



NOMS 2014 Tutorial Sessions

TUTORIAL T4

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Wearable Computers: A Holistic Design Approach

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Wearable Computers: A Holistic Design Approach

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VISION

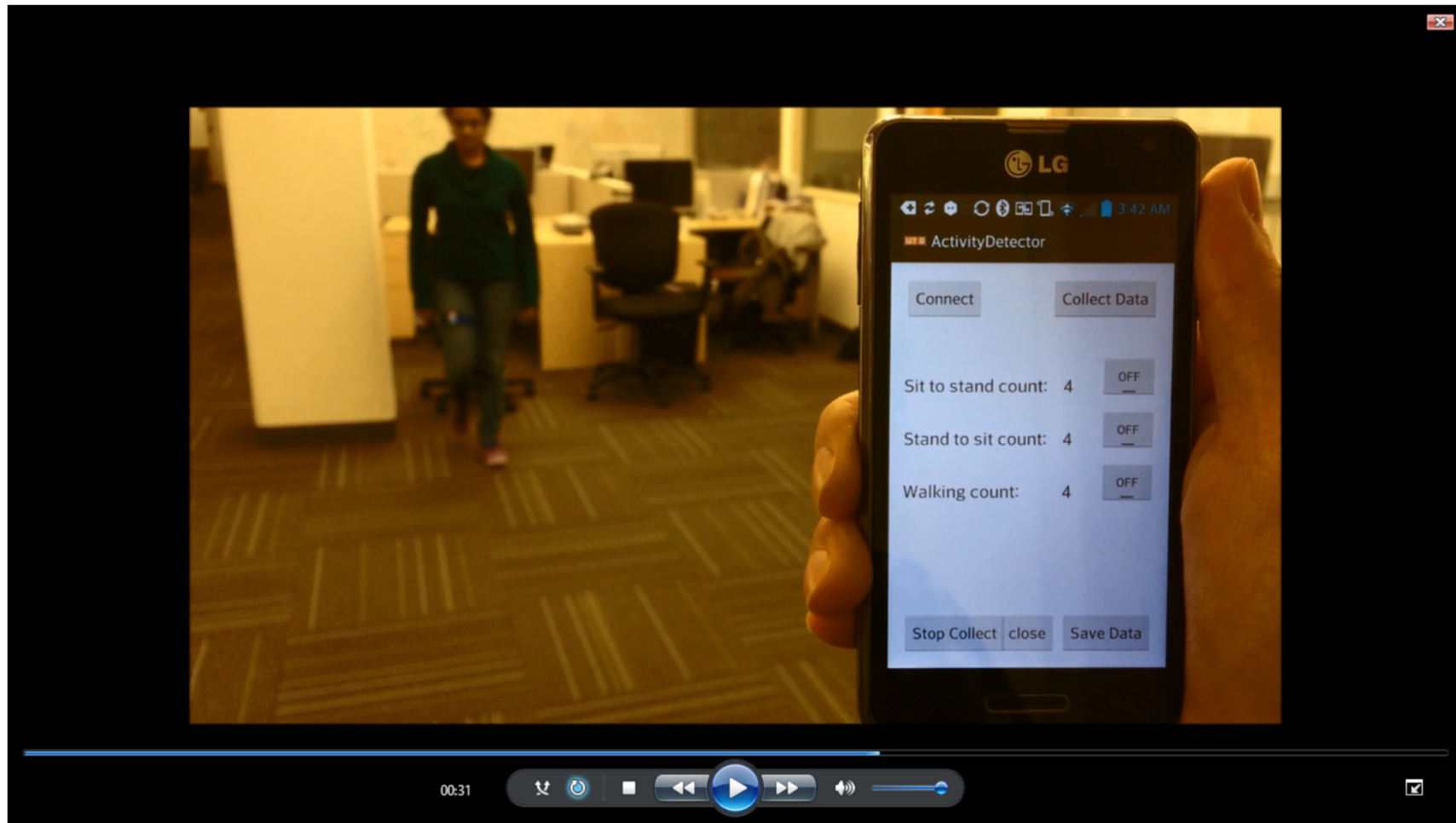
Wearable Computers

Ubiquitous **monitoring** and **intervention** for the applications of health-care, wellness, entertainment and many more!



