A Tutorial on: Assisted Living Technologies for Older Adults

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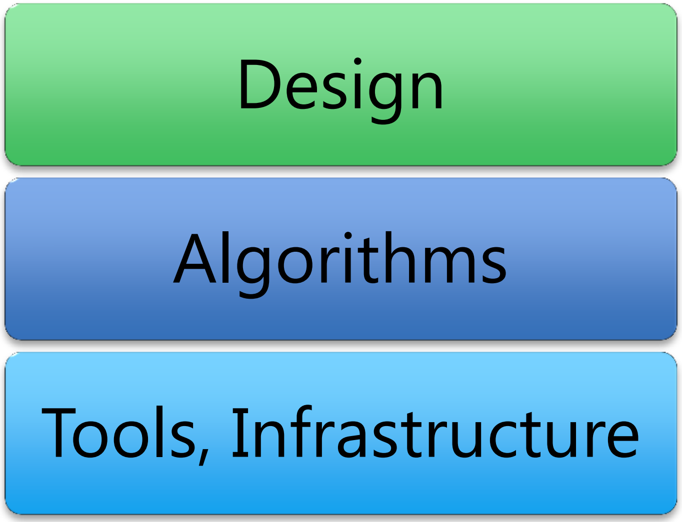
Outline

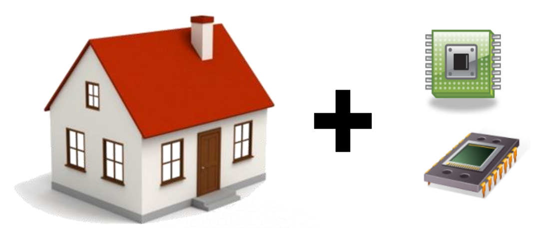
* Introduction
* **Technologies, tools, infrastructure**
* **Algorithms**
* **Use Cases**
* **Design Issues**
* Future



This Tutorial is about …

- Assisted living technologies for older adults, a.k.a
  - Gerontechnology
    - Gerontology + Technology
  - AAL: Ambient Assisted Living
    - Assisted Living + Ambient Intelligence



Introduction

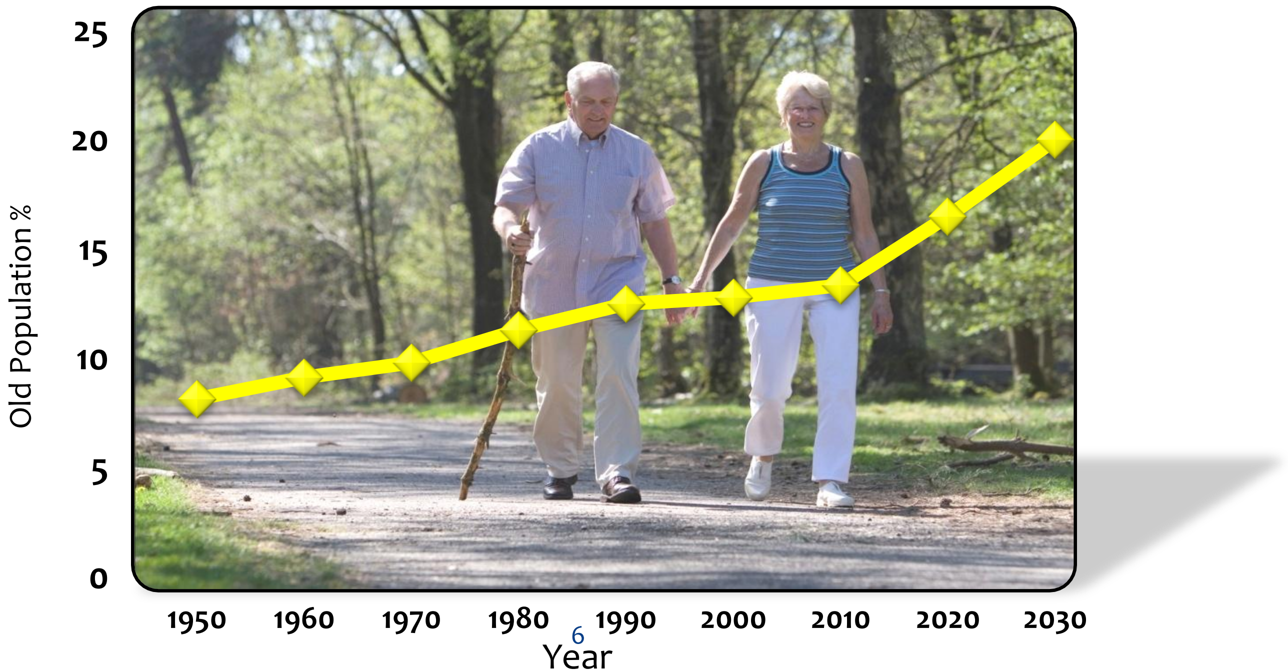
Why Important?

- **Scope**
  - 8.5 million seniors require some form of assistive care
    - 80% of those over 65 are living with at least one chronic disease
    - Every 69 seconds someone in America develops Alzheimer's disease
- **Costs**
  - Alzheimer's Disease: $18,500-$36,000
  - Nursing home care costs: $70,000-80,000 annually
  - Annual loss to employers: $33 billion due to working family care givers
- **Caregiver gap**
  - Nurses shortage: 120,000 and 159,300 doctors by 2025
  - Understaffed nursing homes: 91%
  - Family caregivers in US: 31% of households
    - 70% of caregivers care for someone over age 50

Statistics from http://www.hoaloharobotics.com/

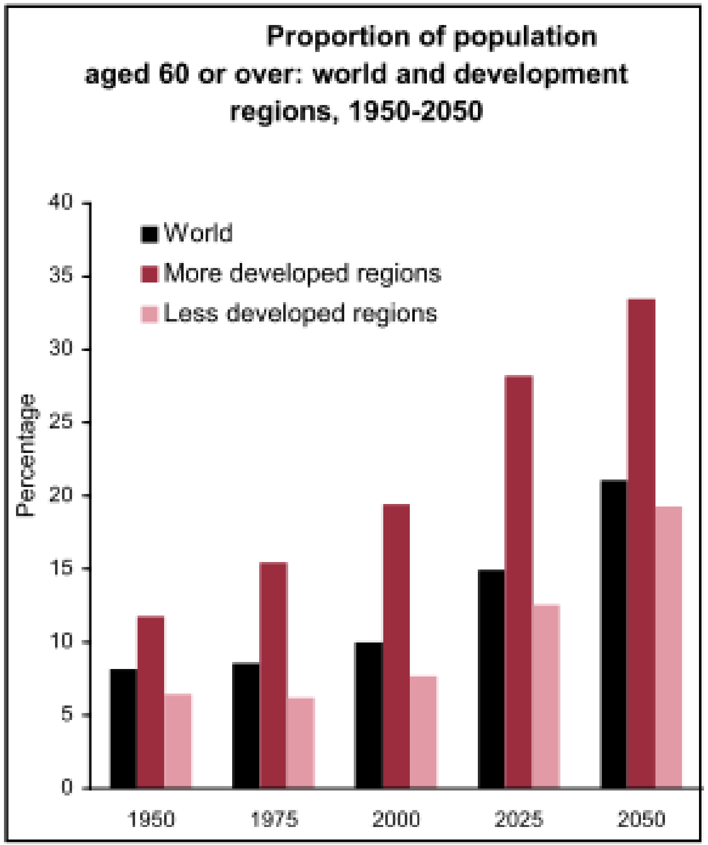
Why Important?

- By 2030, 1 in 5 Americans will be age 65 or older
  - Average life expectancy 81 years
  - By 2040: Alzheimer related costs will be 2 trillion dollars



Why Important?

* By 2050, 1 in 5 person in the world will be age 60 or older



UN Report, Department of Economic and Social Affairs, Population Division , 2001
http://www.un.org/esa/population/publications/worldageing19502050/

Consequences

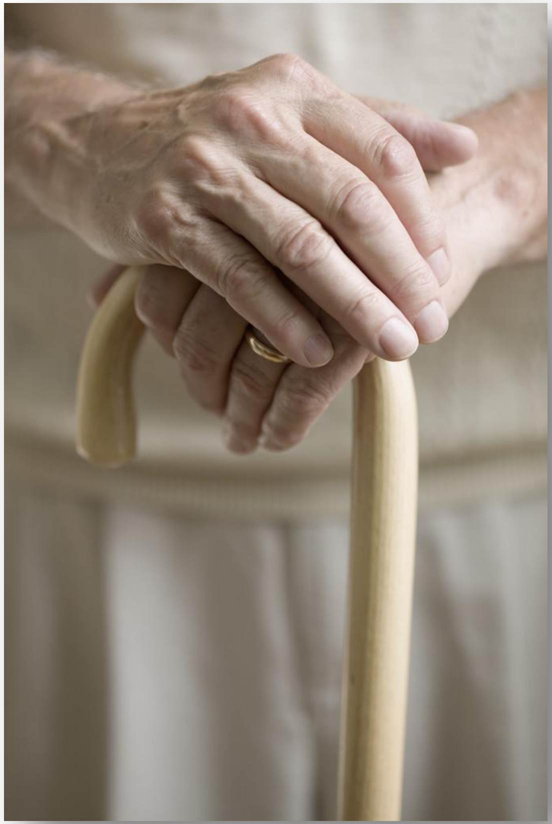
* An increase in age-related disease
* Rising healthcare costs
* Shortage of professionals
* Increase in number of individuals unable to live independently
  * Facilities cannot handle coming "age wave"

Independent Life

?

Older Adults Challenges

* Normal age related challenges
  * Physical limitations
    * Balance, reaching, etc.
  * Perceptual
    * Vision, hearing
  * Cognitive
    * Memory, parallel tasks
* Chronic age related diseases
  * Alzheimer's Disease (AD)



Older Adults Needs

* They need help with daily activities
  * Activities of Daily Living (ADL)
    * e.g. Personal grooming
  * Instrumented Activities of Daily Living (IADL)
    * e.g. Transportation, cooking
  * Enhanced Activities of Daily Living (EADL)
    * e.g. Reading, social engagement
* Memory Functions
* Health monitoring
* Removing the burden from caregiver

Tools and Infrastructure

Tools & Infrastructure

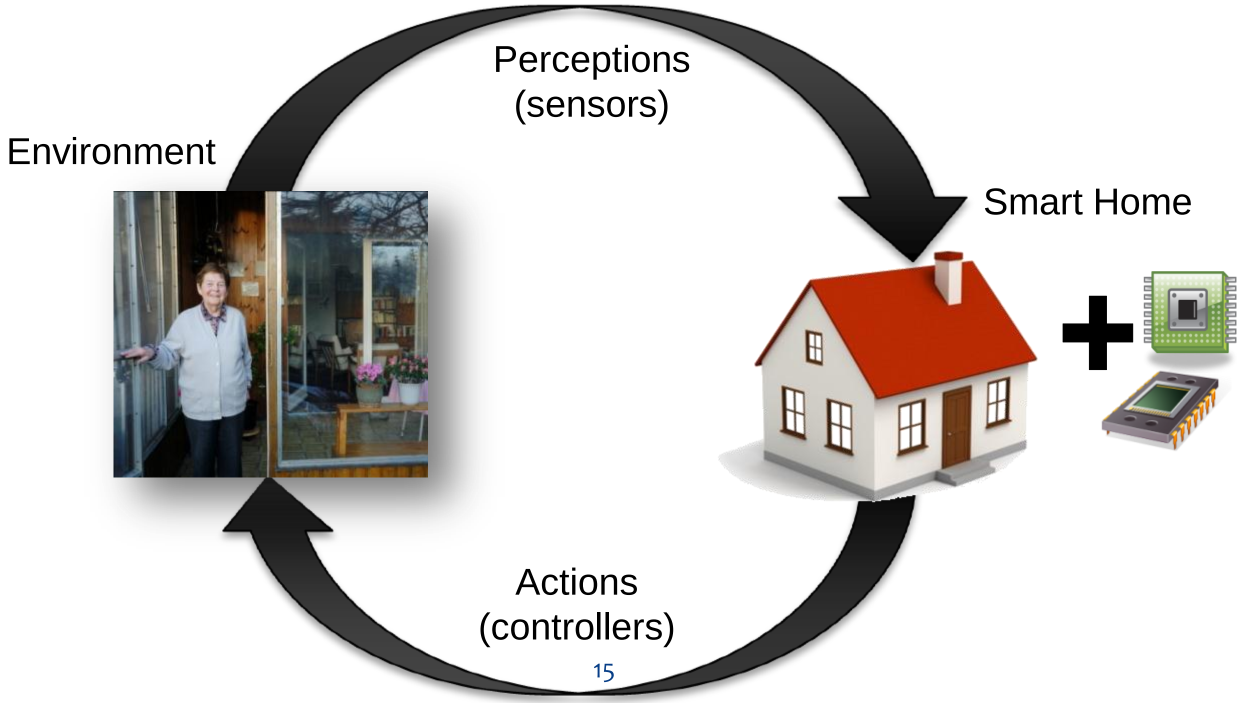
* What makes Ambient Assisted Living (AAL) possible?
  * Smart homes
  * Mobile devices
  * Wearable sensors
  * Smart fabrics
  * Assistive robotics

