# Ubiquitous Computing Applications: Healthcare & Smart Homes


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# Paper 1: Moving out of the Lab: Deploying Pervasive Technologies in a Hospital

- **Many ubicomp ideas, research projects**
- **Few *deployed real world* applications**
- **Hospital application: coordination of operations in large hospital *intense***
- ***iHospital* system:**
  - **Large wall displays, PCs, mobile phones**
    - **Maintain shared view of available resources**
    - **Scheduling new surgeries**
    - **Tracking doctors/nurses and required resources**
    - **Coordination of resources**
    - **Monitoring procedures, doctors and resources**
  - **Uses location tracking and video streaming of info**
  - **Deployed in operating ward of small hospital (Horsens) in Denmark**
  - **Dates: about 1.5 years ending around Nov 2005**
- **Nature of contribution: Experience with deployment**

# AwareMedia

- displays information about work in operating rooms
- Video stream provides overall awareness of operation's state
- Progress bar shows more detailed information about progress
- Chat area allows people communicate unobtrusively
- Schedule shows current operating schedule
- Location-tracking system shows who is in operating room

# AwarePhone

- **Program that runs on Symbian mobile phones**
- **Provides**
  - **Overview of people at work**
  - **Status of surgeries in operating room**
- **Augmented phone book: people’s location, schedule and self-reported status**

# Location Tracking

- Bluetooth used for tracking
- Black item worn by staff
- Sends bluetooth signal to infrastructure
- Chips carried on shirt or pocket during work shift
- Charged at night

# Usage Scenario

- **Many scenarios providing awareness and enhancing communication**
- ***Example Scenario:* Acute patient arrives. Head nurse**
  - **Looks at AwareMedia on large display**
  - **Finds empty operating room**
  - **Touches screen to schedule surgery using that operating room**
  - **Uses location-tracking to find available surgeon**
  - **Sends message to surgeon's mobile phone giving info about surgery**
  - **Regularly scheduled surgery is informed about postponement**

# Deployment Issues
## Getting Infrastructure in Place

- **Balance between cost, security, networking, etc**
- **Cost location tracking systems**
  - **Commercial systems (e.g. Ubisense) precise but expensive.**
  - **Built own coarse-grained location system which could be integrated with staff phones**
- **Limited space: hospitals already confined**
  - **40inch displays, 19 inch touch screens tough to integrate**
  - **No cables on hospital floor. Power sockets in right place tough**
  - **Securing devices so not stolen**
- **Wireless Interference between ubicomp equipment and hospital equipment**
  - **Would GSM phones and bluetooth interfere with hospital equipment?**
  - **Technicians hired. Made sure no interference**

# Deployment Issues:
## Installing and Launching Software

- How to deploy software
- How to keep software up-to-date
  - System ran on 10 PCs, 17 mobile phones
  - Regular (often daily) updates was tough
  - Restricted access to operating rooms, sterilization required, etc
  - Deployed semi-automatic and automatic update strategies
- How to debug running systems
- How to integrate different software systems
  - Integrating AwareMedia scheduling with hospital mainframe scheduler
  - Solution: hired secretary to manually transfer information in pilot
- How to ensure scalable system that performs adequately
  - AwareMedia required lots of bandwidth due to streamed videos
  - Used logically separate network for streaming
  - Heterogeneity: Use loosely coupled subsystems, stateless

# Deployment Issues:
## Involving Users

- End-user system: Designed for usability from start
- Wanted minimal to no end-user training
- All objects visually represented, drag and drop interface
- Training many people who work in shifts?
  - Rumor-based and guerilla-style teaching strategy
  - Taught few people how to use system, encouraged them to pass on the word
  - Five well trained users, help spread the word
  - Also randomly stopped passersby, taught them how to use new additions
- Fully automated context aware vs requiring user input
  - Users without phone supposed to pick up bluetooth chip everyday
  - Since benefit was to other users, users failed to pick up bluetooth
- Privacy: many concerns. Users seemed not to care much

# Discussion Questions

- What were the main contributions of this work?
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# Paper 2: Mobile Phones Assisting with Health Self-Care: A Diabetes Case Study

