- ï Improper sensor placement can pick up motion on the floor ñ such as a person in distress moving their

Sensor placement concerns require an experienced installer.

Results – Occupancy Detection

Occupancy Detection

- Clients did not consistently report absences by turning I.L.S.A. ìOFF.î
- Lack of reliable occupancy information makes real-time mobility assessment unreliable. Long-term trends are still noticeable, but not interpretable.
- The ìNo mobilityî threshold was raised in many cases to prevent false alarms. This reduced its utility for passive detection of emergencies.
- Pressure pad and door sensor combined with other evidence filtered 95% of false alerts when the client was actually away from the apartment.

Results – Machine Learning

Machine learning techniques were explored to reduce false alerts through adaptive approaches:

- Clients were negatively affected by I.L.S.A. reminders when they were trying to ì sleep in.î
- Machine Learning techniques are more accurate, less costly, and less intrusive than interviewing the client and caregivers.
- Through accurate patterns of living, including daily schedules, the rate of false alerts can be significantly decreased.
- The recognition of unexpected activity based on established patterns can provide more robust and flexible alerting of mobility anomalies.

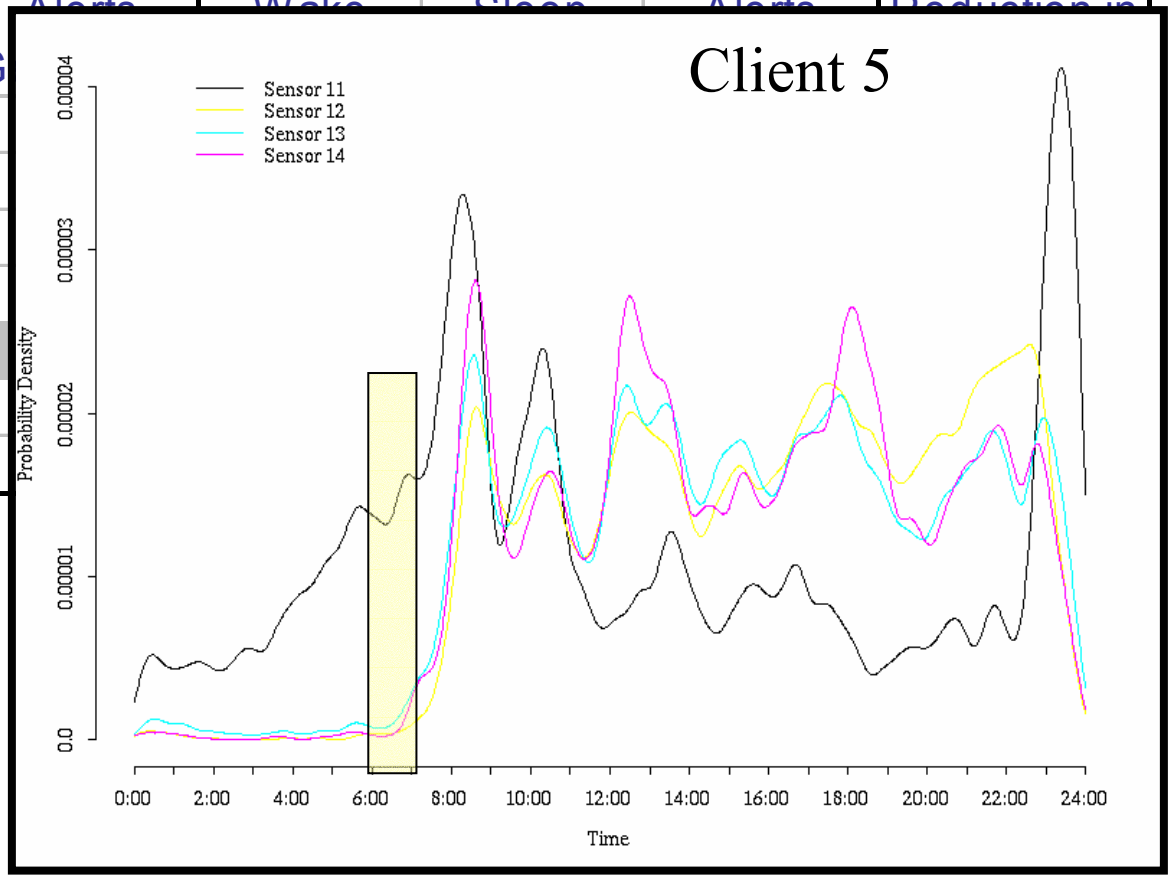
Machine Learning cont.