Tools & Infrastructure:

“Smart Homes”

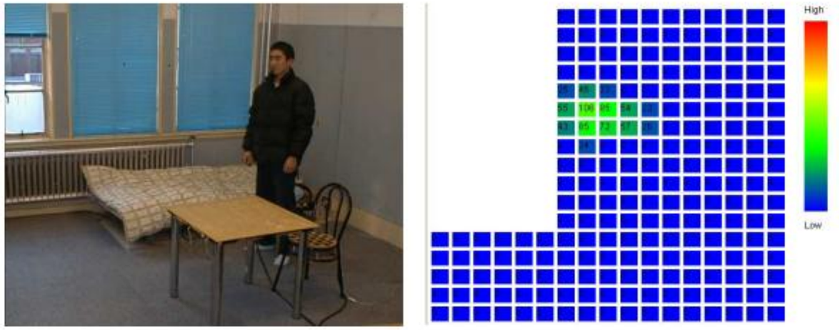
Smart Homes

- Sensors & actuators integrated into everyday objects
- Knowledge acquisition about inhabitant



Smart Home Sensors

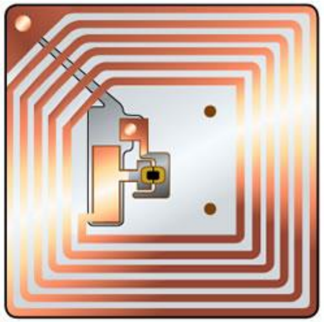
- PIR (Passive Infrared Sensor)
- RFID
- Ultrasonic
- Pressure sensors (in beds, floor)
- Contact switch sensors
- …



A) A photo of the floor B) Floor Sensor Data

Floor Pressure Sensor.
Noguchi et al. 2002


PIR

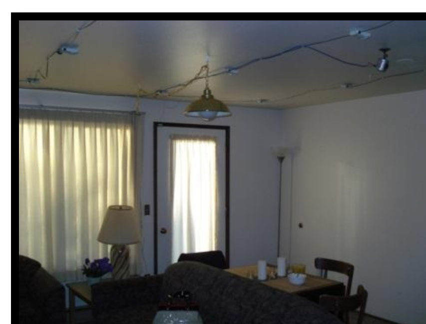

RFID


Ultrasonic

Example Smart Homes

- US
  - Aging in Place, TigerPlace (U. of Missouri), Aware Home (Georgia Tech), CASAS (Washington State U.), Elite Care (OHSU, OR), House_n (MIT)
- Asia
  - Welfare Techno House (Japan), Ubiquitous Home (Japan)
- Europe
  - iDorm (University of Essex), HIS (France)

Takaoka Welfare Techno House



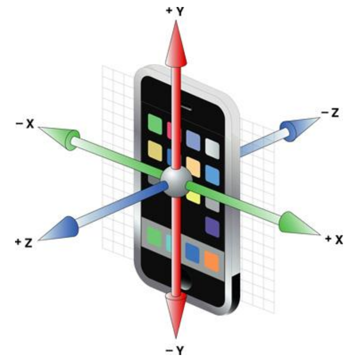
CASAS, WSU

Aware Home, GaTech

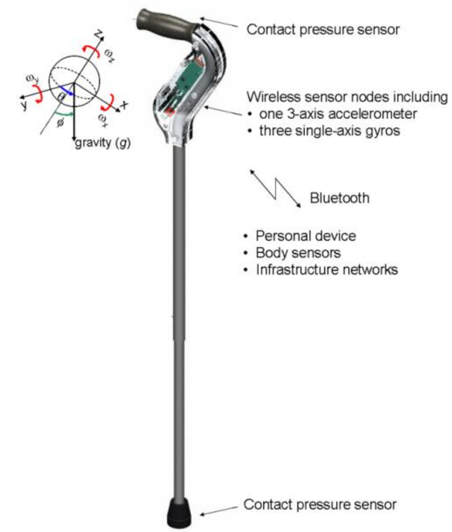
Tools & Infrastructure:
"Wearable & Mobile Devices"

Wearable & Mobile Sensors

* Applications
  * Health monitoring
  * Navigation and stray prevention
  * Mobile persuasive technologies



Smart Cane, UCLA, 2008



LifeShirt By Vivometrics®

AMON, 2003, ETH Zurich

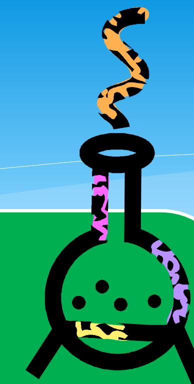
Epidermal Electronics**, 2011**

Measurements & Sensors

Movement

- Accelerometer
- Gyroscope

Biochemical



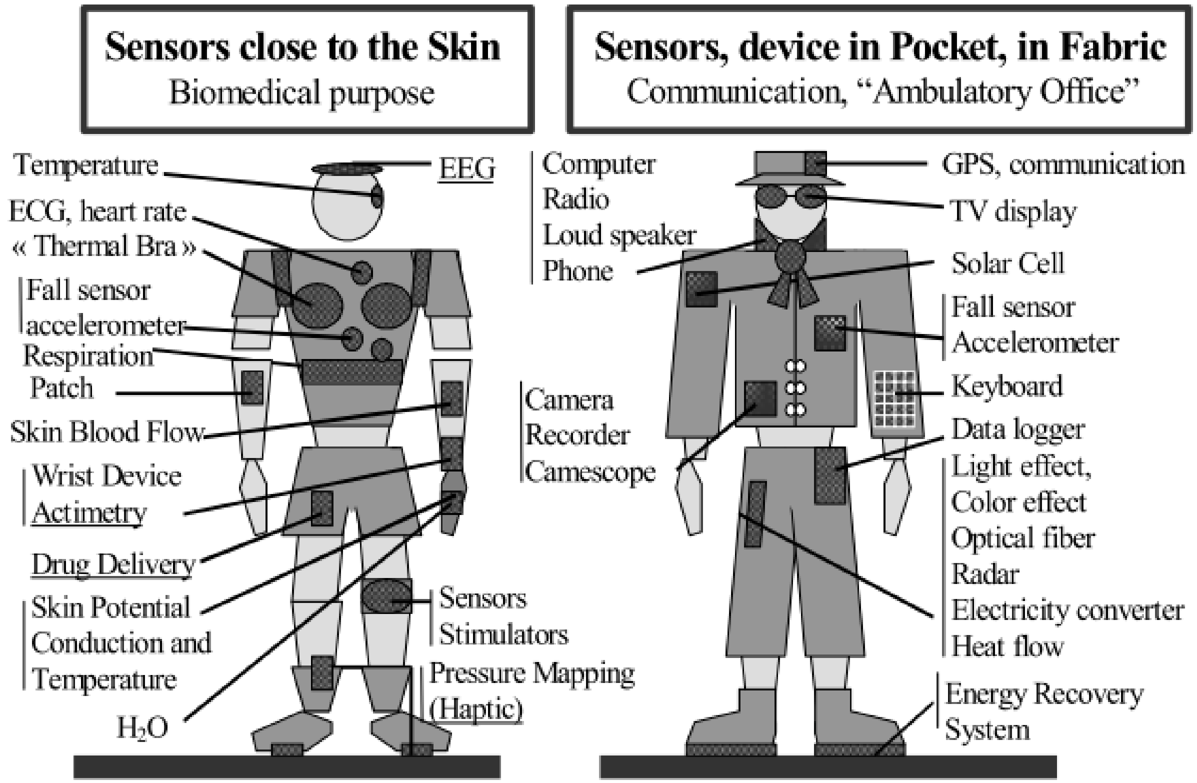
- Stress markers (lactate in sweat)
- Wound healing (pH and infection markers)

Vital Signs

- Respiration sensors
- Thermal sensors
- Galvanic skin response (GSR) sensors
- Cardiac Activity
  - Pulse oximeter
  - ECG devices
  - Doppler radars

Wearable Device Types

* Holter type
* Patches
* Body-worn
* Smart garments
    * Garment level
    * Fabric level
    * Fiber level



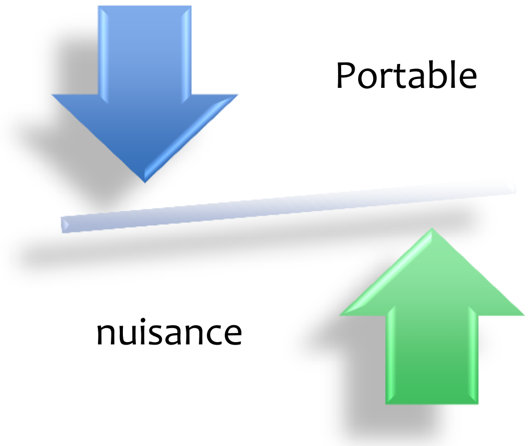
*A. Dittmar; R. Meffre; F. De Oliveira; C. Gehin; G. Delhomme; , "Wearable Medical Devices Using Textile and Flexible Technologies for Ambulatory Monitoring," *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the* , vol., no., pp.7161-7164, 2005

Data Transfer Architecture

- Most common setup
  - Sensors on body + a handheld or wearable data hub to communicate data wirelessly + a central node to process data
- Short range standards
  - Bluetooth (IEEE 802.15.1)
  - ZigBee (IEEE 802.15.4)
- Short range technologies
  - RF
  - Inductive links, Intrabody Communication

Why Wearable and Mobile?

- Pros.
  - Anywhere, anytime
  - Portable
  - Continuous recordings rather than “snapshot “
  - Avoid “white coat” syndrome
- Cons.
  - Anywhere, anytime
  - Should be worn/carried all the time
  - Wearing a tag can be regarded as stigma
  - Privacy concern, 24/7 monitoring



Tools & Infrastructure:
“Robots”

Assistive Robotics

- Helpful in physical tasks
- Communication
  - People consider them as social entities.

Care-O-bot® by Fraunhofer IPA: grasping items and bringing them to resident

RIBA , Japan: Transferring patients, 2009

PARO by U Penn, 2011

How Robots Help with ADL?

Task	# Robots
Support movement	35
Reducing need for movement	34
Feeding	7
Grooming	6
Bathing	4
Toileting	3
Dressing	2

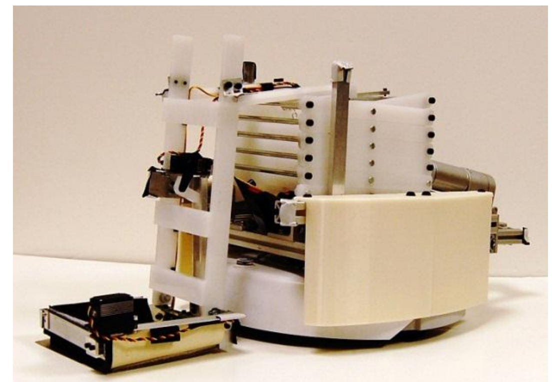
Data from Understanding the potential for robot assistance for older adults in the home environment (HFA-TR-1102). Smarr, C. A., Fausset, C. B., Rogers, W. A. (2011). Atlanta, GA: Georgia Institute of Technology, School of Psychology, Human Factors and Aging Laboratory. Link.

Example ADL Assistive Robots

* Reducing the need for movement

Topio Dio by Tosy

Care-O-bot® by Fraunhofer IPA: grasping items and bringing them to resident



Dusty II by GA Tech: Retrieving objects from floor

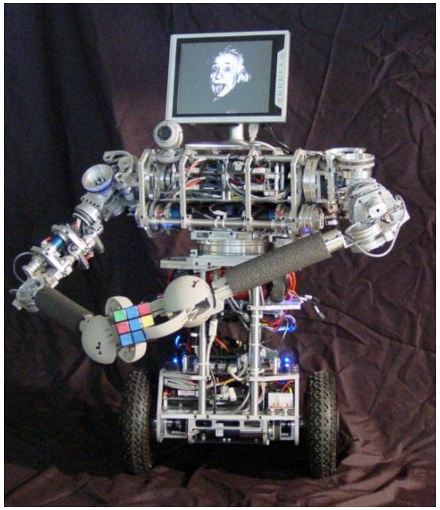
How Robots Help with IADL?

Task	# Robots
Housekeeping	53
Meal preparation	14
Medication Management	13
Laundry	7
Shopping	5
Telephone use	4
Money Management	0
Transportation	0

Data from Understanding the potential for robot assistance for older adults in the home environment (HFA-TR-1102). Smarr, C. A., Fausset, C. B., Rogers, W. A. (2011). Atlanta, GA: Georgia Institute of Technology, School of Psychology, Human Factors and Aging Laboratory. Link.