- Worldwide sufferers increase: 177m in 2000 to 370m in 2030
- 7.8% of US population have diabetes
- Cost per annum: $174 billion
- Paper Investigates mobile phone as tool for personalized health care assistance for individuals diagnosed with diabetes
- Personalized? Away from doctor, monitor patients, provide guidance
- Works without augmenting mobile phone with additional activity sensors (e.g. pedometers, accelerometers or heart rate monitors)

# Diabetes self-care

- Diet/food intake
- Blood glucose levels
- Exercise/User activities
- Insulin dosage
- Monitor Weight

# Application Overview

- Application assists users take well-informed decisions on daily drug dosage to maintain stable glucose levels
- Monitor user location, activity
- Recognize past behavior
- Augment blood glucose data with context data
- Goal NOT just to replace paper methods with phone as recording device
  - Also automatic detection of past behaviors + current context

# Application benefits

- **Diabetes self-care with mobile phones:**
  - **People forget or don’t keep a detailed log**
  - **Recalling similar previous situations becomes difficult**
  - **Create a context-driven recommender application**

- **Benefits of the application**
  - **Time and location monitoring**
  - **User input on food consumption and insulin dosage**
  - **Find correlations between time/location and activities**
  - **Augment blood glucose level logs with contextual data**
  - **Use context to find similar situations in the past**

# Specific Challenges

- Classification of events (eating, exercise, etc)
- Detecting which events affect blood glucose levels
- Life has recurring patterns.
- Find correlations between
  - a) Time and place data
  - b) Types of activities
- Use correlations to find similar past situations
- Since system uses only available sensors on phones, user:
  - Inputs Food intake and insulin dosage
  - Synchronizes with glucose meter to obtain blood glucose levels
  - Determines location using GSM cellular data
  - Determines activity type by learning (training and online user feedback)

# Feasibility Survey

- **Generally good practice to use initial survey to show**
  - a problem exists
  - General approach is feasible
  - Solution would be useful if successful
- **17 participants interviewed, 7 diabetic. Found that**
  - All participants had mobile phones and used it daily
  - 12% used their mobile phone as their main phone
  - 24% turned off mobile phone to sleep, 12% turned off at work
  - Apart from talking, also used SMS/MMS, camera and navigation
  - 88% always had their phones
  - Participants felt phone would make logging easier and quicker
  - Participants were concerned that app would be too complicated, battery may run out, screen too small

# Classification of User Activities and Events

**Table 2: Classification of user activities and events**

| Food Intake | Physical Exercise *(classification)* | |
|---|---|---|
| Breakfast | Profession | *(high/moderate)* |
| Lunch | Household work | *(high)* |
| Dinner | Sports | *(high)* |
| Fruit | Leisure activities | *(moderate)* |
| Snacks | Socializing | *(light)* |
| Water | Sleeping | *(none)* |
| Coffee Break | | |
| Soda | | |
| Alcohol | | |

# Implicit Location-awareness with GSM Cellular data and Markov Chains

- Use GSM cellular data to determine user location
- Coarse grained. Only need to know approximately where user is and activity
- Represented user location as combination of *Cell ID* and *Location Area Code*
- Built up transition probabilities from cell to cell
- Example, given user is in cell S2, what is probability of transitioning to cell S4?
- Represented transition probabilities using markov chains and directed graphs