Learn models of behavior from observation

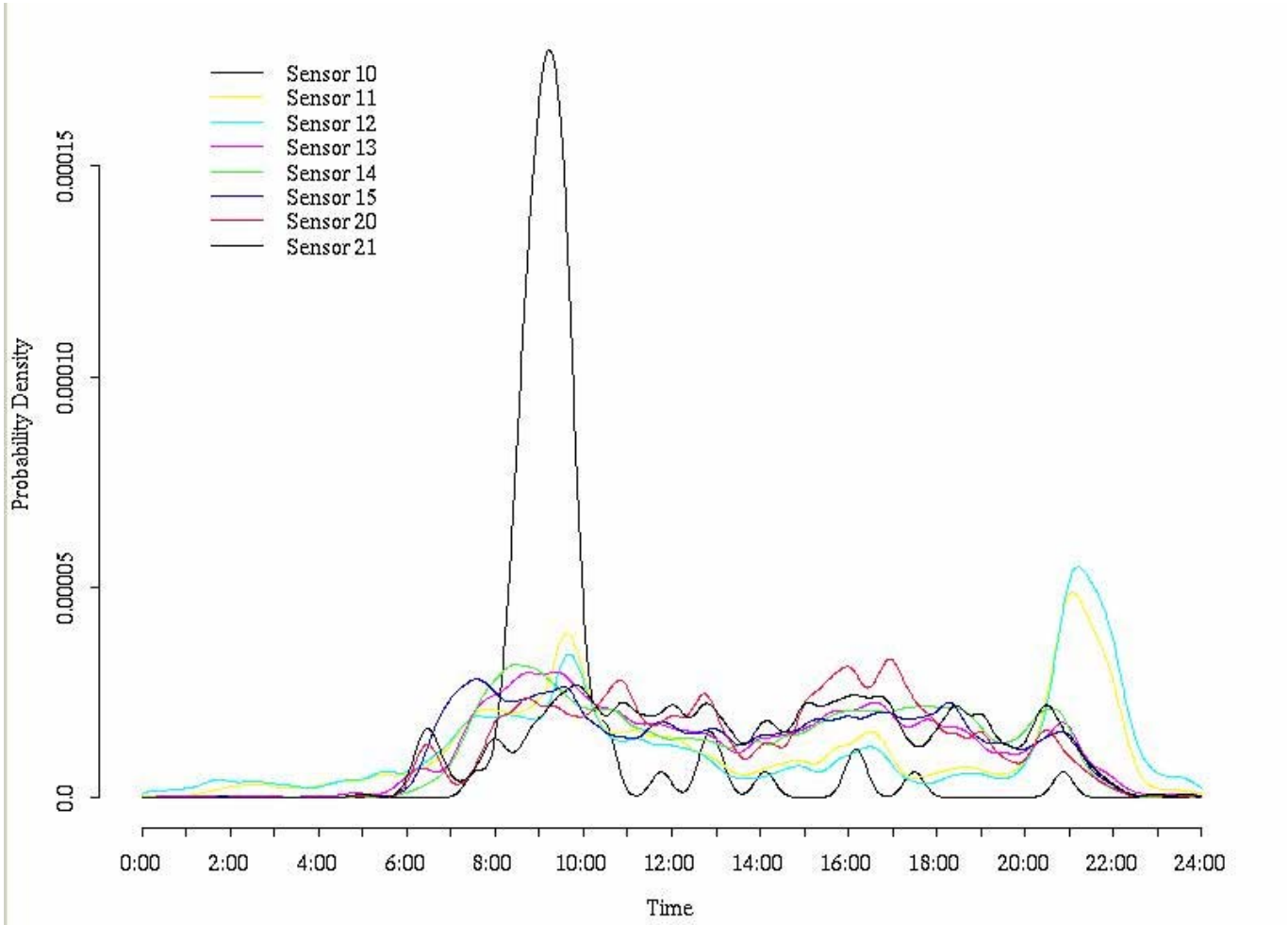
- Regular activities, e.g.
  - In 75% of days, BedroomPreasurePad[04:23-06:12] → KitchenMotion[06:12-08:23] → Cupboard[06:45-09:04] → FrontDoor[06:56-08:43]
- Approach:
  - Probability Density estimates to get time intervals
  - Sequential Patterns discovery to get frequent patterns
  - Post-processing to get "interesting" patterns
  - Clustering for presentation to human for validation
- Results: good models for rich sensor suite
- Impact: task tracking, configuration, customization