Example IADL Assistive Robots

PERMMA by U Penn, 2011



uBot-5 by UMAss, 2011

Roomba by iRobot, 2011

How Robots Help with EADL?

Task	# Robots
Social Communication	46
Hobbies	29
New Learning	16

Data from Understanding the potential for robot assistance for older adults in the home environment (HFA-TR-1102). Smarr, C. A., Fausset, C. B., Rogers, W. A. (2011). Atlanta, GA: Georgia Institute of Technology, School of Psychology, Human Factors and Aging Laboratory. [Link](#).

Example EADL Assistive Robots

PARO, Japan, 1993

Pearl by CMU, 2002

iCat by Philips, 2006

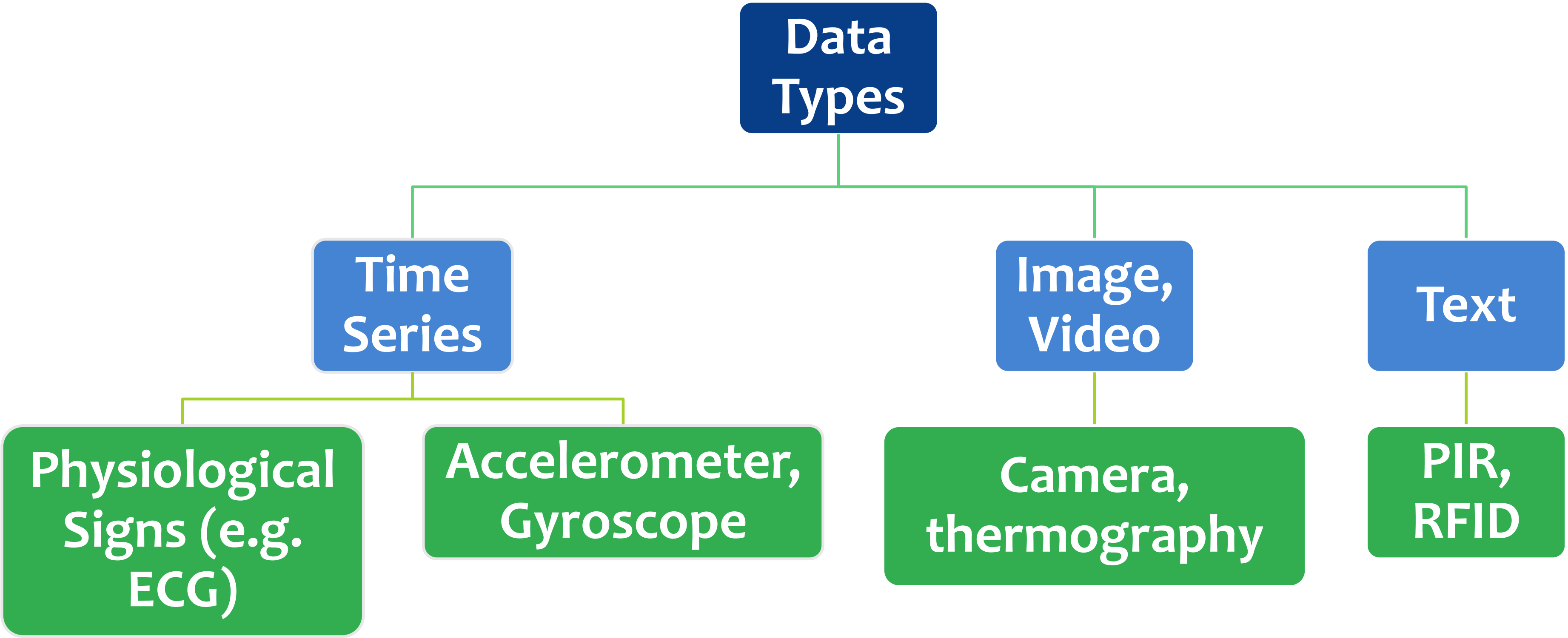
Algorithms & Methods

Algorithms

* The ones we will discuss
  * **Activity recognition from**
    * **Wearable & mobile sensors**
    * **Ambient sensors**
    * **Camera (Vision)**
  * Context Modeling
  * Other algorithms
    * Indoor Location detection
    * Reminding

Data Sources

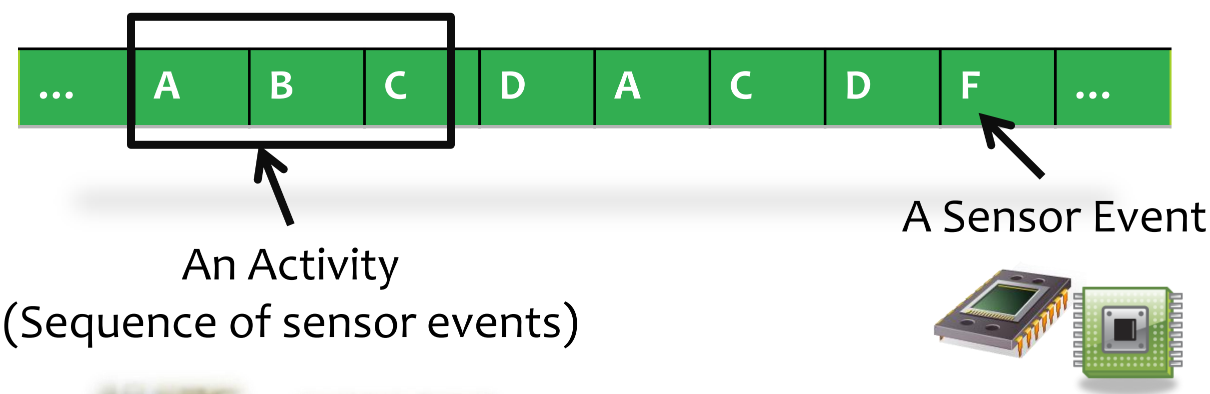
* Different mediums generate different types of data

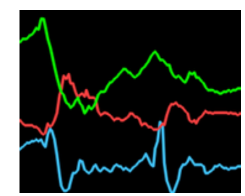


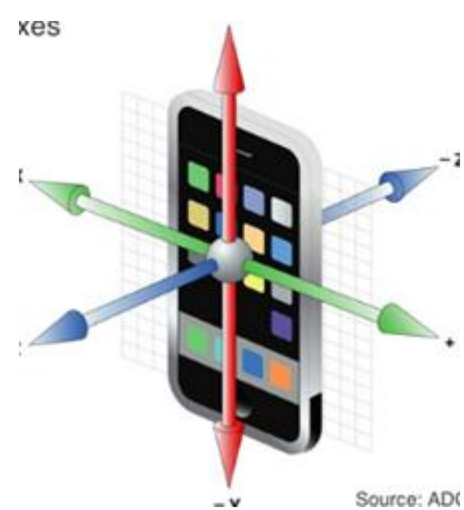
Algorithms & Methods:
“Activity Recognition”

What is Activity Recognition?

- The basic building block in many applications
  - Recognizing user activities from a stream of sensor events







Activity Resolution

* Fine grained (individual movements, especially in vision)
* Coarse grained (activity)

Complexity

Movement: e.g. stretching arm

Action: e.g. walking

Activity: e.g. preparing meal

Group Activity: e.g. team sports

Crowd Activity: e.g. crowd surveillance

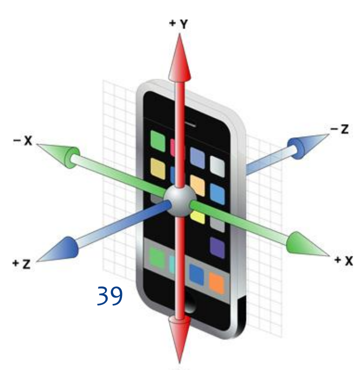
Algorithms & Methods:

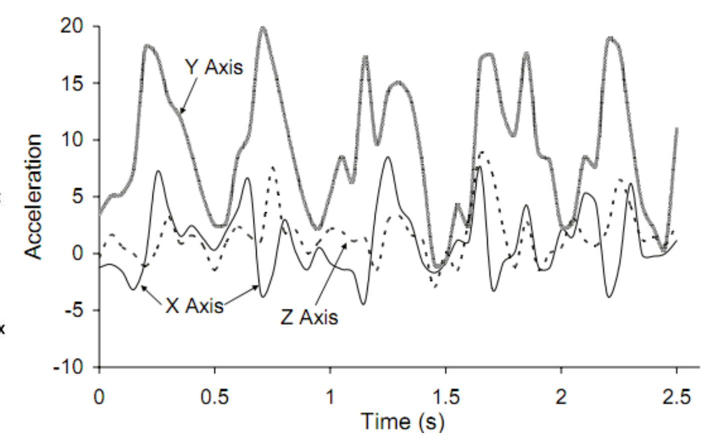
Activity Recognition:

“**Wearable & Mobile**”

Activity Data from Wearable Sensors

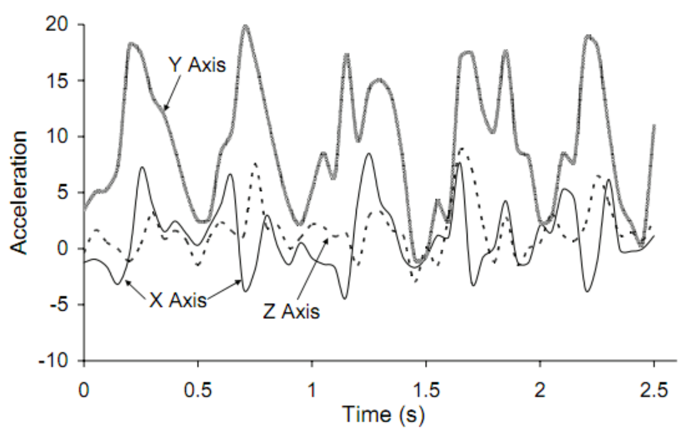
* Mostly in form of time series
  * Accelerometer [& gyroscope]
* Most actions in form of distinct, periodic motion patterns
  * Walking, running, sitting,..
* Usual features
  * Average, standard deviation
  * Time between peaks, FFT energy, Binned distribution
  * Correlation between axes
  * …



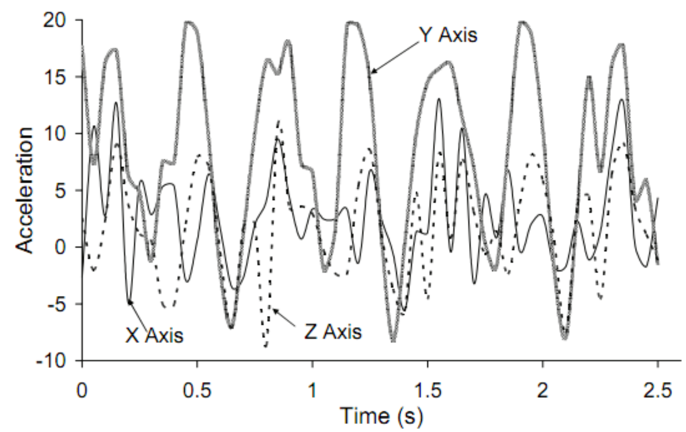


Example Activities

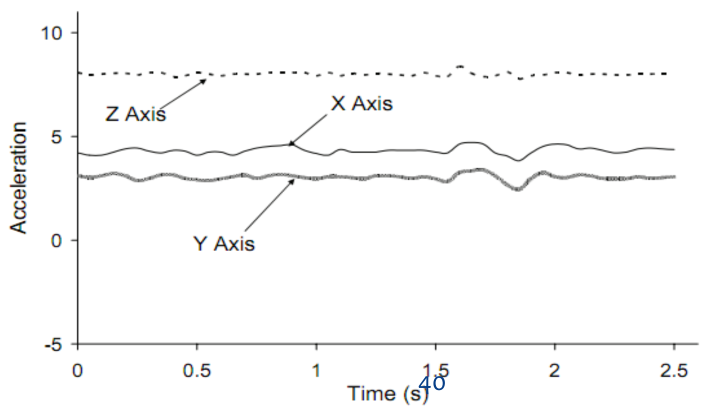
* Example activities from mobile phone accelerometer