# Location Awareness

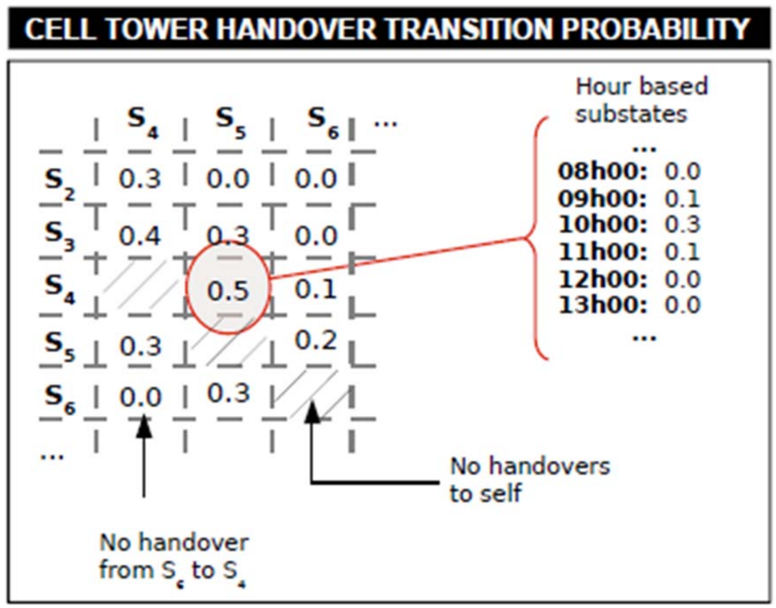
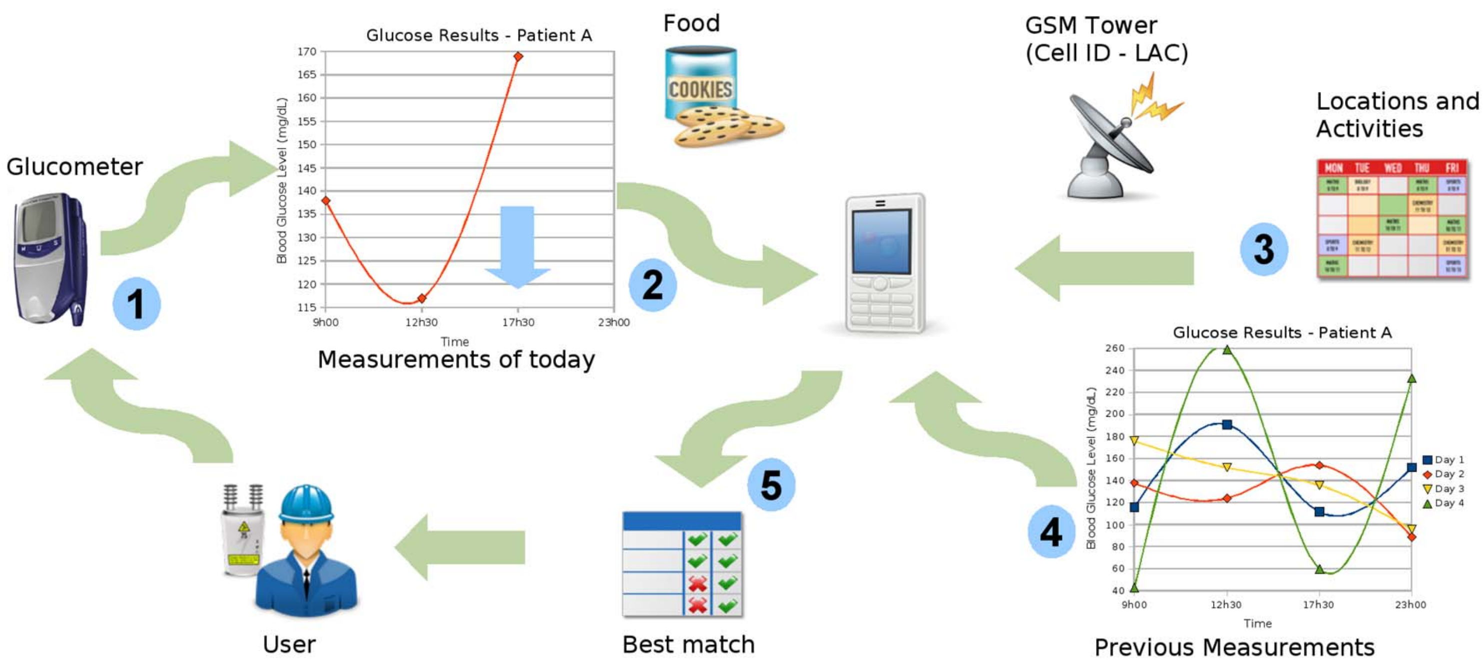



Figure 2: The state transition probability matrix for the implicit location-awareness Markov model. Each state transition probability is subdivided into a 24-hour time dependent subclassification.