ML: Sleep/Wake Cycles

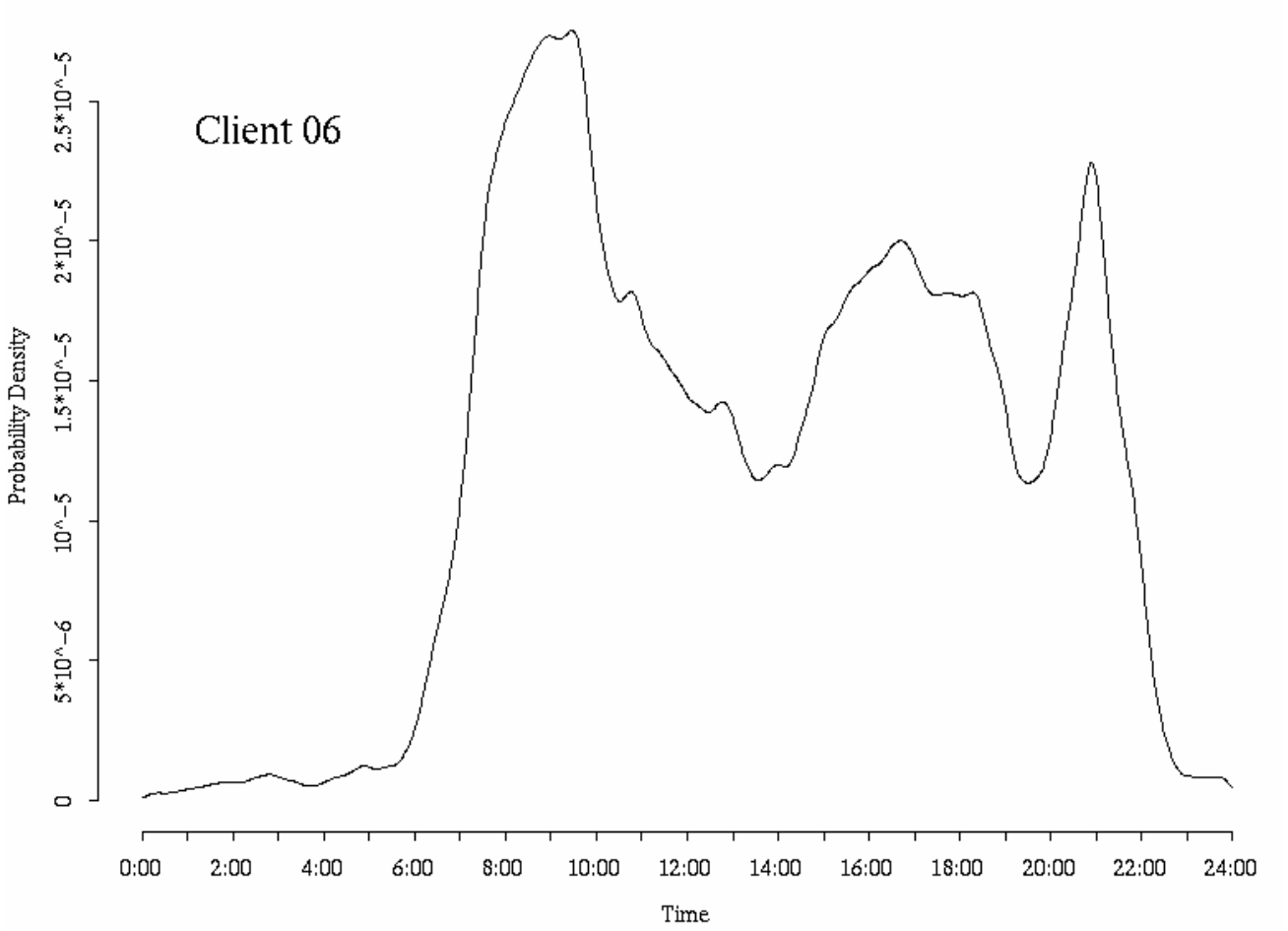
Client	Reported Wake	Reported Sleep	Number of Alerts G	Observed Wake	Observed Sleep	Number of Alerts	Percent Reduction in
1	06:30	23:00					
2	07:30	20:30					
3	07:00	22:30					
4	08:00	23:30					
5	06:00	23:30					
6	07:00	22:00					
7	07:30	22:00					



Client 6


Sensor 10
Sensor 11
Sensor 12
Sensor 13
Sensor 14
Sensor 15
Sensor 20
Sensor 21
Probability Density
0.0
0.00005
0.00010
0.00015
0:00
2:00
4:00
6:00
8:00
10:00
12:00
14:00
16:00
18:00
20:00
22:00
24:00
Time