(a) Walking



(b) Jogging

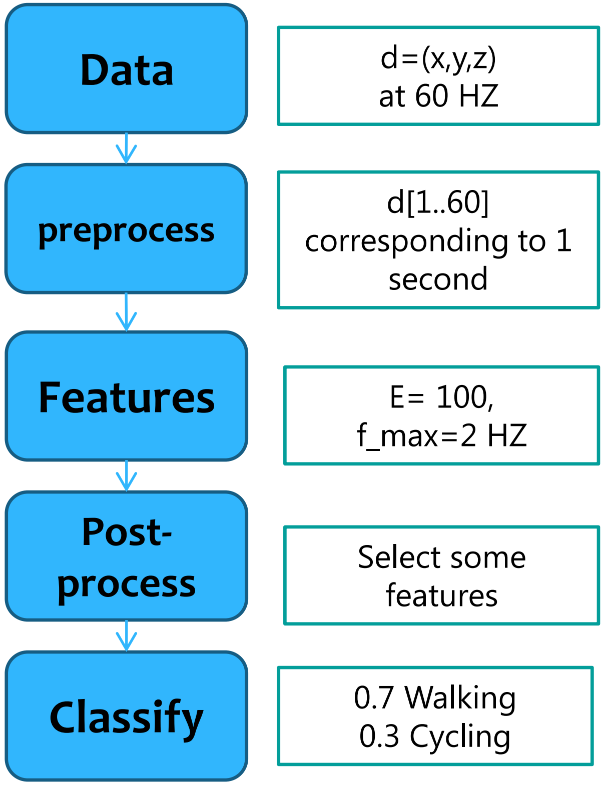


(e) Sitting

Kwapisz et al, SIGKDD exploration, 2010

Processing Steps

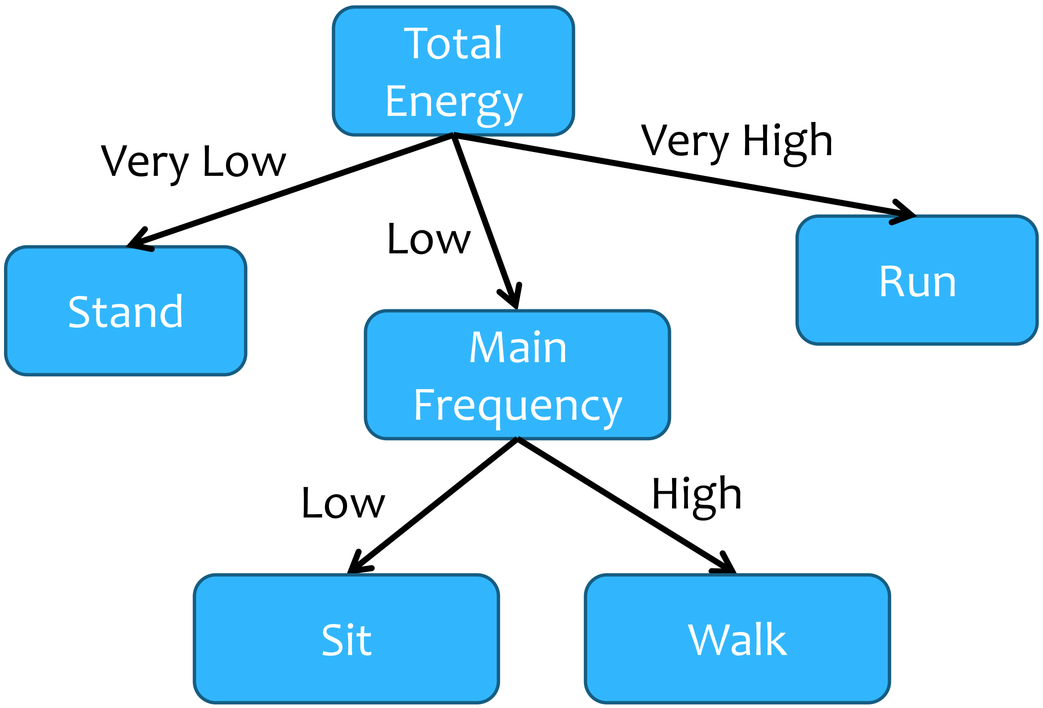
- Stages
  - Data collection
  - Preprocessing
  - Feature extraction
    - Mean, SD, FFT coefficients
  - Dimensionality Reduction
  - Classification



*See: A Tutorial Introduction to Automated Activity and Intention Recognition by Sebastian Bader, Thomas Kirste. Link

Classification

* Supervised
  * SVM, DT, …
* Semi-supervised
* Unsupervised
  * Clustering
  * Motif discovery



A simple decision tree

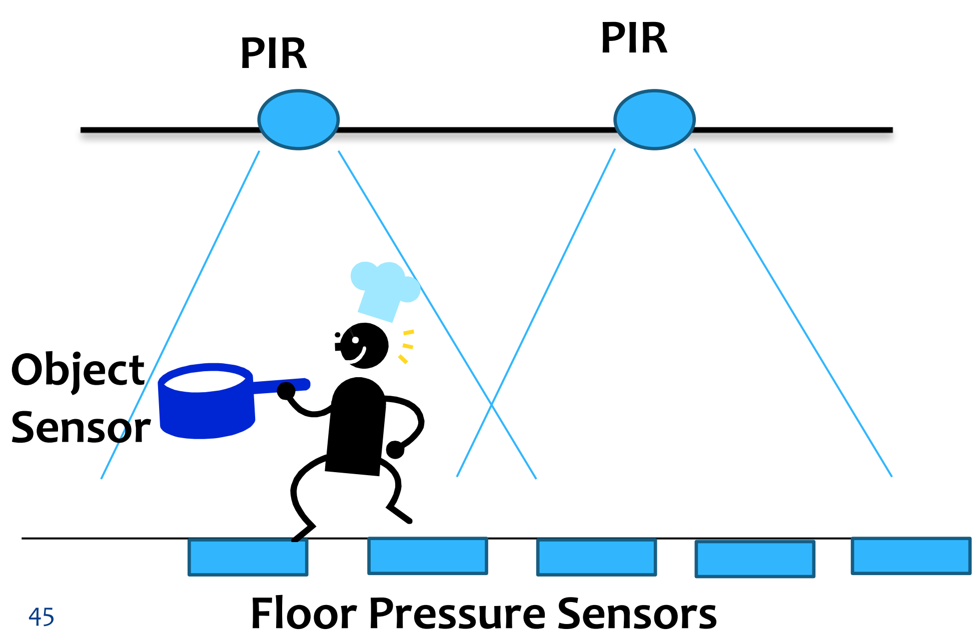
*See: A Tutorial Introduction to Automated Activity and Intention Recognition by Sebastian Bader, Thomas Kirste. Link

Algorithms & Methods:

Activity Recognition:
“Ambient Sensors”

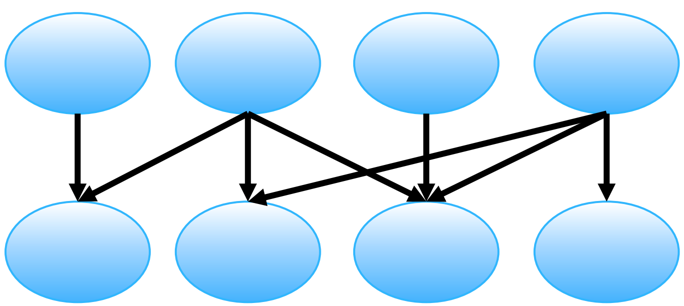
Activity Recognition

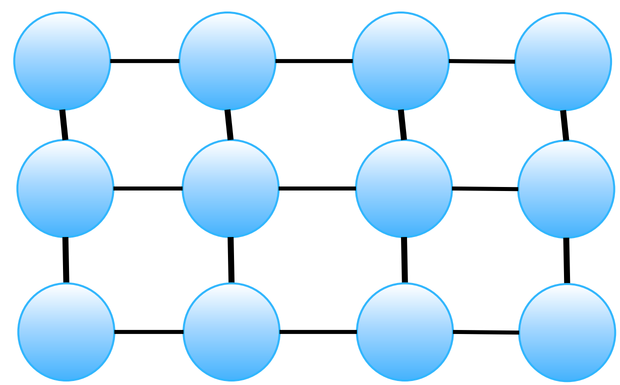
* More complex activities need more sophisticated sensors
  * Sensor networks of PIR sensors, contact switch sensors, pressure sensors, object sensors, etc.
* Approaches
  * Supervised
    * Probabilistic
  * Semi/Unsupervised



Probabilistic Approaches

- Graphical models
  - Naïve Bayes (NB)
  - Hidden Markov Model (HMM)
  - Dynamic Bayesian Network (DBN)
  - Conditional Random Field (CRF)

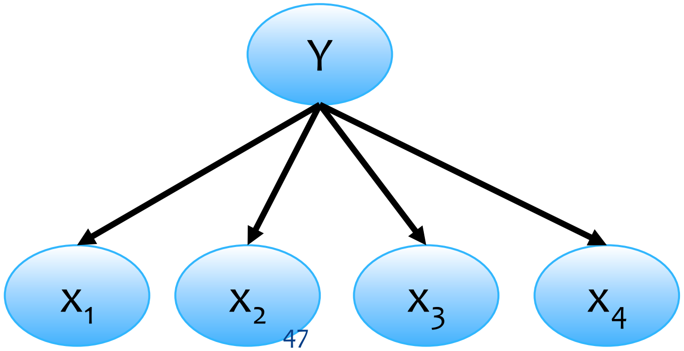




Naïve Bayes

* A very simple model, yet effective in practice [Tapia 2004]
* Assumes observations are independent of each other
* Y = activity (e.g. taking medications)
* X = observation (e.g. sensor M1 is ON)

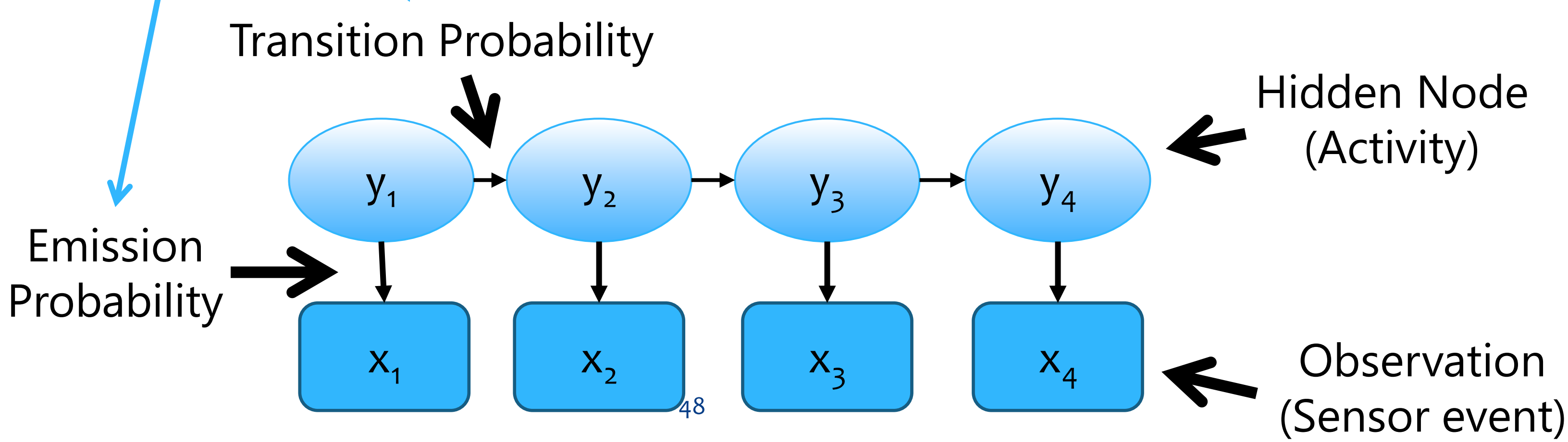
$$P(y|x) = P(y) \prod_{m=1}^{M} P(x_m|y)$$



Hidden Markov Model (HMM)