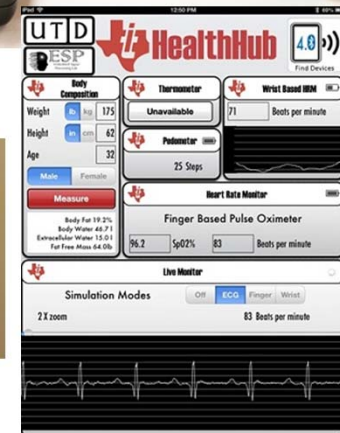
Photo courtesy of Misha Pavel

Video

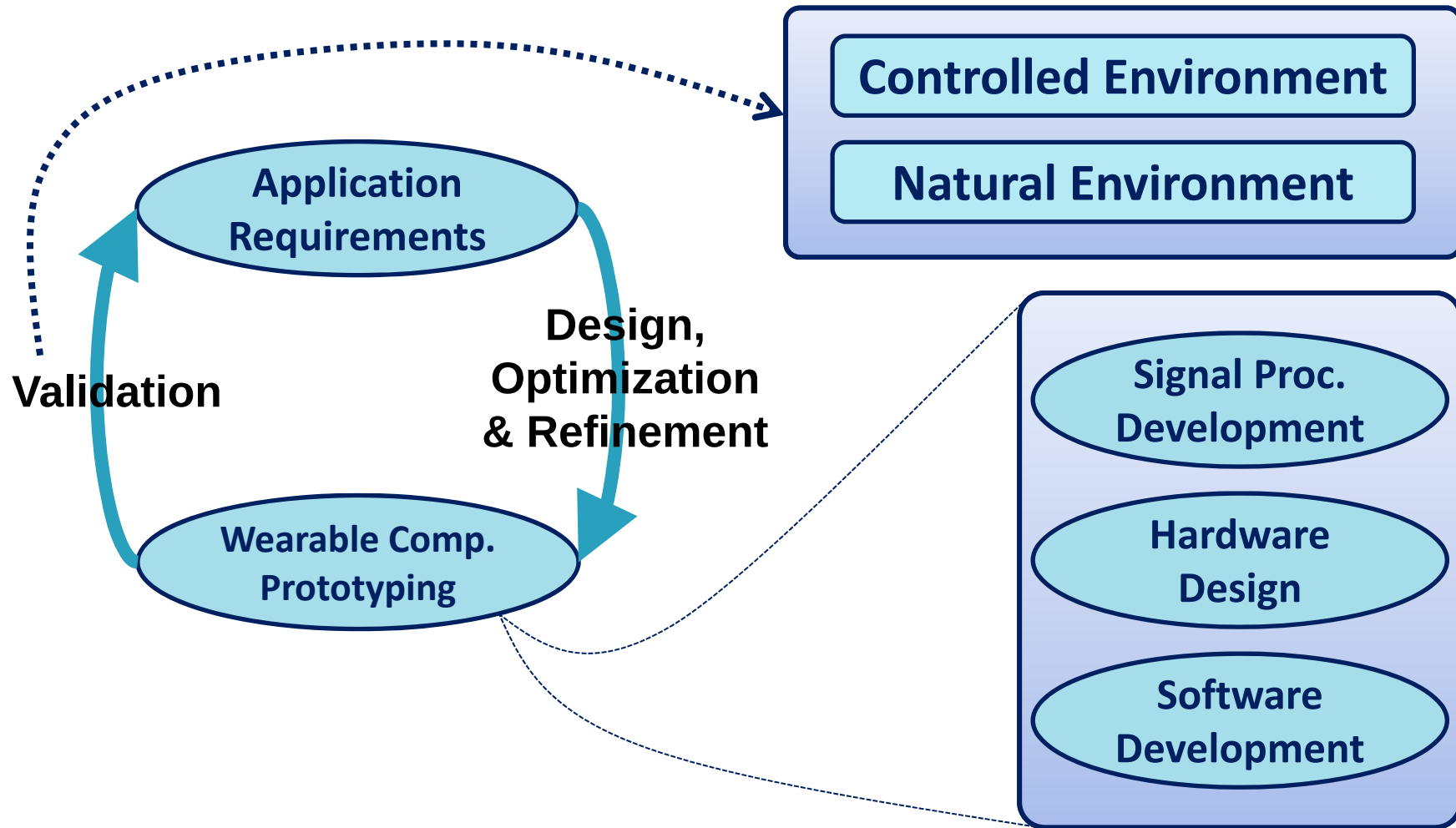


Vision

- Enhance wearability and programmability
 - Miniaturization: power optimization for sensors, circuits and signal processing
- Enhance usability (sensors deployed in the wild)
 - Quality framework
 - Anomaly detection
 - Repository framework



Design Flow



Validation

- Controlled environment
- Natural environment

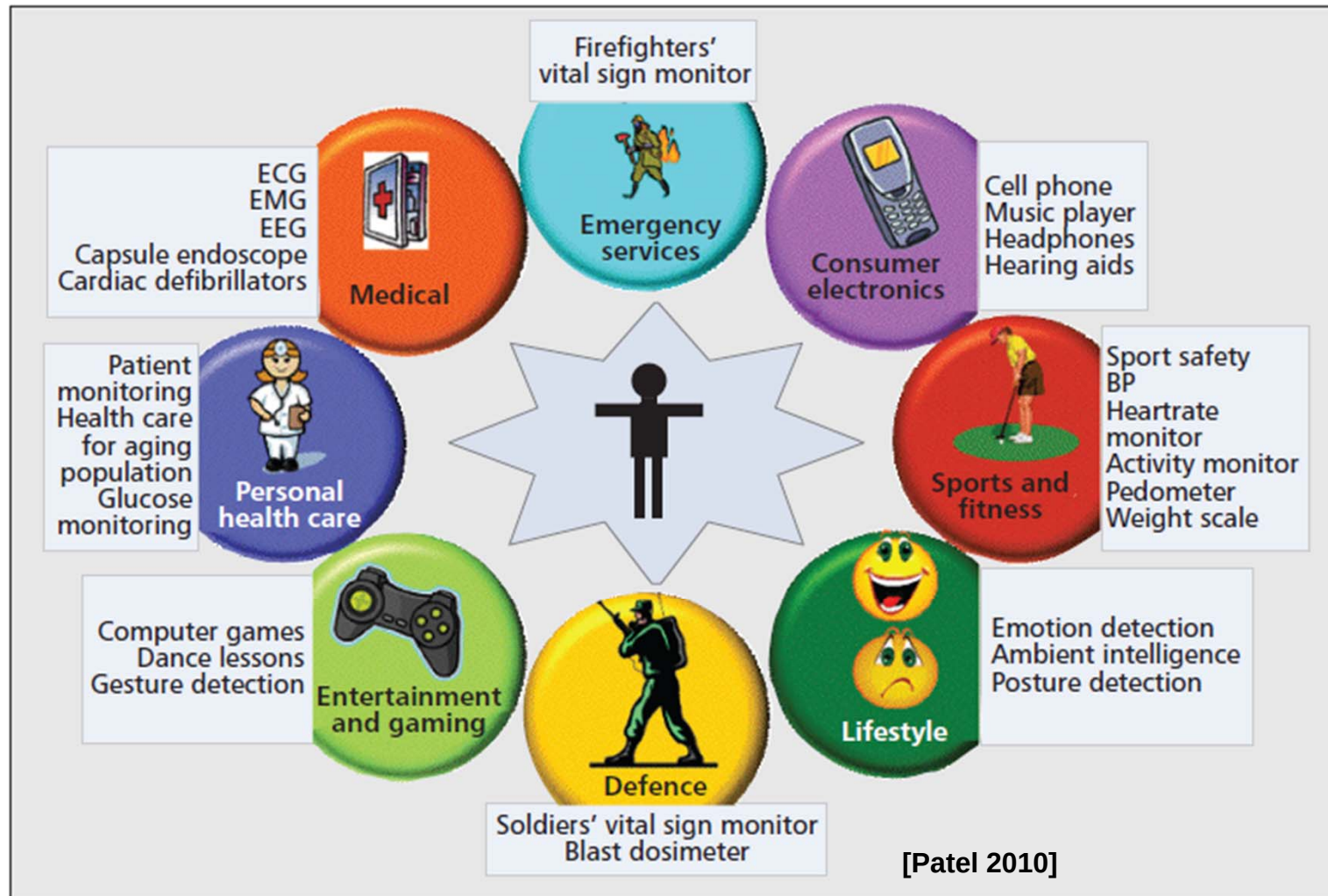


Agenda

- Applications
- Hardware, Sensors & Actuators
- Software & Signal Processing
 - Introduction to SW and SP
 - Feature Extraction
 - Event Classification
 - MET Calculation
- Optimization
 - Hardware Optimization
 - Signal Processing Optimization
 - Feature Selection
 - Sensor Selection
 - Communication Optimization
- Evaluation

APPLICATIONS

Applications



System Examples

Project Title/Institution	Hardware Description	Communication Module	Measured Signals	Medical Applications
LiveNet (MIT)	PDA, Microcontroller board	Wires, 2.4GHz radio, GPRS	ECG, BP, R, T, SaO2, EMG, GSR	Parkinson symptom & epilepsy seizure detection, behavioral modeling
AMON (EU IST FP5 Program)	Wrist worn device	GSM link	ECG, BP, T, SaO2, A	High-risk cardiac-respiratory patients
LifeGuard (Stanford Univ. & NASA)	Custom uC based device & commercial biosensors	Serial cables, Bluetooth	ECG, BP, R, T, SpO2, A	Medical monitoring in extreme environments (space & terrestrial)
MyHeart (EU IST FP6 program)	PDA, Textile & electronic sensors on cloths + heart belt	Conductive yarns, Bluetooth, GSM	ECG, R, other vital signs, A	Prevention and early diagnosis of CVD
WEALTHY (EU IST FP5 program)	Textile and electronic sensors on jacket	Conductive yarns, Bluetooth, GPRS	ECG, R, T, EMG, A	Monitoring of rehabilitation and elderly patients, chronic diseases
MagIC (Univ. of Milan, Italy, Bioeng. Centre & Cardiac Rehab. Unit)	Vest with textile sensors, custom electronic board, PDA	Bluetooth	ECG, R, T	Recording of cardiorespiratory and motion signals during spontaneous behavior in daily life and in a clinical environment
MERMOTH (EU IST FP6 program)	Garment with knitted dry electrodes, PDA	Conductive yarns, RF link	ECG, R, T, A	General health monitoring
Smart Vest (National Pr. On Smart Materials, India)	Vest with woven sensors, microcontroller	Woven wires, 2.4 GHz ISM RF	ECG, BP, T, PPG, GSR	General remote health monitoring
CodeBlue (Harvard Univ.)	Sensor motes with custom processing boards	Zigbee	ECG, SpO2, A	Real-time physiological status monitoring with wearable sensors
Body Area Network (Valencia, Spain & Malta Univ. & Microvitae Tech)	Zigbee-based motes & Zigbee based custom device	Zigbee, WiFi, GPRS	ECG, BP, R	Detection and prediction of human physiological state (wakefulness, fatigue, stress) during daily activities