# Activity-Awareness with Hidden Markov Model

- Relate activities types (none, light, moderate, high) to locations
- Observed patient’s blood glucose and insulin levels as a proxy for activity level
- Filtered out non-exercise related causes of glucose and insulin changes
- Did not consider other factors that may influence blood glucose levels in unexpected ways (stress, sickness, etc)

# Similarity Analysis




- **Use heuristics to consider context:**
  - Time, location, activity, history
  - Blood glucose levels, food intake, …
- **Goal: Determine insulin dosage by finding past situation similar to current situation**

# Measuring glucose levels


**Represent blood glucose data visually**

# Results: Daily logs of Glucose Levels on Four Random days

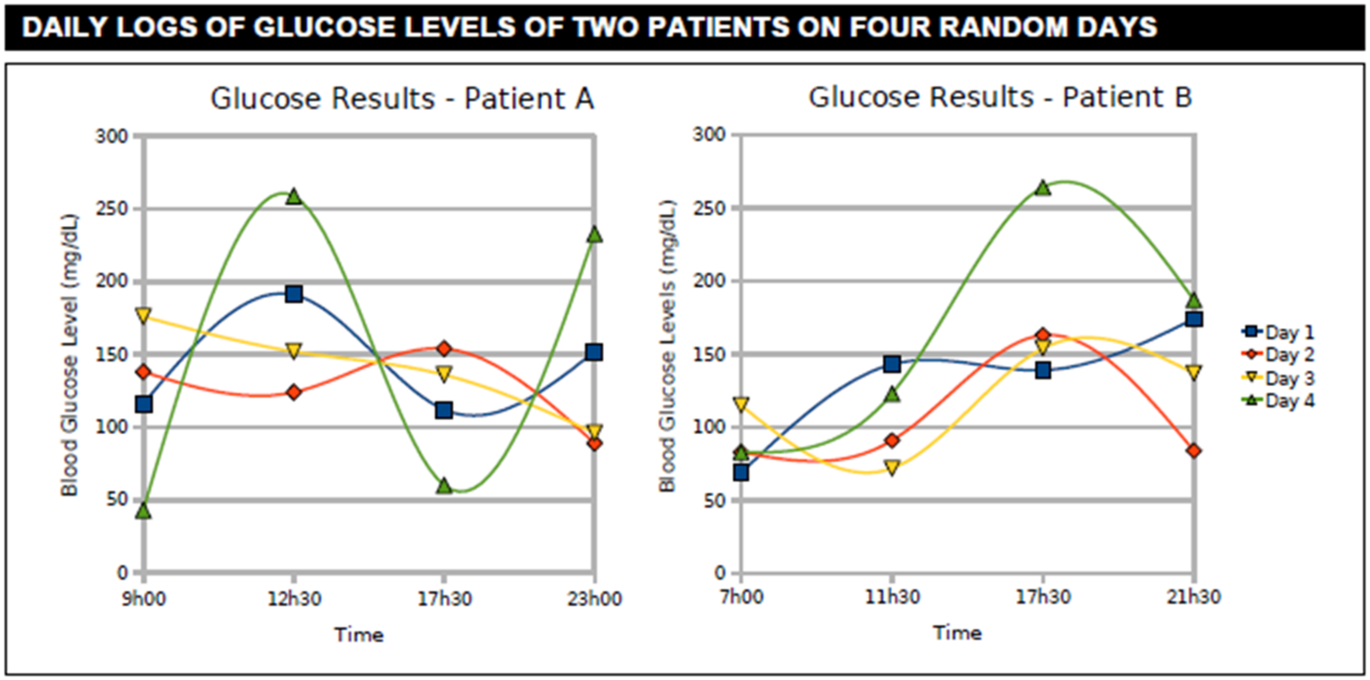



Figure 5: Daily log of blood glucose readings at different times of a day. The ideal blood glucose levels are 70 to 140 mg/dL before a meal and 110 to 180 mg/dL about 1 hour after a meal.

# Results: Location and Activity Prediction

- **Predicting most likely next location and corresponding activity given location**