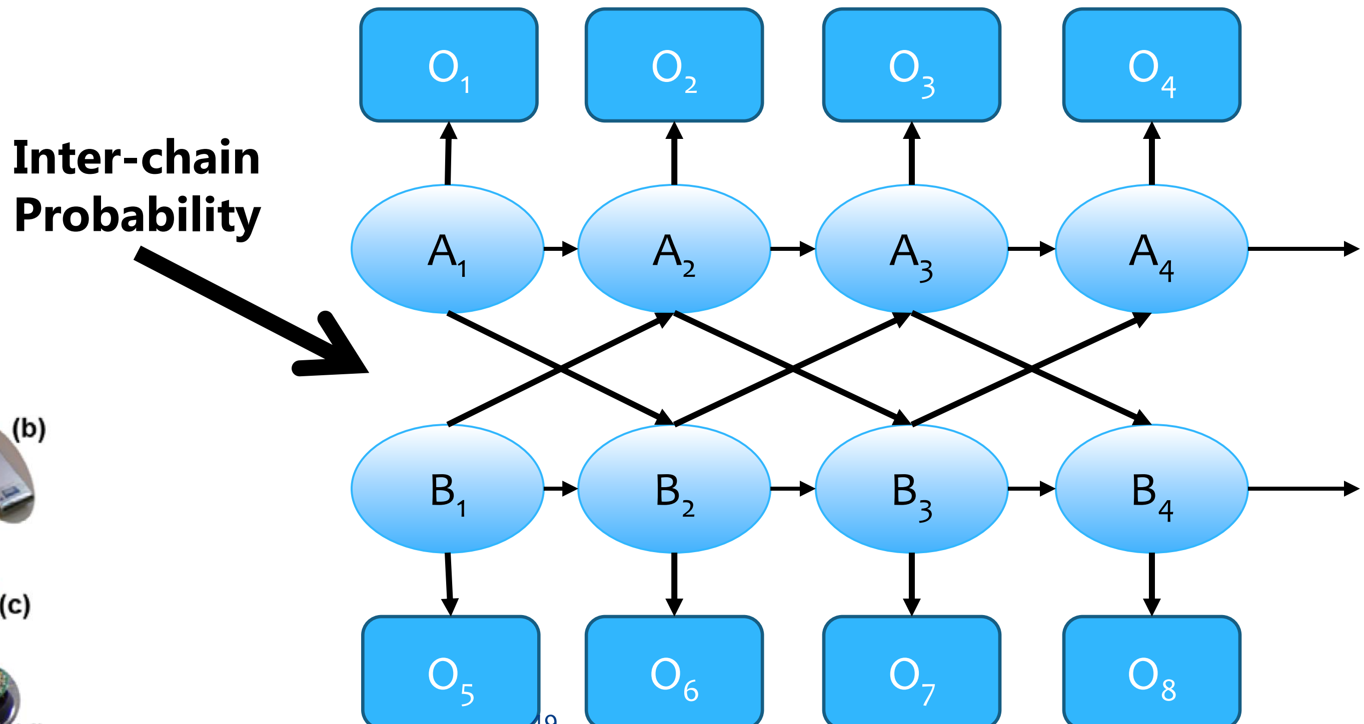
- A model for inferring hidden states from observations
- Well known, efficient algorithms

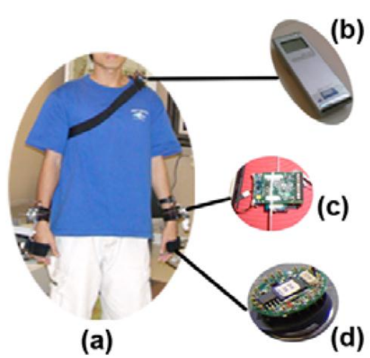
$$P(y,x) = \prod_{t=1}^{T} P(x_t|y_t).P(y_t|y_{t-1})$$



Multiple Residents?

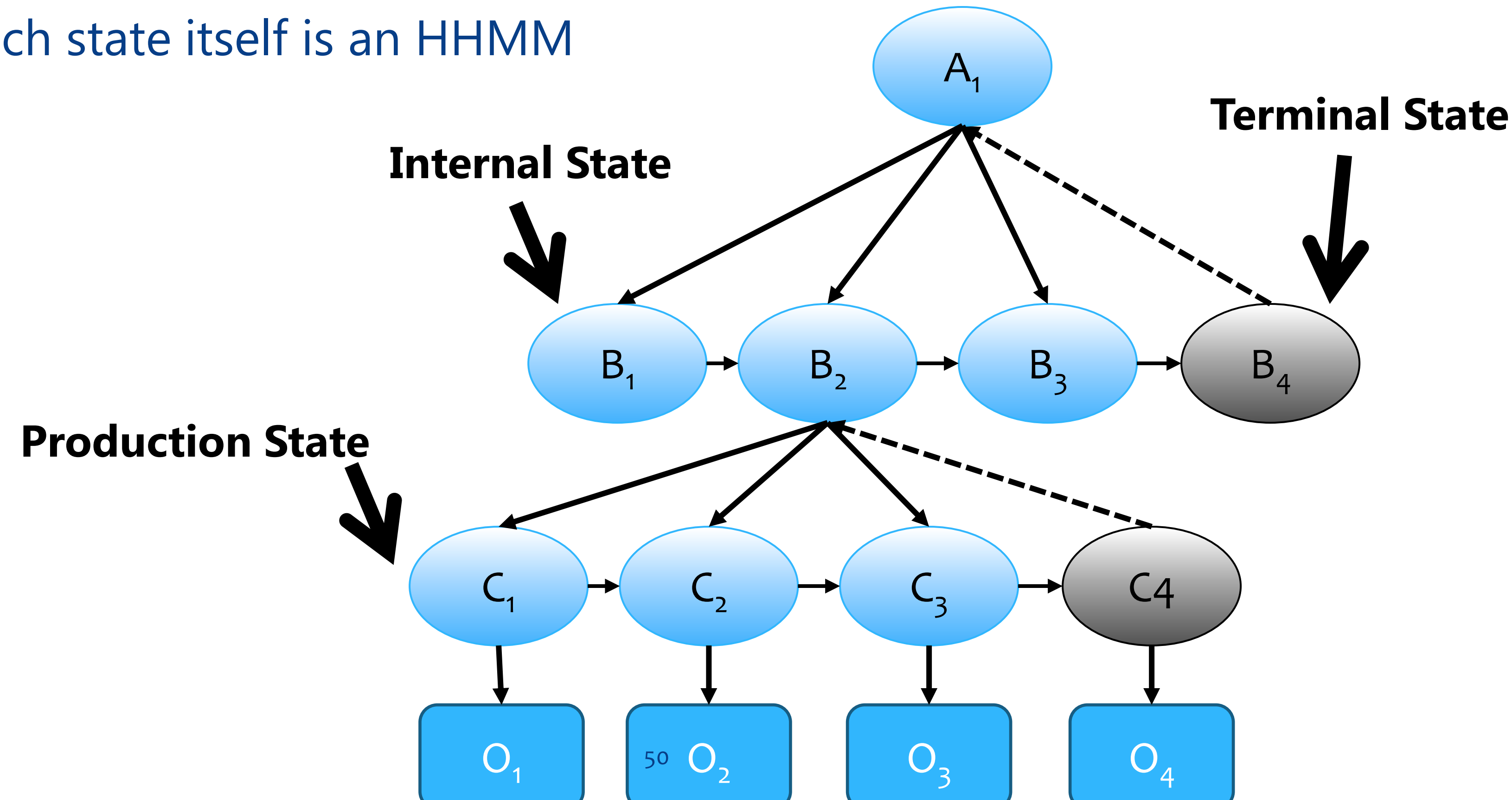
- Coupled Hidden Markov Model (CHMM) [Wang 2010]
  - O = observations
  - A, B = activities





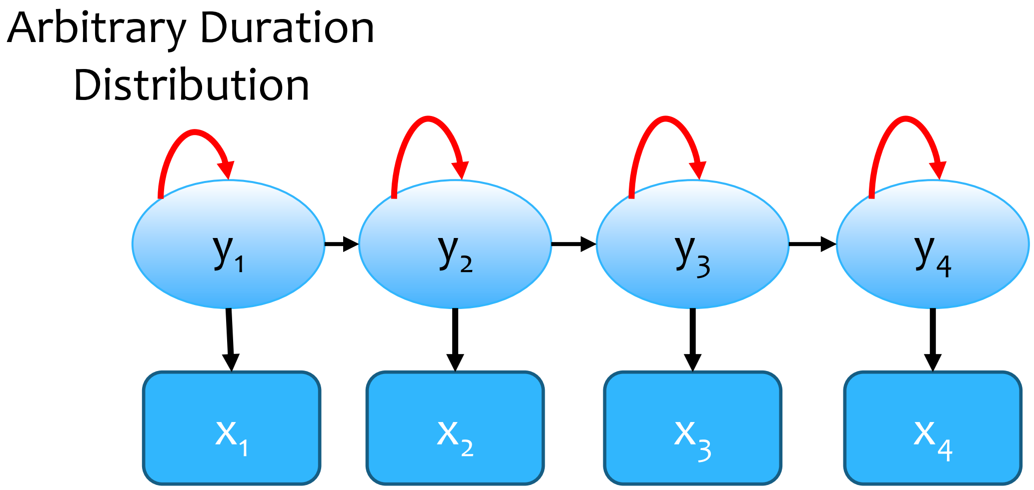
Hierarchal Definition of Activities?

* Hierarchal Hidden Markov Model (HHMM) [Choo 2008, Nguyen 2006]
  * Each state itself is an HHMM



Hidden Semi-Markov Model

* Hidden Semi-Markov Model (HSMM) [Duong 2006]
* Activity duration modeling
  * Arbitrary probability distribution of staying in a state



Markov Logic Network

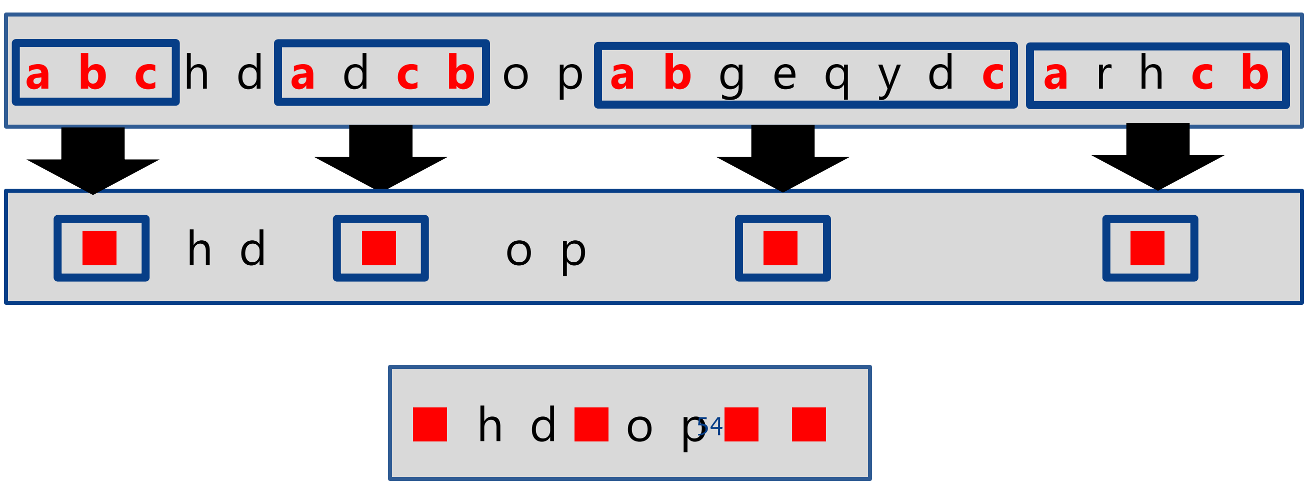
* Markov logic networks [Helaoui 2011]
  * Easily including background knowledge of activities + non-deterministic approach
  * First order logic + Markov network

Other Graphical Models

* Dynamic Bayesian Network (DBN)
* Conditional Random Fields (CRF)
* …

Unsupervised Methods

- Data annotation problem!
- Emerging patterns
  - Mining frequent patterns [Gu 2009, Heierman 2003]
  - Mining periodic sequential patterns [Rashidi 2008]
- Stream mining
  - Tilted time model [Rashidi 2010]



Other Techniques

- Transfer learning [TLM van Kastere 2010, VW Zheng 2009]
  - Bootstrap for a new resident
  - Bootstrap in a new building
  - …
- Semi-supervised learning [D Guan 2007,]
  - Co-training
- Active learning [M Mandaviani 2007, Rashidi 2011]

Algorithms & Methods:

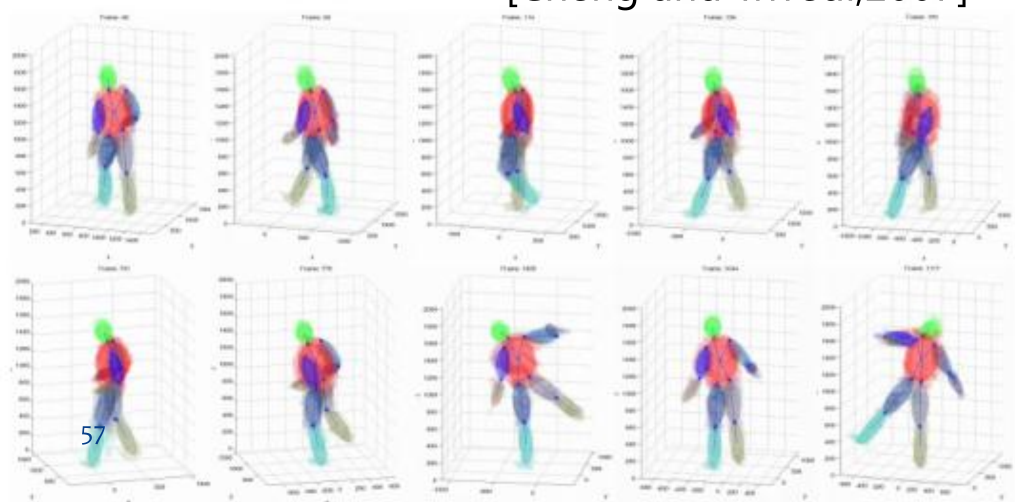
Activity Recognition:

“Vision”

Vision Based Systems

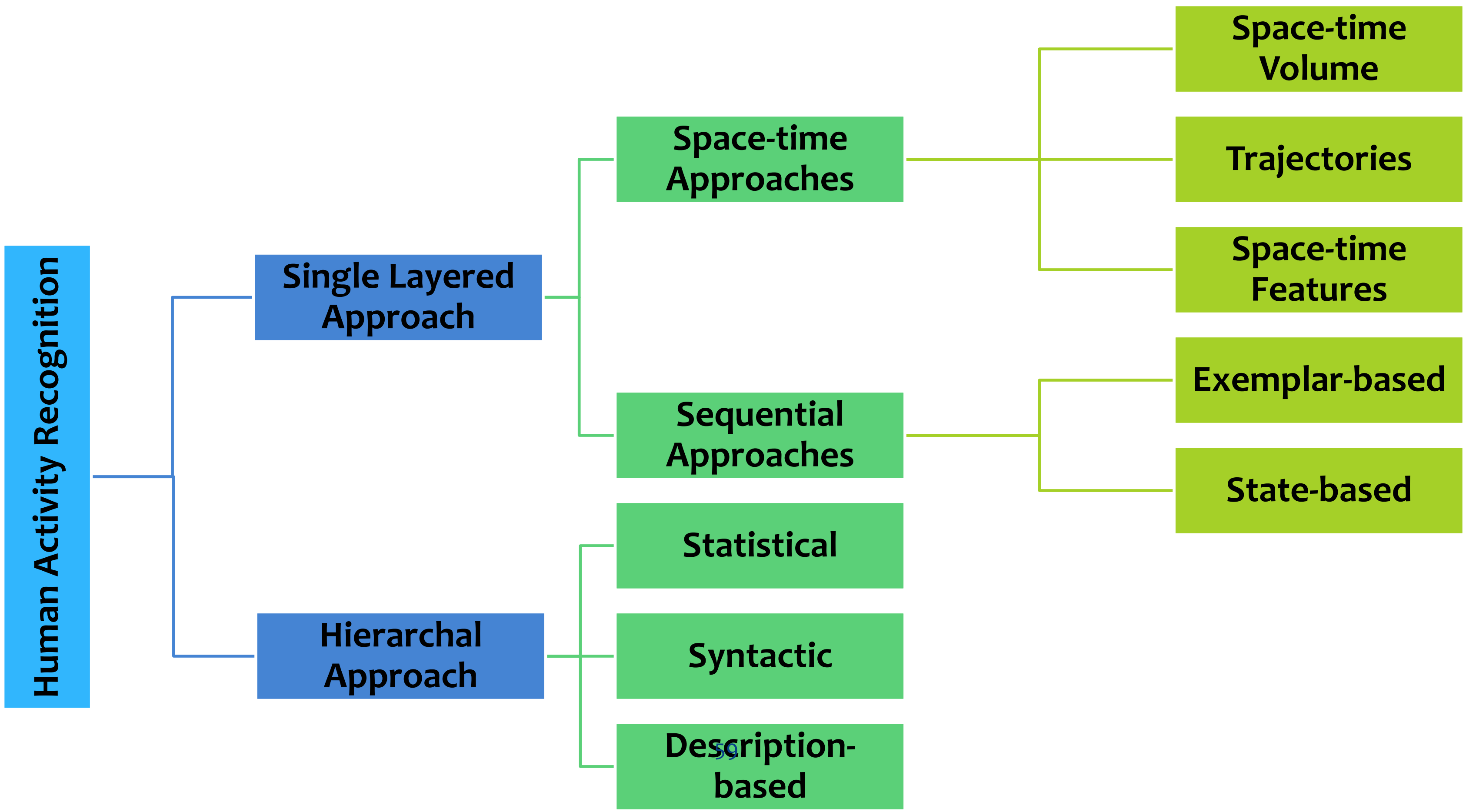
- Used in many related application domains
  - Video surveillance, sports analysis, …
- Advantages
  - Rich information
- Disadvantages
  - Highly varied activities in natural environment
  - Privacy concerns
  - Algorithm complexity

[Cheng and Trivedi,2007]



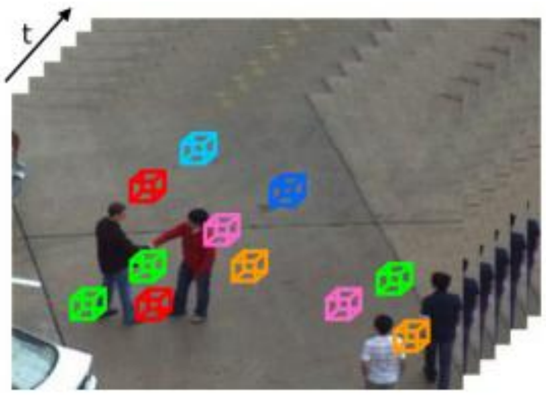
Algorithms

* Taxonomy of methods [Aggarwal & Ryoo 2011]



Single Layered

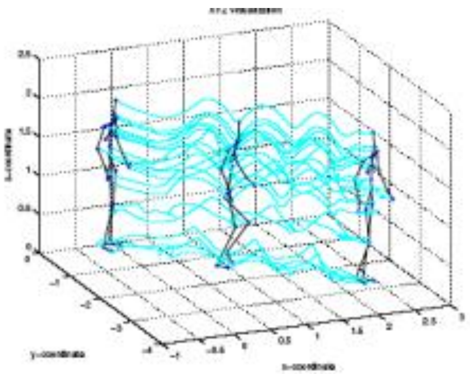
* Suitable for recognition of gestures & actions
* Two different representations
  * Space-time distribution
    * Data oriented, spatio-temporal features
  * Sequence
    * Semantic oriented, tracking

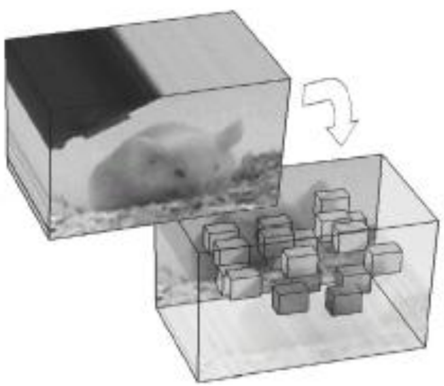


Space-time Approaches

- Space-time approach representation
  - Volume
  - Trajectories
  - Local features

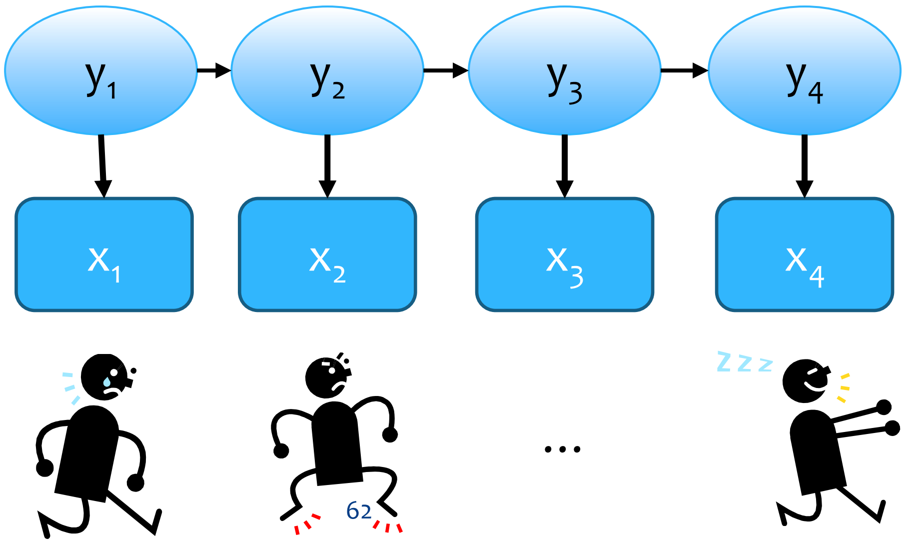
2D nonparametric template matching, Bobick & Davis, IEEE Trans. Pattern Anal. Mach. Intel, 2001





Sequential Approaches

- Sequential approach
  - Exemplar:
    - Directly build template sequence from training examples
  - State-based
    - Build a model such as HMM



Hierarchal Approach

Hierarchal

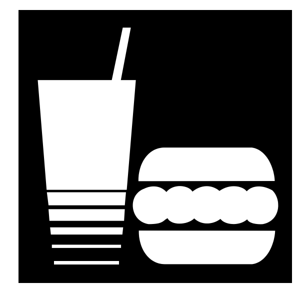
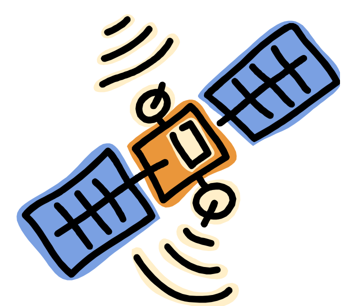
- Statistical: As states (e.g. HHMM, LHMM, …) — Robust to Uncertainty
- Syntactic: As Symbols (e.g. CFG, SCFG, ..) — Deep Hierarchy
- Descriptive: As Logical Relations (MLN …) — Encoding Complex Logic

Algorithms & Methods: "…"

Context Information

* Different types of context data
  * Information from sensors
  * Activities and their structure
  * User profile & preferences
  * Static data (e.g. rooms)



Context Modeling Approaches

1. Key-value models
   e.g. Context Modeling language (CML)
2. Simple markup schema
   e.g. HomeML
3. Ontology
   e.g. SOUPA
4. Uncertain context
   e.g. Meta-data (e.g. freshness, confidence, resolution)
5. Situation modeling & reasoning
   e.g. Situation calculus

Indoor Location Identification

Method	Disadvantage
Smart floor	Physical reconstruction
Infrared motion sensors	Inaccurate, sensing motion (not presence)
Vision	Privacy
Infrared (active badge)	Direct sight
Ultrasonic	Expensive
RFID	Range
WiFi	Interference, inaccurate

Person Identification

- Multiple residents
  - Active Identification
    - RFID Badges
  - Anonymous
    - Motion models (Wilson 2005, Crandall 2009)

Reminders

* Problems [Pollack 2003 , Horvitz 2002, 2011]
  * When to remind?
  * What to remind?
  * Avoiding activity conflicts
* Solutions
  * Planning & scheduling
  * Reinforcement learning

Some Case Studies

Applications

Cognitive Orthotics

- Reminders
- Planners
- Navigation and stray prevention

Health Monitoring

- Continuous Monitoring of Vital Signs
- ADL
- Sleep Monitoring

Therapy & Rehabilitation

- Tele-Health

Emergency Detection

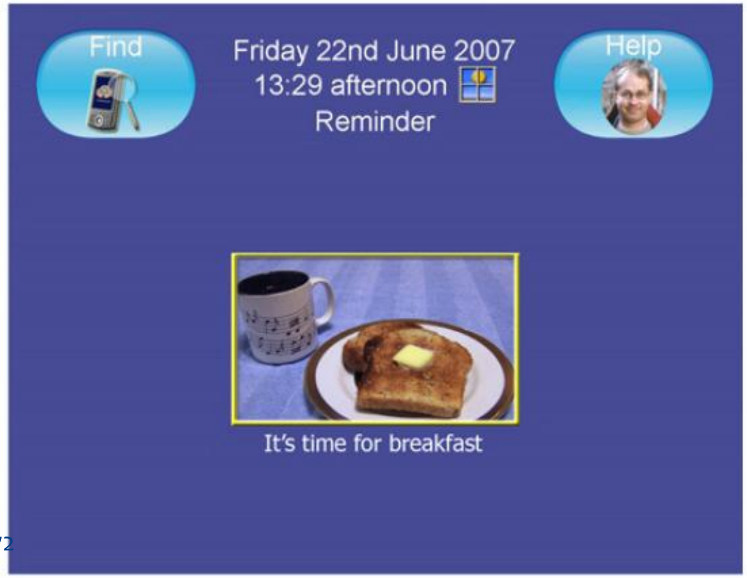
- Fall Detection
- Medical emergency

Emotional Wellbeing

- Social Connectedness
- Facilitating Communication

Reminders

* Simple reminders
  * NeuroPager (1994), MAPS (2005), MemoJog (2005)
* AI-based
  * PEAT (1997), Autominder (2003)



[Davies 2009]