System Examples (2)

Project Title/Institution	Hardware Description	Communication Module	Measured Signals	Medical Applications
WSN u-Healthcare system (Dongseo Univ., Korea)	Custom tiny motes, cell phone & commercial sensors	Zigbee, CDMA	ECG, BP, SpO2, A	Health monitoring and remote identification of suspicious health patterns for further evaluation by physicians
Human++ (IMEC)	Miniature low-power BAN nodes, energy scavenging	Zigbee	ECG, EEG, EMG	Enable autonomous wearable sensor networks for general health monitoring
HealthGear (Microsoft)	Custom sensing board, commercial sensors and cell-phone	Bluetooth	HR, SpO2	Monitoring users during their sleep to detect sleep apnea events
HeartToGo (Univ. of Pittsburgh)	Cell phone and commercially available BT bio-sensors	Bluetooth, GPRS	ECG, A	Individualized remote CVD detection
Personal Health Monitor (Univ. of Tech. Sydney)	Cell phone & commercially available BT bio-sensors	Bluetooth, GPRS	ECG, BP, A	Heart-attach self test for CVD patients
Wearable ECG, arrhythmia detection (Eng. + Med. Depts., Norway)	Microcontroller board, PDA	Wires, Zigbee GPRS	ECG	Remote detection of cardiac arrhythmias
AUDABE (Dept. of Medical Physics, Ioannina, Greece)	Mask, glove, chest sensors	Wires, Bluetooth, Wi-Fi	ECG, R, GSR, EMG	Evaluation of the emotional state of an individual at environments where subjects operate at extreme stress conditions
Lifeshirt (Vivometrics)	Sensors embedded in vest, PDA	Bluetooth & wires	ECG, R, A	All-day remote health monitoring
Bioharness (Zephyr Inc)	Chest belt	Bluetooth or ISM RF	ECG, T, A, P	Remote monitoring of human performance and condition in real world
VibMotion (UTDallas)	Microcontroller based custom board	Bluetooth and Bluetooth Low Energy	A	Activity analysis and real time feedback
Wireless EEG (UTDallas)	Microcontroller based custom board	Bluetooth and Bluetooth Low Energy	EEG	EEG data analysis and brain computer interface

Many Opportunities

- A handful of ECG, PPG, motion sensors
 - Heart rate
 - Blood pressure
 - Energy expenditure
 - Emotional state (heart rate variability – HRV)
 - Activity profile
- Integration with the Cloud
 - Interactions with other sensors
 - Leverage social networking
 - Incorporate history

CHRONIC DISEASE MANAGEMENT

Applications

Statistics on Chronic Disease

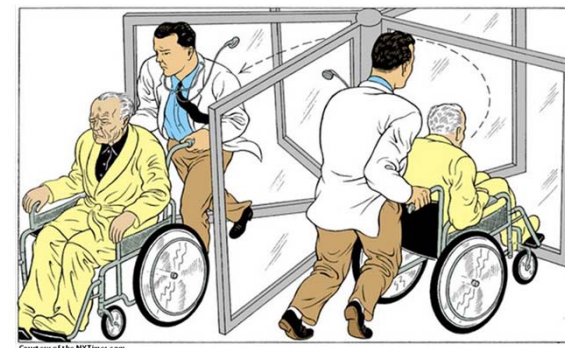
- Chronic Disease Management is **80+%** of all Healthcare Costs
- **1 in 3 Adults** < 65 have at least 1 Chronic Disease
- 8 in 10 Seniors >65 have at least 1 Chronic Disease
- U.K. spends **8.4%** of current GDP on Healthcare
- U.S. spends **17%** of current GDP on Healthcare

(Geyman and Thorpe Reports & World Economic Forum 2011)

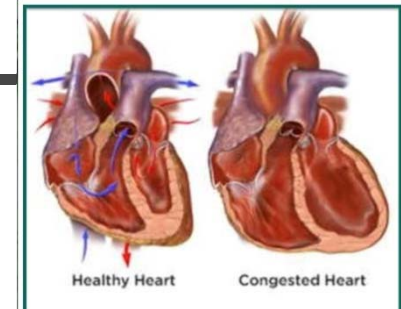


Heart Failure (HF)

- United States
 - ~\$40 billion Medicare cost every year (20% of all Medicare payments)
 - Affects nearly 6 million Americans
 - 1 million patients admitted to hospitals each year
 - 20% are **readmitted** within a month
 - Leading cause of hospitalization in people older than 65



What is HF?



- Does not mean heart stopped working
- Heart's pumping power is weaker
- Heart cannot pump enough oxygen to meet the body's needs
- Kidneys respond to this by causing the body to retain fluid (water)
- Fluid builds up in arms, legs, ankles, feet, and lungs, ...
 - Body becomes congested, and **congestive heart failure** is the term used to describe the condition