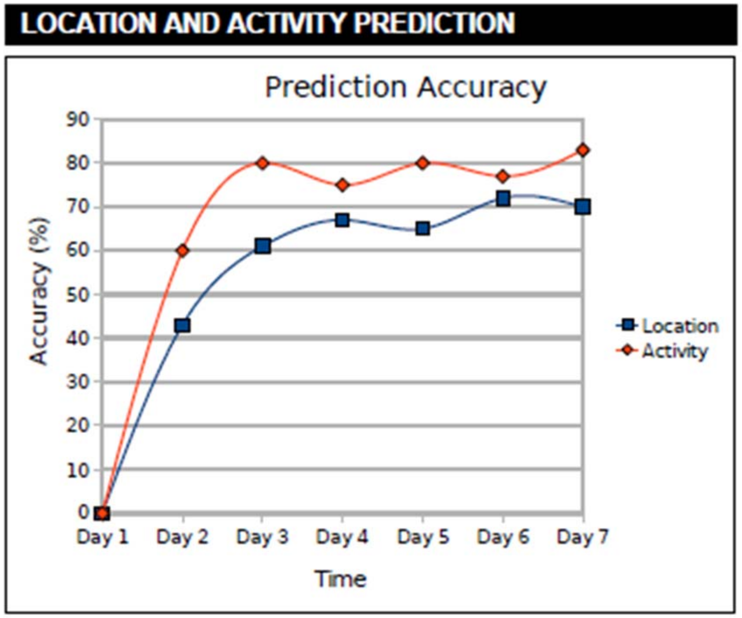



Figure 7: Predicting the most likely next location, and the corresponding activity given the location.

# Results: Matching Glucose Results and Insulin Dosage of Best Match

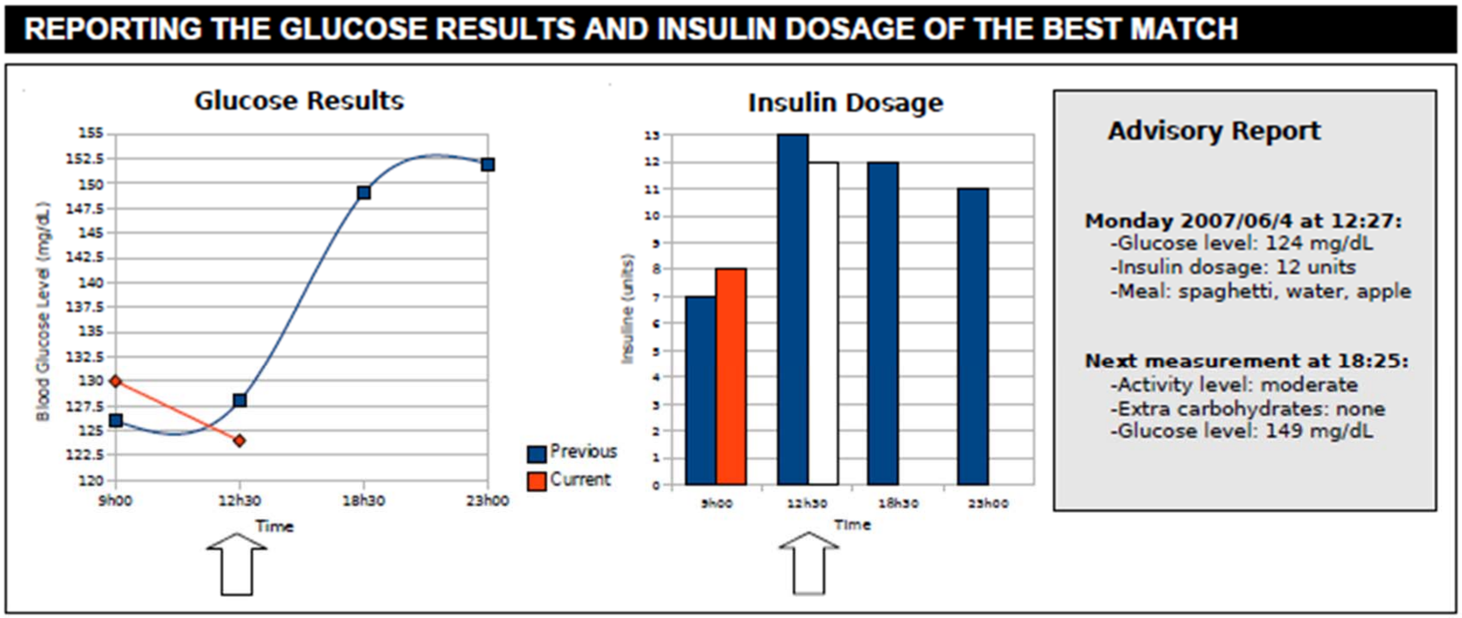



Figure 6: Reporting back after similarity analysis. The values in blue represent the best match while the current values are shown in red.