Autominder

* Developed by Martha E. Pollack et al. (U. Of Michigan)
* Reminders about daily activities
  * Plan manager to store daily plans
  * Resolving potential conflicts
  * Updating the plan as execution proceeds
* Models plans as Disjunctive Temporal Problems
  * Constraint satisfaction approach
  * Payoff function

COACH

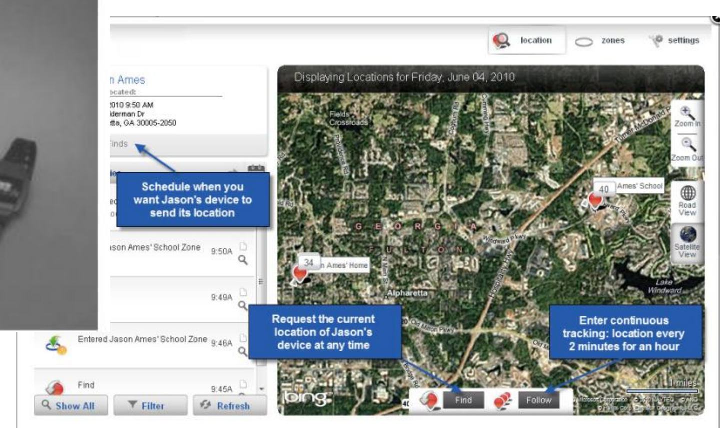
* COACH: Monitoring hand-washing activity and prompting [Mihailidis 2007, U Toronto]
* Vision
* Detecting current state
  * Markov Decision process (MDP)
* Prompting

Outdoor Stray Prevention

* Opportunity Knocks (OK): public transit assistance [Patterson 2004]
* iRoute: Learns walking preference of dementia patients [Hossain 2011]
* Commercial
  * GPS shoes
  * ComfortZone

GPS Shoes

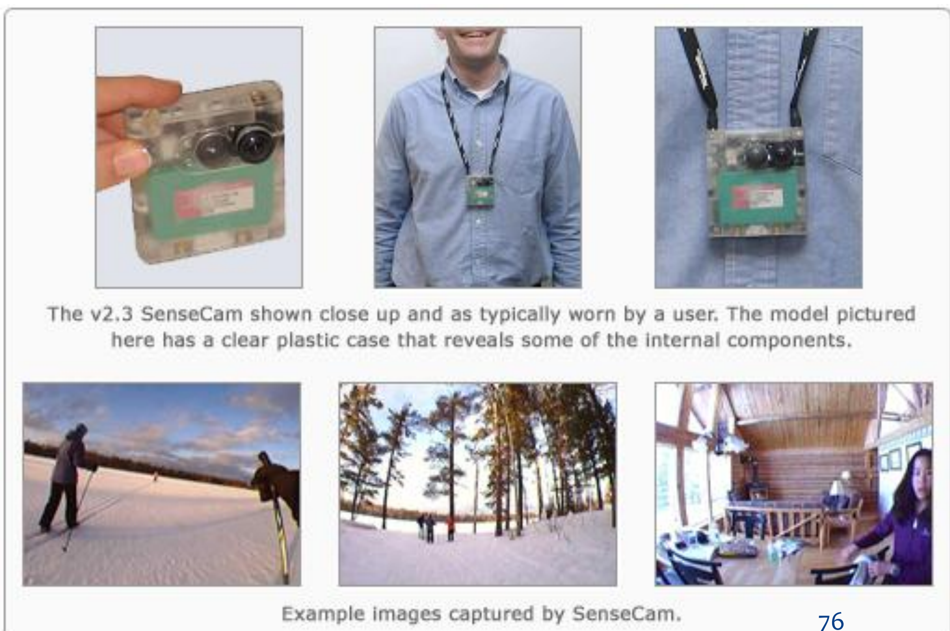
Bracelet for tracking patients



ComfortZone

Memory Aid

- SenseCam
  - Microsoft Research, Cambridge, UK, 2004-2011
  - Now commercially available as REVUE

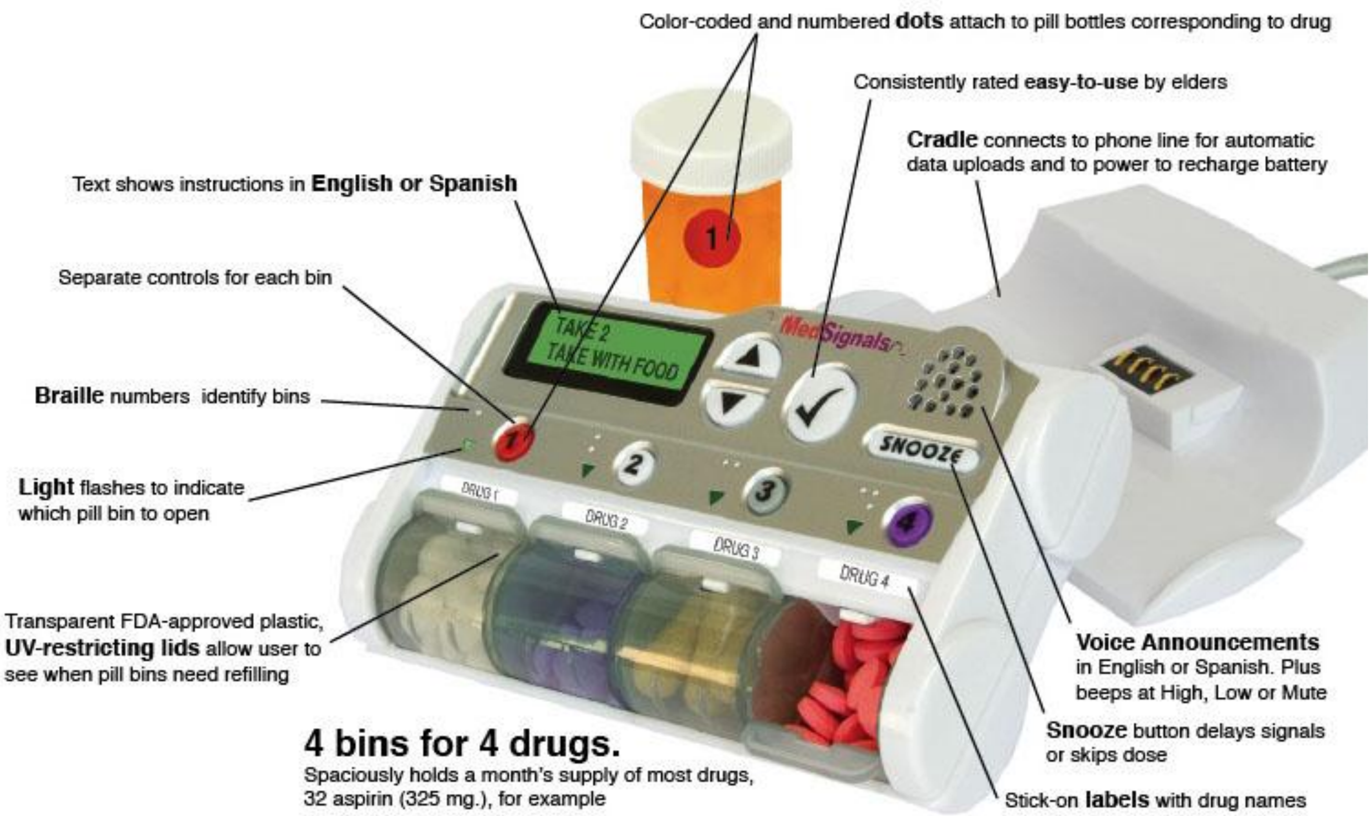


The v2.3 SenseCam shown close up and as typically worn by a user. The model pictured here has a clear plastic case that reveals some of the internal components.

Example images captured by SenseCam.

Medication Management

* MedSignals
* MD.



MedSignals

Case Studies:

“CASAS Smart Home”

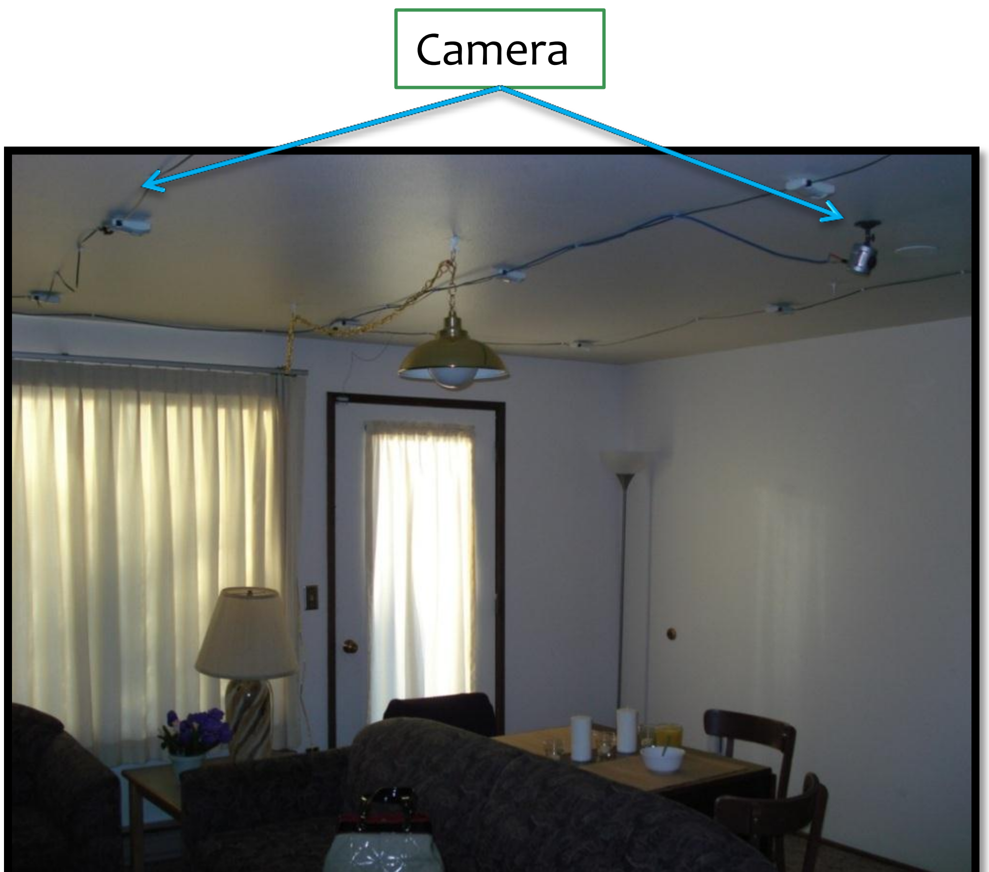
CASAS Project

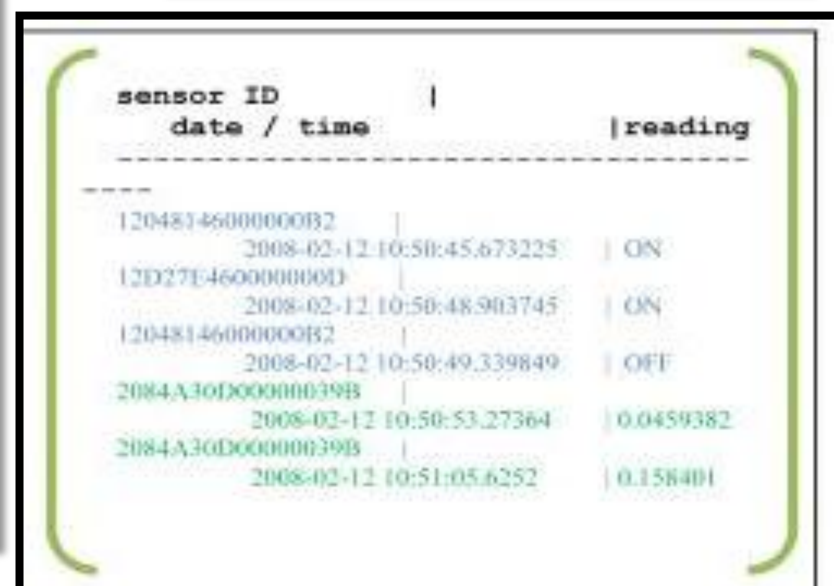
- **C**enter for **A**dvanced **S**tudies in **A**daptive **S**ystems
- One of the large-scale smart home projects in the nation
  - A couple of on campus testbeds
  - Dozens of real home deployment
- A smart home data repository