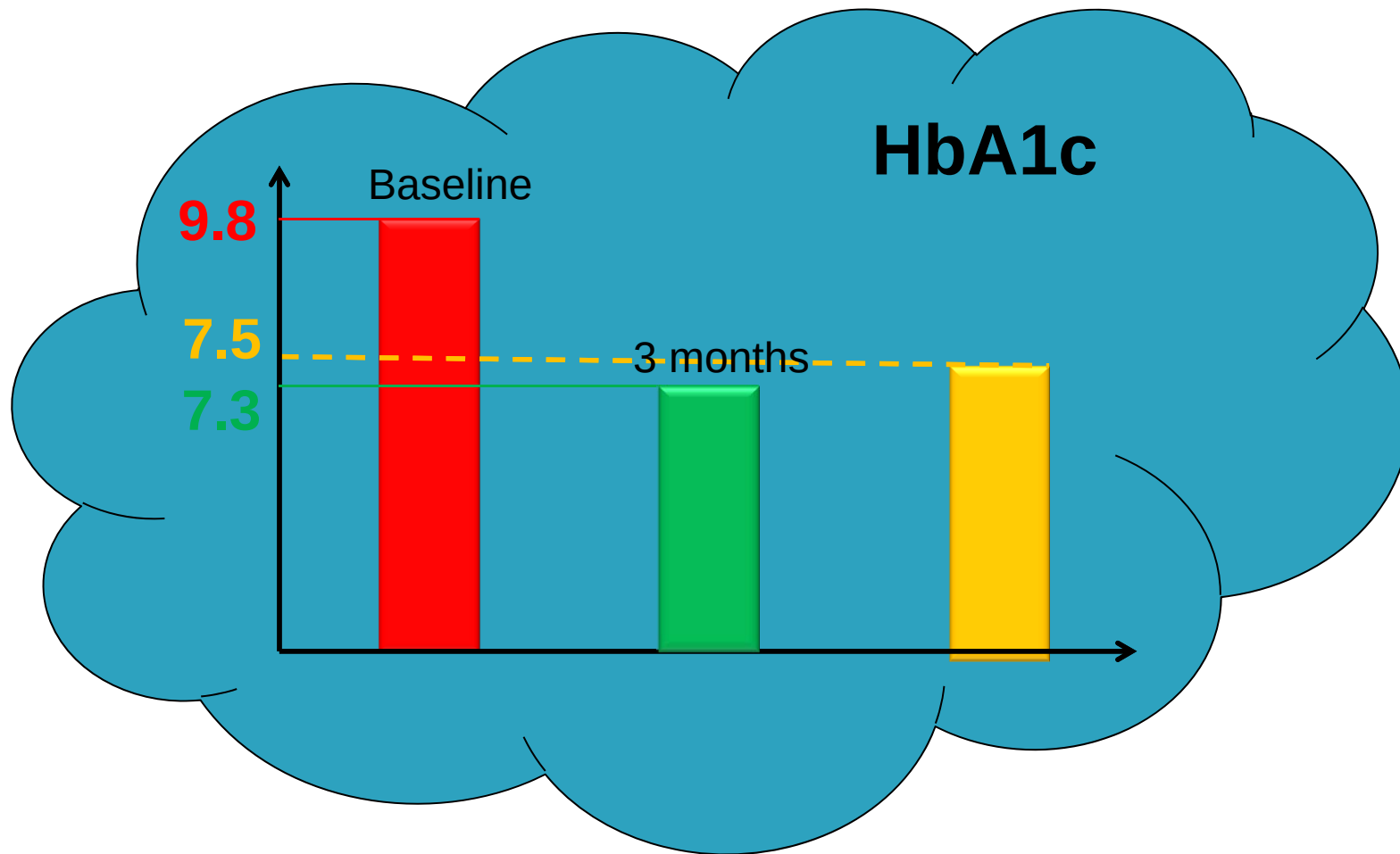
HF Symptoms

- Shortness of breath
 - Blood "backs up" in vessels that return blood from the lungs to the heart. This causes fluid to leak into the lungs.
- Persistent coughing or wheezing
 - Fluid builds up in the lungs
- Buildup of excess fluid in body tissues (edema)
- Tiredness, fatigue
 - The heart can't pump enough blood to meet the needs of body tissues
- Increased heart rate
 - To "make up for" the loss in pumping capacity, the heart beats faster
- Decreased physical activities

Diabetes

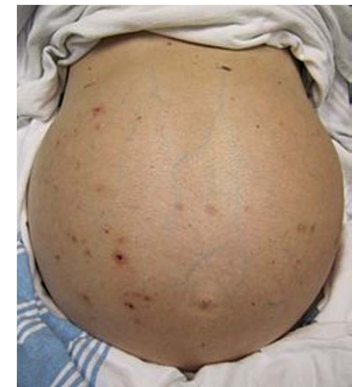
- United States
 - 8.3% of the US population has diabetes, resulting in **\$174 billion** spent per year.
- Europe
 - In 5 European Union Member States, the total direct cost of diabetes was **€90 billion** in 2010.
- China
 - Diabetes costs **\$26 billion** a year
 - 92.4 million people with diabetes

Remote Monitoring - Diabetes



Liver Disease : Ascites

- What is it?
 - When liver damage progresses to an advanced stage, fluid collects in the legs, called edema, and in the abdomen, called ascites.
 - Abnormal accumulation of fluid
 - Healthy liver tissue is replaced with scar tissue
 - Scar tissue blocks the flow of blood through the liver
 - Most common complication of liver disease
- Results in
 - Poor quality of life
 - Readmission

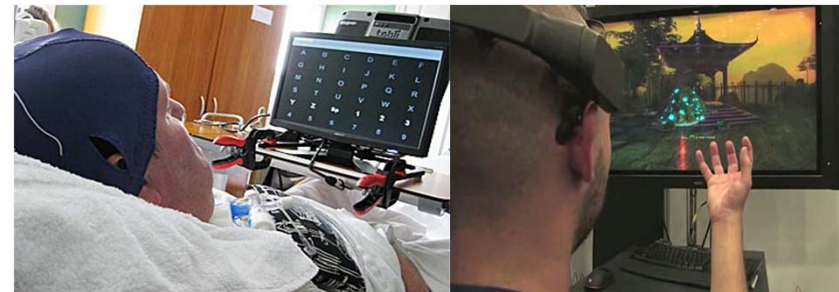
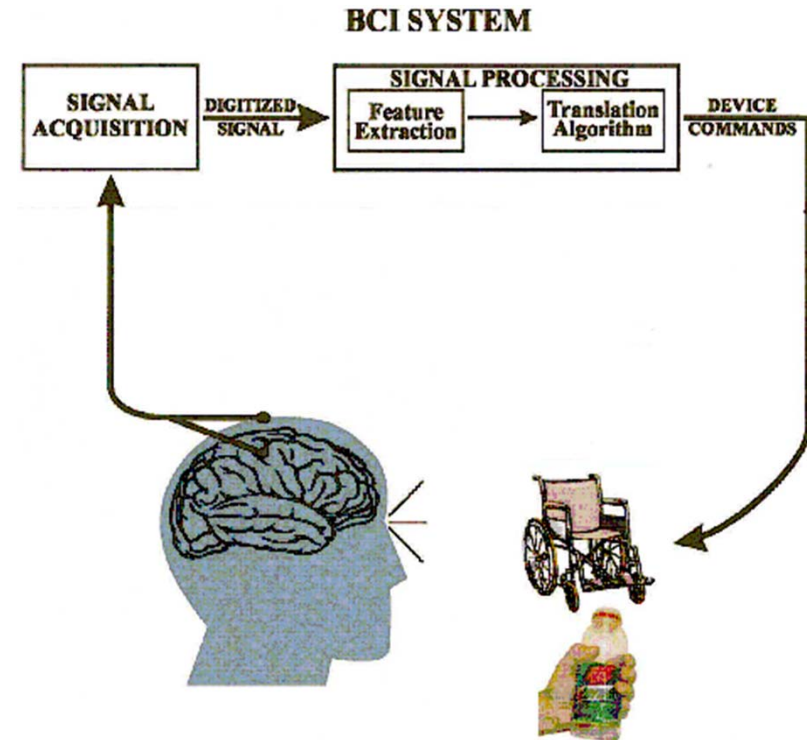


BRAIN COMPUTER INTERFACE

Applications

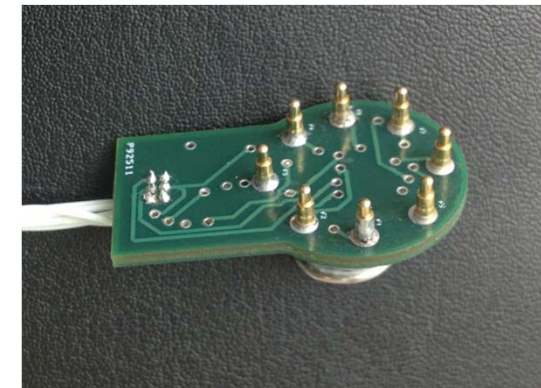
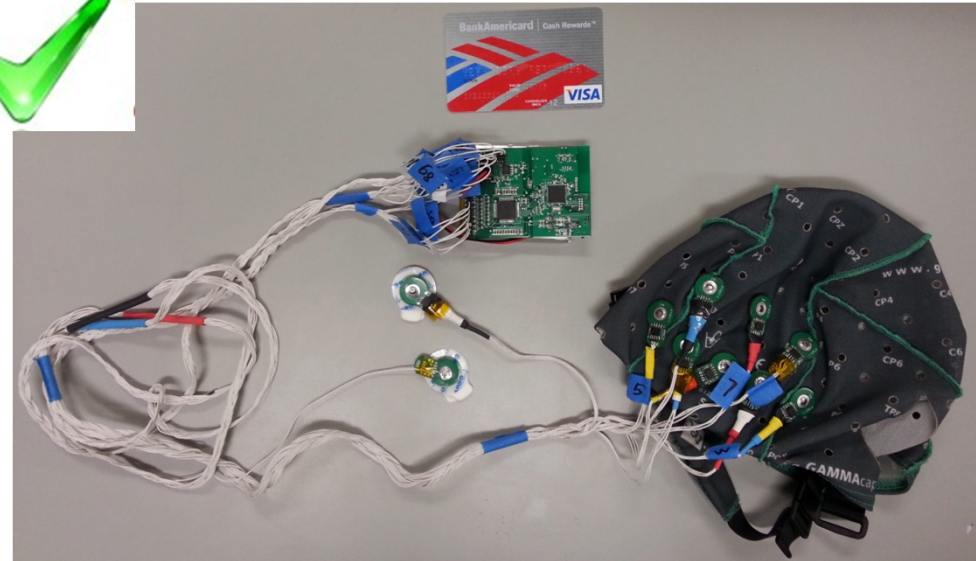
Brain Computer Interface