# User Studies: Takeaways

- Compared with previous pen and paper approach
- App forced keeping more detailed logs
- Graphical display of data appreciated
- Users wanted locations to be labelled
- In reality, changing base insulin plan is not straight forward

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# Paper 3: Electrisense paper

- **Automatically detecting and classifying use of electronics devices in home from a single point of sensing**
- **Activity sensing in home useful for ubicomp**
- **Disaggregated electricity usage often reveals resident's current activity. Examples**
  - **Stove usage implies cooking**
  - **TV, light and electric furnace on in living room**

# Switch Mode Power Supplies (SMPS)

- **Relies on emerging Switch Mode Power Supplies (SMPS) or soft switch**
- **Many new appliances have SMPS (including consumer electronic and florescent tubes)**
- **SMPS generates high frequency electromagnetic Interference (EMI) during operation**
- **EMI propages throughout home's power wiring**

# Frequency EMI Signatures

- **Narrowband noise when device is turned on**
- **Frequency-domain EMI signatures**
  - **Are unique and differ per device**
  - **Repeatable, similar for same device in different homes**
  - **Can be classified, used to distinguish devices in home**
  - **can identify which appliance was turned on**

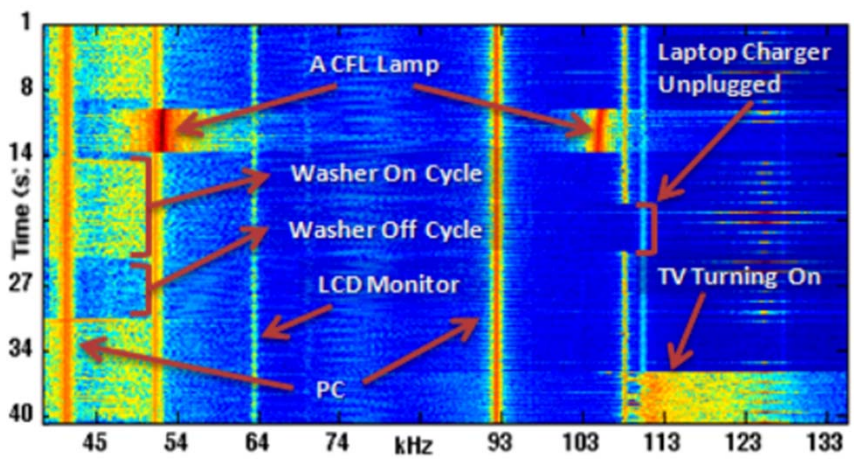


Figure 2: Frequency spectrogram showing device actuation in a home.

# System Prototype

- Single custom Power Line Interface (PLI) plug-in module, plugged into any electrical outlet
- PLI output connected to high speed data acquisition system that digitizes the analog signal from PLI
- Data acquisition output streamed to data collection and analysis PC running GNU radio
- GNU radio samples and conditions incoming signal in real time
- Electrisense algorithms then watch for events and extract features used to identify and classify device causing the event

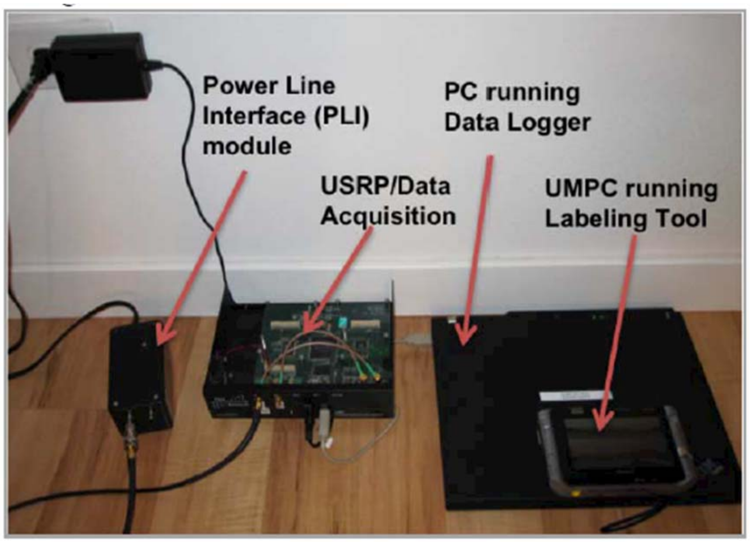


Figure 3: Our prototype system consists of a single plug-in module, acquisition hardware and the supporting software