Data Repository

http://ailab.eecs.wsu.edu/casas

On-campus Testbeds

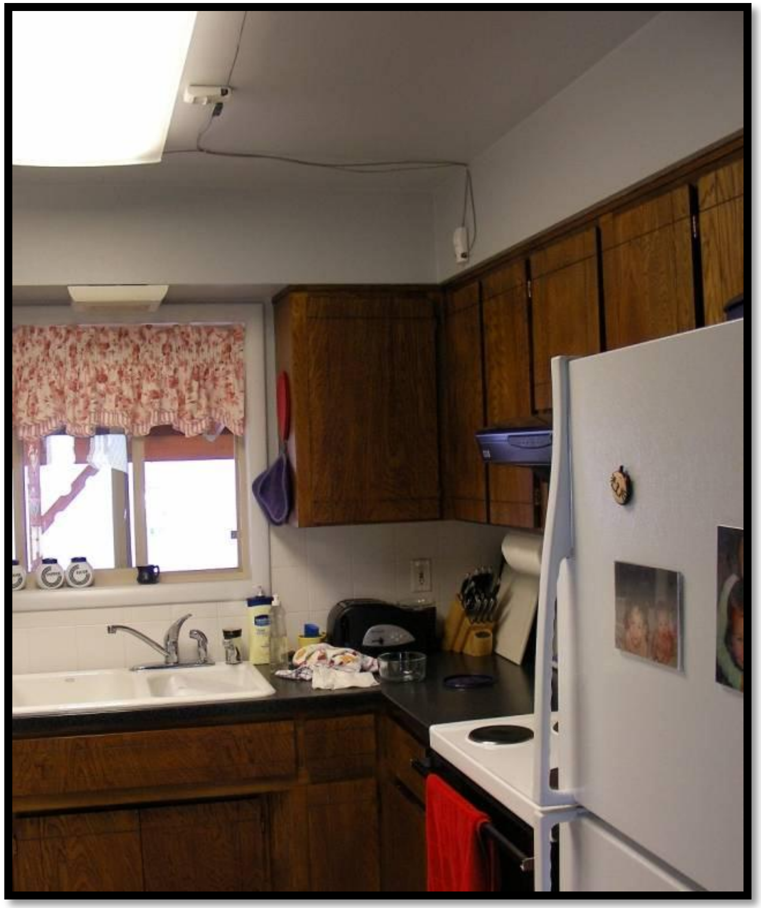




```
sensor ID              |
   date / time                 |reading
--------------------------------------
----
120481460000000B2      |
          2008-02-12 10:50:45.673225   | ON
12D27E460000000D       |
          2008-02-12 10:50:48.903745   | ON
120481460000000B2      |
          2008-02-12 10:50:49.339849   | OFF
2084A30D00000039B      |
          2008-02-12 10:50:53.27364    | 0.0459382
2084A30D00000039B      |
          2008-02-12 10:51:05.6252     | 0.158401
```

Actual Deployments

* Patients with mild form of dementia
* Noninvasive deployment
* Prompting systems



Prompting Technology

- Context-based
- Prompt only if task not initiated
- Prompt can be re-issued

I will do it now | I will do it later | I've done this task | I won't do this task

Design Issues

Wearable & Mobile Design Issues

* Issues:
  * Physical interference with movement
  * Difficulty in removing and placing
  * Weight
  * Frequency and difficulty of maintenance
    * Charging
    * Cleaning
  * Social and fashion concerns
* Suggestions:
  * Use common devices to avoid stigmatization
  * Lightweight
  * Easy to maintain

User Interface Design Issues

* Simple Interface
* Limit possibility of error
* Avoid cognitive overload
  * Limit options
  * keep dialogs linear
  * Avoid parallel tasks
* Consider all stakeholders
  * Patient, formal onsite/offsite caregivers, informal onsite/offsite caregivers, technical personnel

Privacy & Ethics

- Ethics
  - Perfect transparency
  - Control over the system
  - Fight laziness
- Privacy
  - Encrypt data
  - Patient authentication (Owner aware)

Challenges & Future

Are they ready to adopt?

- Healthy older adults use technology more often*
  - "Not being perceived as useful" *
- Better a known devil than an unknown god
- Privacy Concerns
  - Big brother
  - Stigmatization

*Heart and Kalderon, Older adults: Are they ready to adopt health-related ICT?, 2011

Smart Home Challenges

* Smart homes
  * Location detection
    * Privacy/unobtrusiveness vs. accuracy
    * Difficulty with multiple residents
    * PIR sensor proximity is important
  * Reliability
    * Distinguishing anomalies from normal changes
  * Become more context aware
  * Standard protocol

Wearable & Mobile Challenges

- Wearable & mobile
  - Power harvesting
  - Size
- Smart fabrics
  - Limitations when skin is dry or during intense activity
  - Still hybrid

Assistive Robotics Challenges

- Assistive robotics
  - Marketing and price
  - Lack of reliable technology
  - A robot fully capable of helping with all ADLs
  - Adaptive robots
  - More user studies

Legal & Ethical Challenges

* Legal, ethical
  * Telemedicine
    * Lack of regulations
      * Which state regulations? Patient's or Physician?
      * Who is responsible for malpractice?
    * Risk of fake physicians
    * Physician out-of-state competition
  * Insurance & reimbursement
  * Patient confidentiality

Future

* Technology
  * Device interoperability
* Legal issues
* Patient centric
* Integrate all
  * Robots + smart home + wearable/mobile sensors + e-textile
* Technology transfer, go beyond prototype

Resources

Assistive Robotics

* 2011 technical report on "robot assistance for older adults"
  * Understanding the potential for robot assistance for older adults in the home environment (HFA-TR-1102). Smarr, C. A., Fausset, C. B., Rogers, W. A. (2011). Atlanta, GA: Georgia Institute of Technology, School of Psychology, Human Factors and Aging Laboratory.
* 2009 review article on "Assistive social robots in elderly care"
  * *Broekens J., Heerink M., Rosendal H. Assistive social robots in elderly care: a review. Gerontechnology 2009; 8(2):94-103*
* 2011 technical report on "Robot acceptance"
  * Beer, J. M., Prakash, A., Mitzner, T. L., & Rogers, W. A. (2011). Understanding robot acceptance (HFA-TR-1103). Atlanta, GA: Georgia Institute of Technology, School of Psychology, Human Factors and Aging Laboratory.

Vision

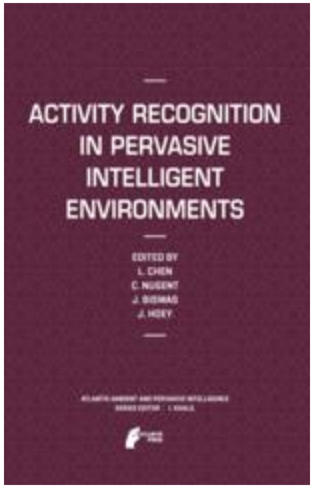
* Human Activity Analysis Survey
  * J.K. Aggarwal and M.S. Ryoo. 2011. Human activity analysis: A review. ACM Comput. Surv. 43, 3, Article 16.
* Survey: Recognition of Human Activities
  * Turaga, P.; Chellappa, R.; Subrahmanian, V.S.; Udrea, O.; , "Machine Recognition of Human Activities: A Survey," Circuits and Systems for Video Technology, IEEE Transactions on , vol.18, no.11, pp.1473-1488, Nov. 2008.
* CVPR 2011 Tutorial on Human Activity Recognition: Frontiers of Human Activity Analysis
  * http://cvrc.ece.utexas.edu/mryoo/cvpr2011tutorial/

Wearable Sensors

- Wearable monitoring systems book
  - Bonfiglio, Annalisa; De Rossi, Danilo, Wearable Monitoring Systems, Springer, 2011.
- On-board data mining book
  - S. Tanner et al., On-board data mining, Scientific Data Mining and Knowledge Discovery, , Volume . ISBN 978-3-642-02789-5. Springer-Verlag Berlin Heidelberg, 2009, p. 345
- Excellent tutorial on time series
  - Eamonn Keogh's VLDB06 Tutorial

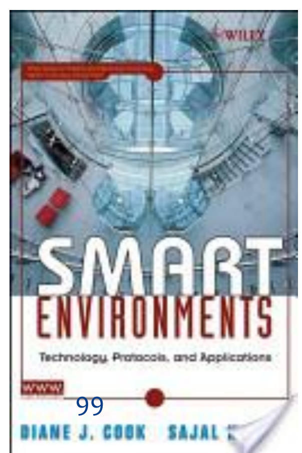
Activity Recognition

* Activity Recognition Book
  * Chen, Liming, Nugent, CD, Biswas, J and Hoey, J. "Activity Recognition in Pervasive Intelligent Environments", 2011, Springer.
* Context Aware Modeling Survey
  * Claudio Bettini, et al., "A survey of context modeling and reasoning techniques", Pervasive and Mobile Computing, Volume 6, Issue 2, April 2010, Pages 161-180.
* HMM Tutorial
  * Rabiner, L.R.; , "A tutorial on hidden Markov models and selected applications in speech recognition," Proceedings of the IEEE , vol.77, no.2, pp.257-286, Feb 1989.



Smart Homes

- Intelligent Environments Book
  - Monekosso, Dorothy; Kuno, Yoshinori. “Intelligent Environments: Methods, Algorithms and Applications”, 2011, Springer.
- Smart Environments Book
  - Diane J. Cook, Sajal K. Das. Smart environments: technologies, protocols, and applications. John Wiley and Sons, 2005.
- Smart Home Survey
  - Marie Chan, Daniel Estve, Christophe Escriba, and Eric Campo. 2008. A review of smart homes-Present state and future challenges. *Comput. Methods Prog. Biomed.* 91, 1 (July 2008)

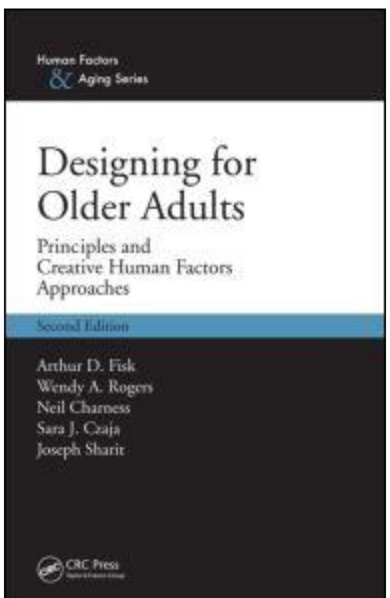


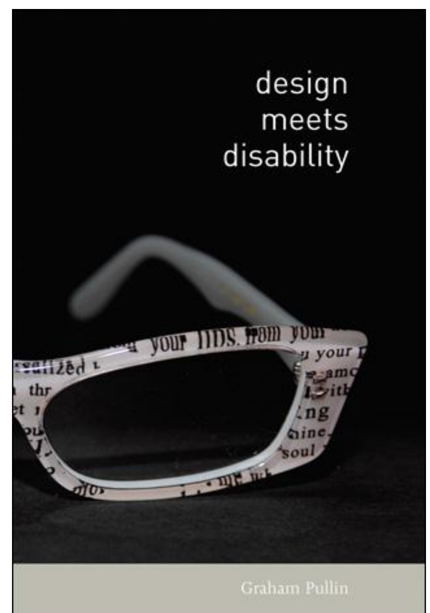
Legal, Ethical

* Legal and ethical issues in telemedicine and robotics
  * B.M. Dickens, R.J. Cook, Legal and ethical issues in telemedicine and robotics, Int. J. Gynecol. Obstet. 94 (2006) 73–78.
* Telemedicine: Licensing and Other Legal Issues
  * Gil Siegal, Telemedicine: Licensing and Other Legal Issues, Otolaryngologic Clinics of North America, Volume 44, Issue 6, December 2011, Pages 1375-1384
* Older adults: Are they ready to adopt health-related ICT?
  * Tsipi Heart, Efrat Kalderon, Older adults: Are they ready to adopt health-related ICT?, International Journal of Medical Informatics,, ISSN 1386-5056, 2011.

Design

* # Designing for Older Adults
  * Arthur D. Fisk, Wendy A. Rogers, Neil Charness, Joseph Sharit. Designing Displays for Older Adults. CRC Press, 26.3.2009.
* # Design meets disability
  * Graham Pullin.“Design meets disability”, 2009, MIT Press.





General Resources

* **Gerontechnology Journal:** International journal on the fundamental aspects of technology to serve the ageing society
  * http://www.gerontechnology.info/Journal/
* **Assistive Technology**: Journal of Assistive Technologies
  * http://www.emeraldinsight.com/journals.htm?issn=1754-9450
* Ambient Assisted Living Joint Programme of EU
  * http://www.aal-europe.eu/

Datasets

* Washington State University CASAS dataset
  * http://ailab.eecs.wsu.edu/casas/datasets/index.html
* My collection of links
  * http://www.cise.ufl.edu/~prashidi/Datasets/ambientIntelligence.html
* PAIR datasets
  * http://homepages.inf.ed.ac.uk/cgeib/PlanRec/Resources.html

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3. Latfi, Fatiha, and Bernard Lefebvre. Ontology-Based Management of the Telehealth Smart Home , Dedicated to Elderly in Loss of Cognitive Autonomy.*Management* 258: 12-12, 2007.
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