- Brain Computer Interface
 - Provide a non-muscular avenue for the user to communicate with others and to control external devices
 - Infer user's intentions using brain activities
- Applications
 - Assist locked-in individuals to interact with cyber and physical system
 - Gaming
 - Diagnosis and treatment for neurological disorder

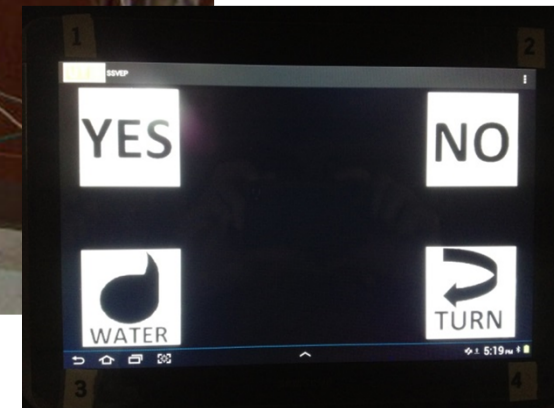


EEG Systems

- **Smaller form factor** (size of a credit card vs. bulky amps)
- **Quicker setup time** (seconds vs. 30 mins)
- **Faster software training** (5 mins vs. 30 mins)
- **Quicker EEG signal detection** (seconds vs. minutes)
- **No need for EEG tech**



ICU Units



Communication Board

GP30

TOUCH FOR "NO"



No = eyes closed

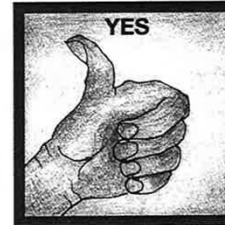
Greenhouse Publications

Health Care Communication Board

For Medical, Physical and Emotional Information

INSTRUCTIONS: Have patient touch pictures to request wants and needs.
If unable, caregiver touches pictures and gets yes/no response from patient.
Yes = thumbs up, nod, or eyes wide open;
No = thumbs down, nod or eyes closed.

TOUCH FOR "YES"

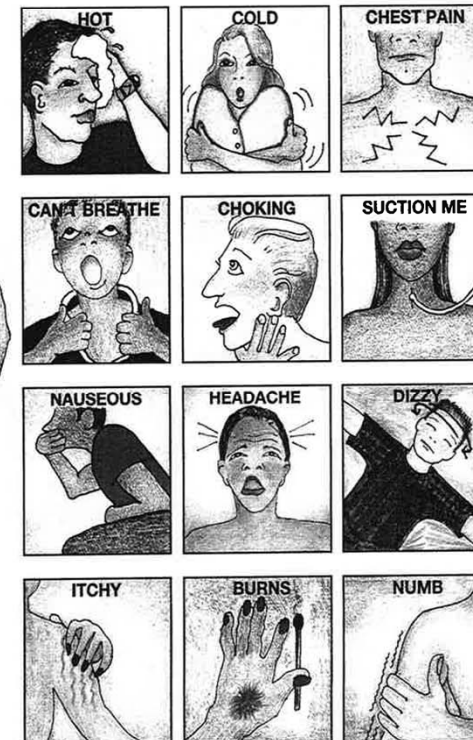
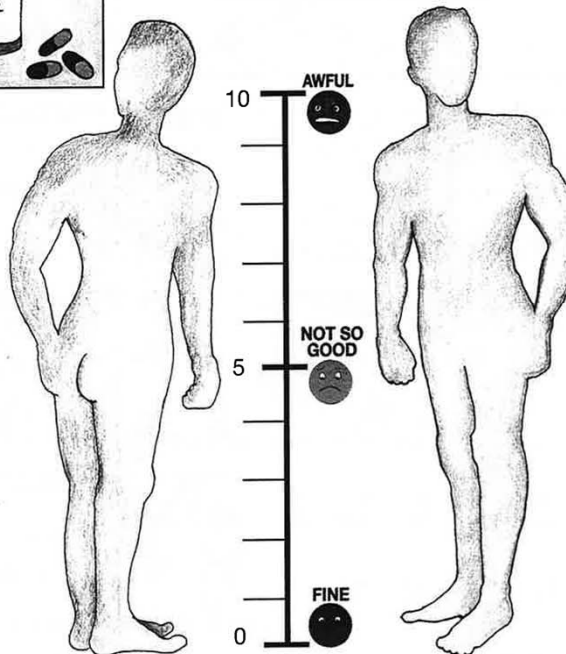


Yes = eyes wide open



Pain Scale

Touch Where It Hurts



BIOWATCH FOR PHYSIOLOGICAL MONITORING

Applications

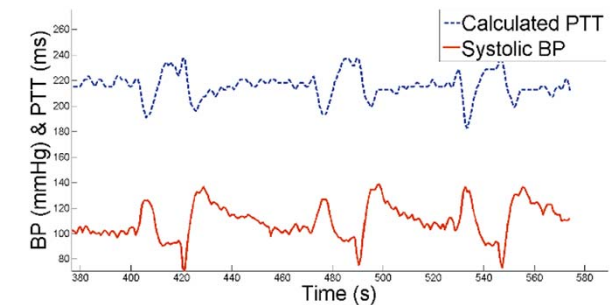
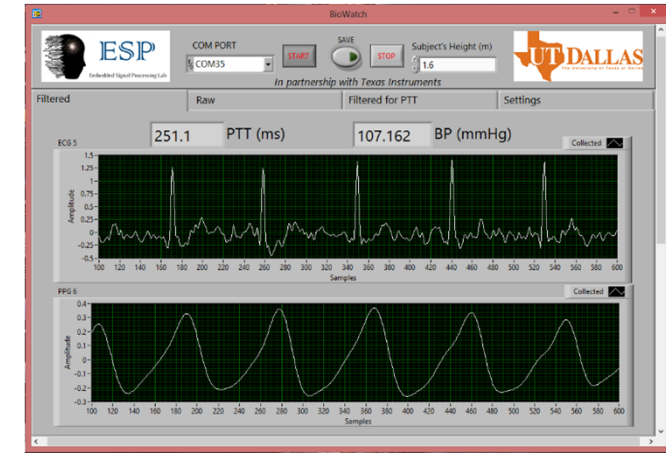
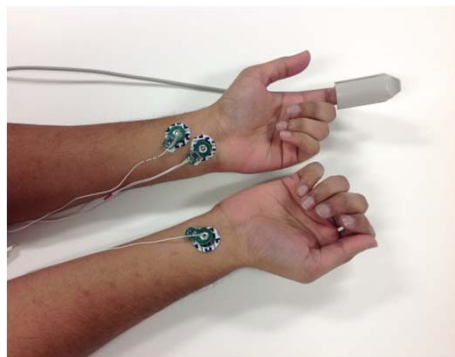
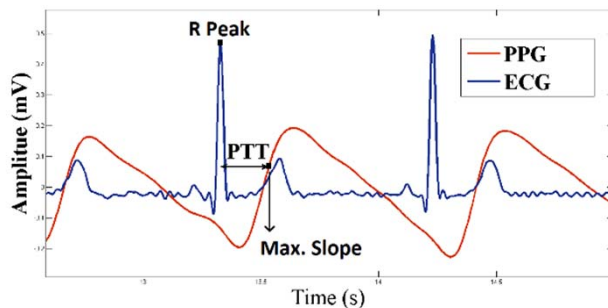
Monitoring Blood Pressure