# Block diagram of components

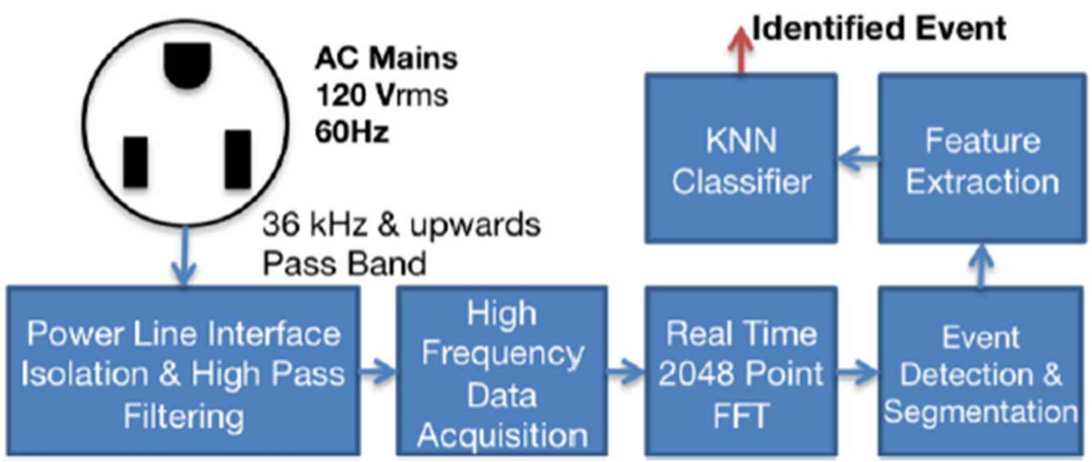


**Figure 4. Block diagram of major components of our system.**

# Sample Results

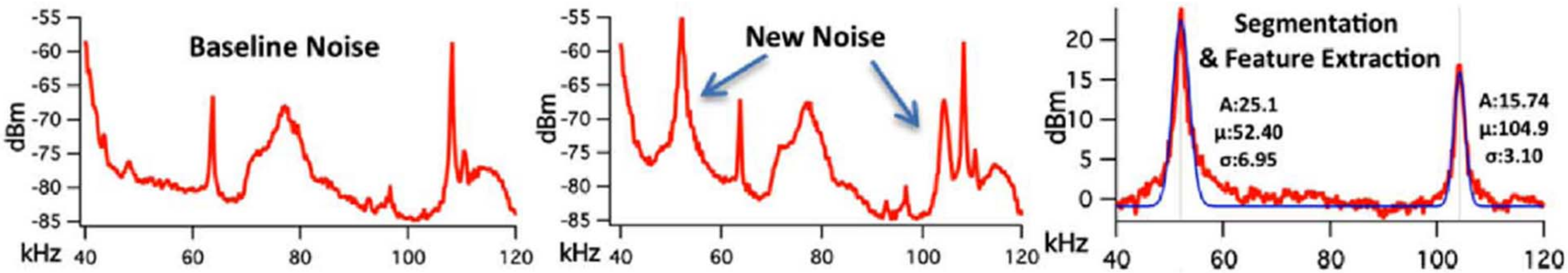


**Figure 6: (Left) Background noise observed on a particular power line. (Center) A new device is turned on, producing EMI that introduces new signals to the power line. (Right) After background subtraction the new signal features are extracted. The resulting Gaussian fit and its features amplitude (A), mean (µ) and variance (σ) are also shown.**

# Results: Classification of Events within Home

- Experimental trials in 7 homes
- Deployed for 6 months in one home
- 91% accuracy in classifying specific devices in given home
- Occasional misclassification due to physical device proximity

| ID | Style/Built/ Remodeled | Size/Floors | No. of Test Devices | No. of Events |
|---|---|---|---|---|
| H1 | Apartment/1985/ NA | 750 sq. ft./ 1 flr. | 10 | 135 |
| H2 | Single Family/2003/NA | 3000 sq. ft./ 2 flrs. | 15 | 203 |
| H3 | Single Family/1974/2009 | 1200 sq. ft./ 2 flrs. + basement | 13 | 170 |
| H4 | Apartment/1910/ NA | 450 sq. ft./ 1 flr. | 7 | 108 |
| H5 | Single Family/1960/NA | 1700 sq. ft./ 1 flr. | 13 | 198 |
| H6 | Single Family/1926/2003 | 2800 sq. ft./ 2 flrs. + basement | 20 | 404 |
| H7 * | Apartment/2009/ NA | 657 sq. ft./ 1 flr. | 16 | 1358 |

Table 1: A summary of the homes showing the style, size, number of appliances we tested and the number of events (* Long-term 6-month deployment).