Client 06: Merged



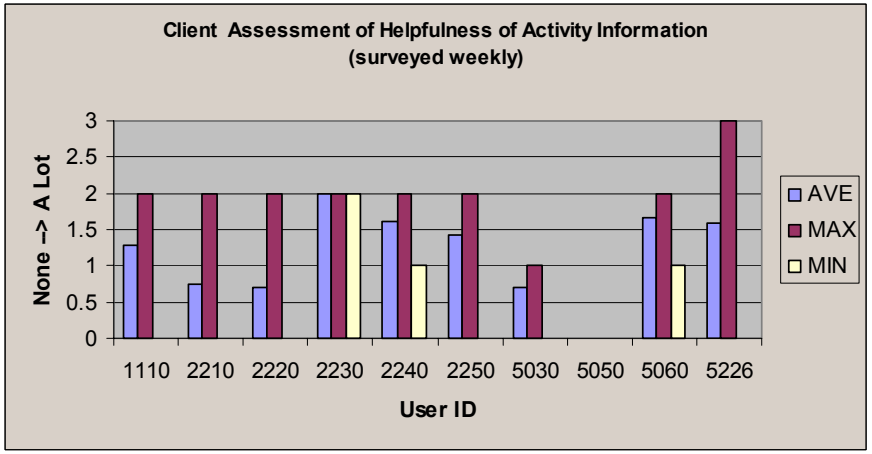
ML: Unexpected Activity

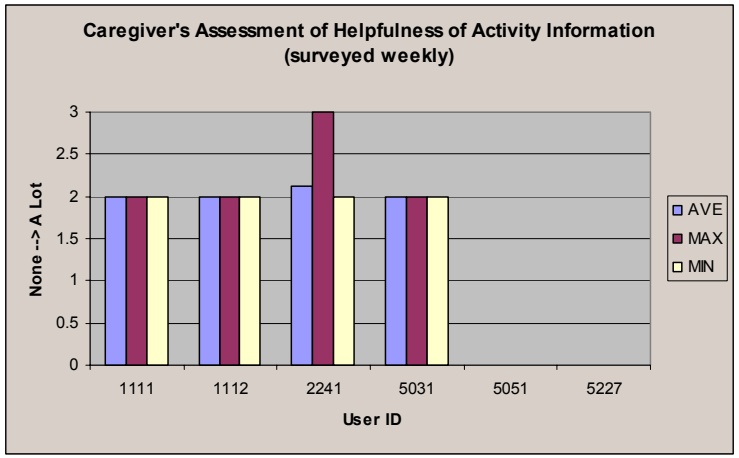
Raise alarms when activity happens unexpectedly

- Approach:
  - Probability Density estimates to get profile of normal activity
  - Raise alerts for activity below thresholds
- Results:
  - Alerts based on single sensor readings are faulty (noise)
  - Alerts based on multi-sensor profile are useful IFF below threshold for significant time
- Impact: configuration, customization, mobility

❖ *During the field test, these alerts were recorded, but not shared with participants.*

Mobility Feature Acceptance





not at all	18.29%
very little	20.73%
some	31.71%
a lot	1.22%
not applicable	28.05%

Clients: ~33%

not at all	30.77%
some	38.46%
a lot	3.85%
not applicable	11.54%

CGs: ~42%

Caregiver survey responsiveness was poor overall.

Results -- Client Reactions

- Privacy
  - Initial concerns about privacy were forgotten within a day or so of installation.
  - Caregivers often had more significant negative reaction to privacy than their parent.
  - Having access to the same information shared with caregivers may have made elders feel less spied upon.
- Interactions with ILSA On/Off Modes
  - Clients didnít want to use this feature because they were afraid theyíd forget to reset I.L.S.A. when they returned.
- Interest in mobility reporting
  - Clients were keenly interested in the reports of their mobility and wanted to be able to send feedback about the accuracy of reports.

Results – Caregiver Reactions

Privacy

- Most responded negatively to the idea of placing video cameras in their parentís home as an alternative to motion sensors.

Interest in Reports

Inaccuracy of some alerts due to lack of occupancy data, as well as already good peace-of-mind about the parent led to generally low caregiver interest in mobility reports.

E

behavior and uncovered a urinary tract infection.

- Daytime activity status reports alleviated the concerns of one caregiver when her parent was in a particularly frail condition.
- Most believed that this information could provide value when their parent became more frail *IF* the methods were improved.

Conclusion

- Mobility reports can provide value to both clients and caregivers.
- Access to reliable, real-time information can reduce caregiver stress.
- Access to reports has the potential to increase elder interaction and acceptance of monitoring.
- Activity sensors by themselves can not provide 100% accurate detection of normal or abnormal mobility events.
- The cost of installation of activity sensors is the single most significant barrier to wide-spread application of this technology.

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I.L.S.A. References

Visit the I.L.S.A. web site for links and references to other publications and related work:

www.htc.honeywell.com/projects/ILSA