Significance

- Monitoring blood pressure and vital signs have numerous applications from wellness to health-care

Approach

- Measuring blood pressure using the notion of pulse transit time (PTT)
- Calibration techniques for individuals/postures



Fitting Function	RMSE for Different Postures in mmHg (mean ± std)		
	Supine	Sitting	Standing
1	8.18 ± 1.57	9.25 ± 0.84	10.39 ± 1.67
2	8.17 ± 1.48	9.24 ± 0.96	10.21 ± 1.41
3	8.22 ± 1.66	9.27 ± 0.86	10.27 ± 1.66
4	8.12 ± 1.42	9.62 ± 0.88	10.03 ± 1.52
5	8.26 ± 1.70	9.27 ± 0.87	10.23 ± 1.67

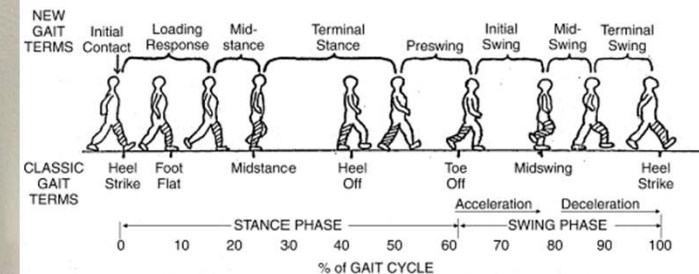
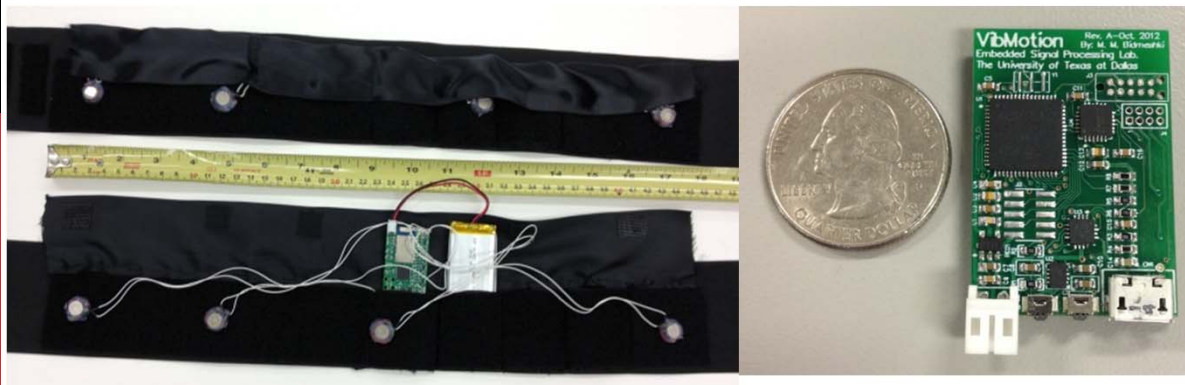
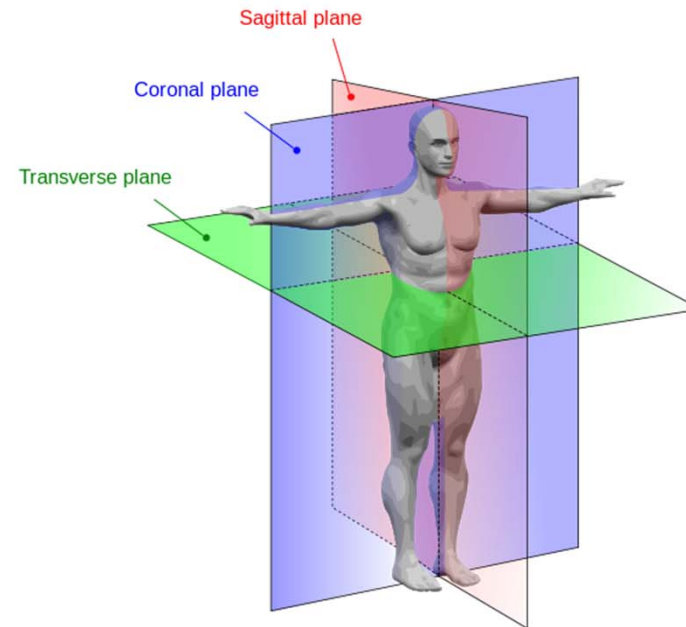
with C. Ray