# Classification of Events across homes

| Device | 10 Fold Cross Validation (%) |
|---|---|
| Camera Charger | 100 |
| Laptop | 87.5 |
| 23W CFL Lamp | 100 |
| 12W CFL Lamp | 100 |
| **Aggregate** | **96.87** |

**Table 4: The performance of four of our own devices across different homes using a 10-fold cross validation classification.**

# Degradation in features over time

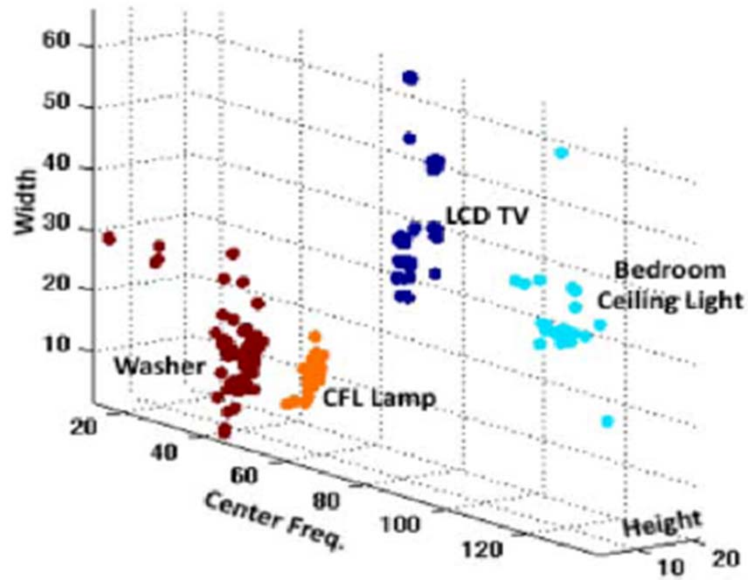


Figure 8: Variation of features over 6 months for four devices shown in the feature space. Note that no cluster overlaps.

# Specific Problem Cases

- **Multiple similar devices: (e.g. same TV in multiple rooms)**
  - **Distinguishable based on their amplitudes (fig 9(b) below)**
- **Dimmers: Ranges of values (see figure 9 ( c ) below)**
  - **Not modelled for now**

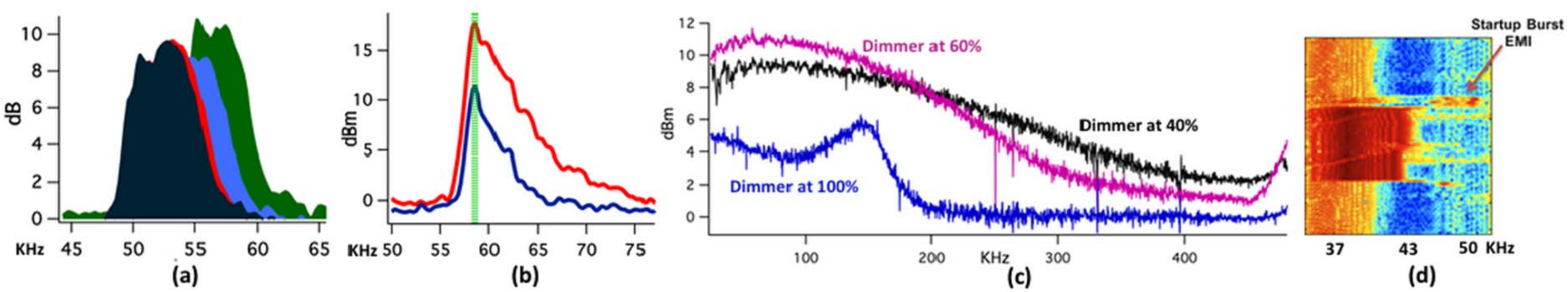


**Figure 9: (a) Small, but discernable variation in the mean of the EMI peaks for four same model and brand CFLs. (b) Same CFL lamp plugged into different regions of the home producing EMI amplitude variations. (c) Band limited EMI generated by a dimmer shown at various dim levels. (d) Startup burst of EMI signal generated by CFL lamps on ignition.**

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