USING GAIT AND SWAY BIOFEEDBACK TO REDUCE FALLS IN THE ELDERLY

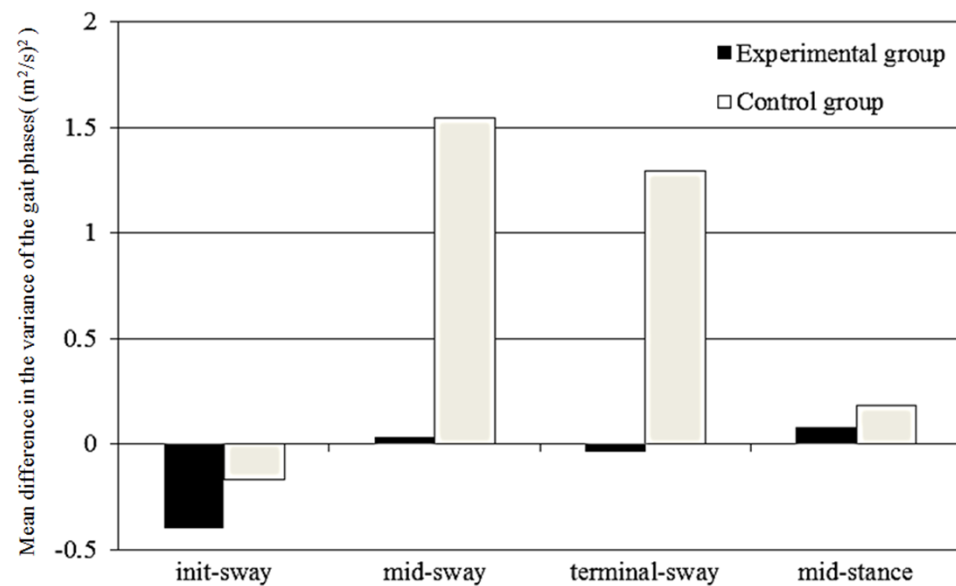
Applications

Sway Biofeedback for Fall Prevention

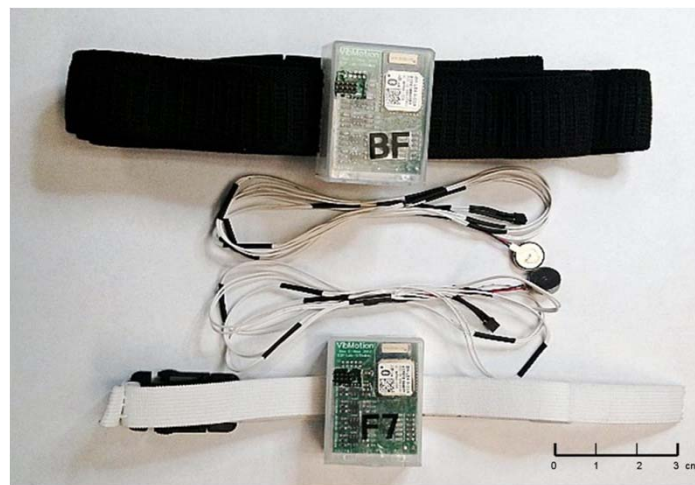
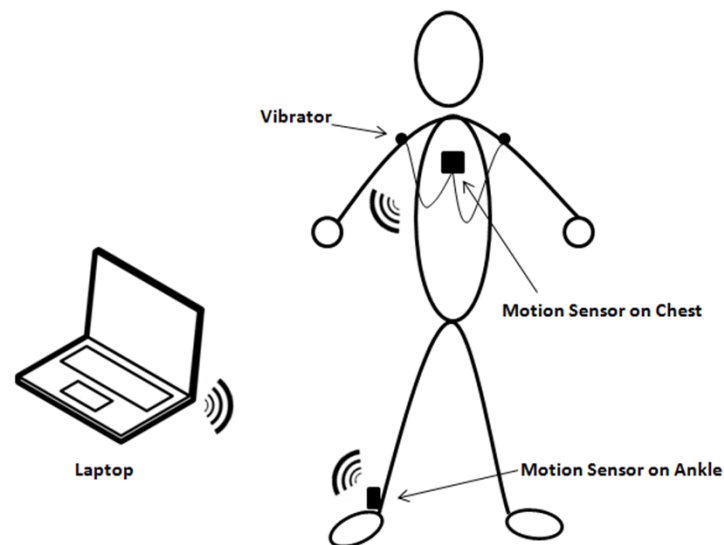
- Fall is a considerable health concern in the elderly
- Wearable kinematic biofeedback system to detect pre-cursors of falls based on the sway of the upper body and other gait parameters, and activate biofeedback



Results



12 older adults (age: M = 75.5, SD = 4.32 years; 10 females)



with N. Kehternavaz and C. Ray

SENIOR FITNESS TEST

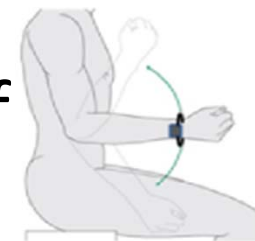
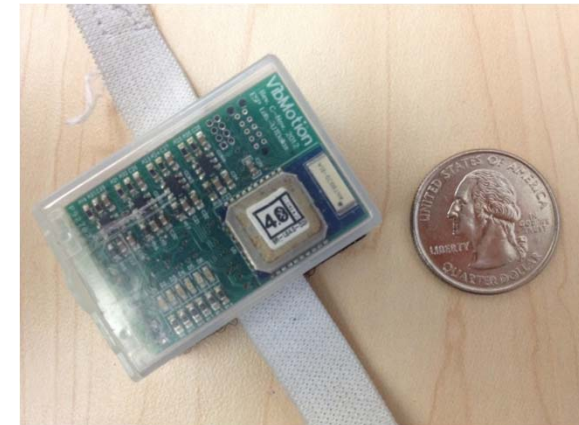
Applications

Senior Fitness Test

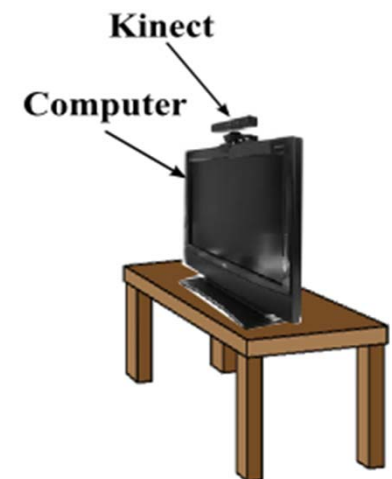
- Simple, easy-to-use battery of test items that assess the functional fitness of older adults.
 - Chair Stand Test: testing lower body strength
 - Arm Curl Test: testing upper body strength
 - Chair Sit and Reach Test: lower body flexibility test
 - Back Scratch Test : upper body flexibility test
 - 8-Foot Up and Go Test: agility test
 - Walk Test (6 mins) or Step in Place Test (2 mins)

Objectives

- A low-cost technology (wearable sensors and cameras) to measure motor functions during SFT
- Provide visualization for coaching the users
- A suitable interface for the clinicians to visualize the baseline, the performance of the users, and their progress over time.



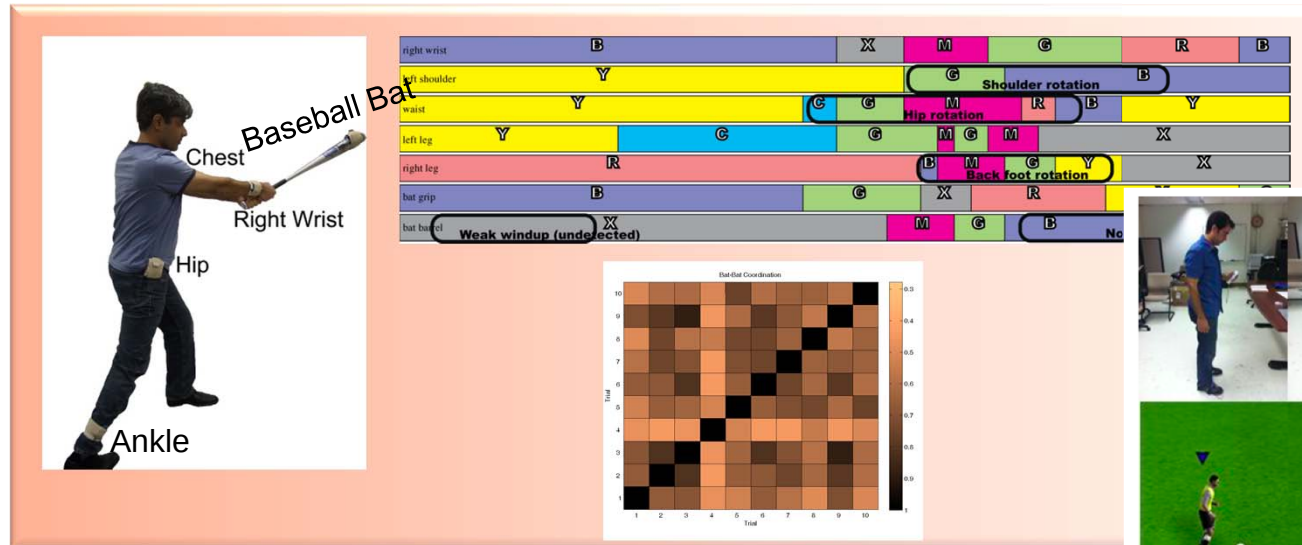
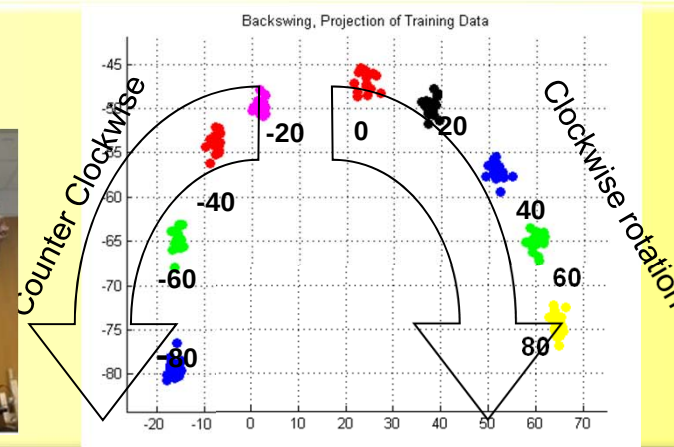
Wearable sensor tied to the subject's wrist



SPORTS APPLICATIONS

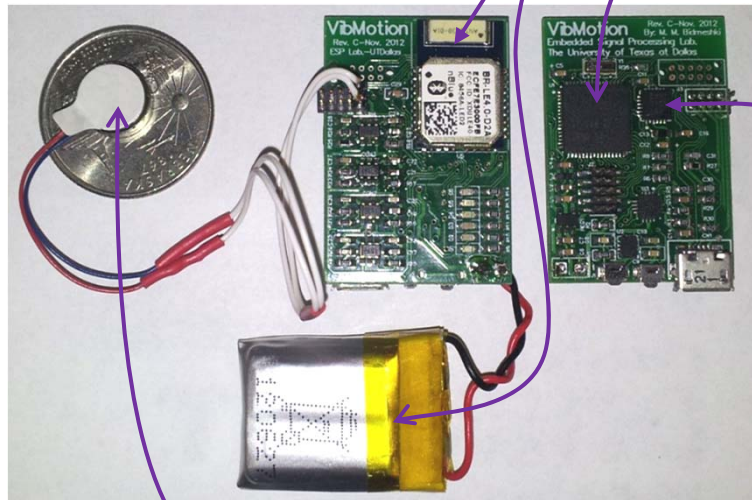
Applications

Sports Applications



HARDWARE, SENSORS AND ACTUATORS

Architecture



A wearable biofeedback system for fall prevention

Wearable device designed in ESP lab at UT-Dallas

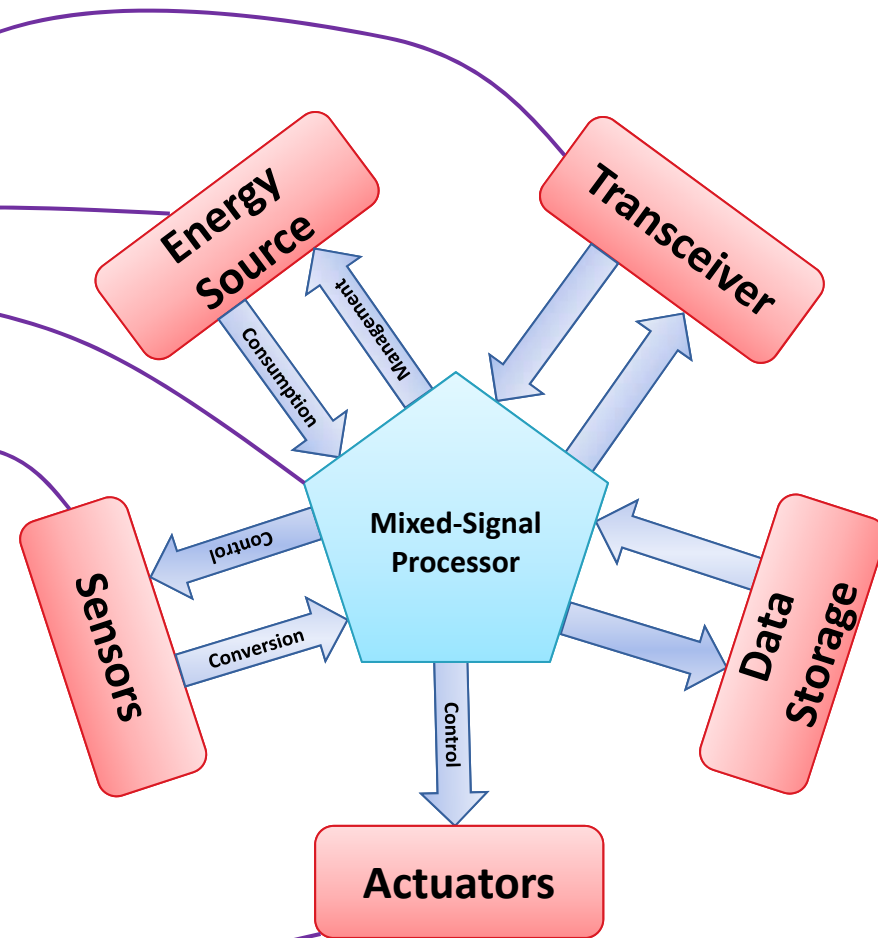
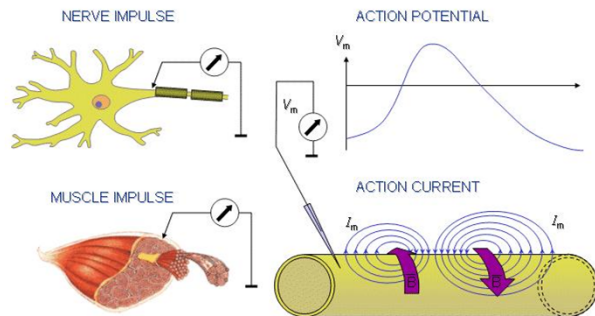


Photo courtesy of [Hanson 2009]

Biosensors

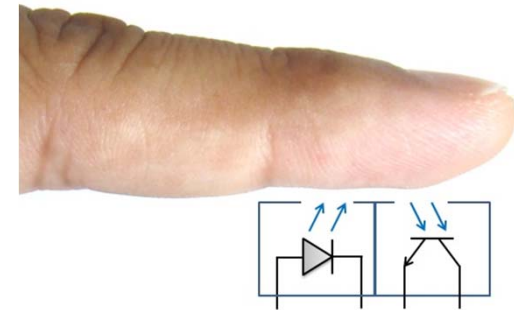
Bio-potential Sensing



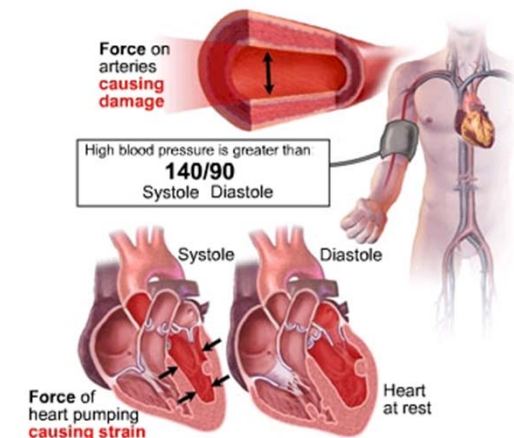
Inertial Sensing



Photo-based Sensing



Pressure Sensing



Biosensors and Biosignals

Type of Bio-signal	Type of Sensor	Description of Measured Data
Electrocardiogram (ECG)	Skin/chest electrodes	Electrical activity of the heart
Electromyogram (EMG)	Skin electrodes	Electrical activity of the skeletal muscles
Electroencephalogram (EEG)	Scalp-placed electrodes	Measurement of electrical spontaneous brain activity and other brain potentials
Oxygen saturation	Pulse Oximeter	Indicates the oxygenation or the amount of oxygen that is being carried in a patients blood
Heart rate	Pulse Oximeter/skin electrodes	Frequency of the cardiac cycle
Body/skin temperature	Temperature probe or skin patch	A measure of the body's ability to generate and get rid of heat
Perspiration or skin conductivity	Galvanic skin response	Electrical conductance of the skin is associated with the activity of the sweat glands
Blood pressure	Arm cuff-based monitor	Refers to the force exerted by the circulating blood on the walls of blood vessels
Heart sounds	Phonocardiograph	A record of heart sounds, produced by a properly placed on the chest microphone (stethoscope)
Respiration rate	Piezoelectric/ piezoresistive sensor	Number of movements indicative of inspiration and expiration per unit time (breathing rate)
Blood glucose	Strip-base glucose meters	Measurement of the amount of glucose in blood
Body movements	Accelerometer/Gyroscope	Measurement of acceleration forces/rotational velocity in the 3D space

Biosensor Examples

ECG



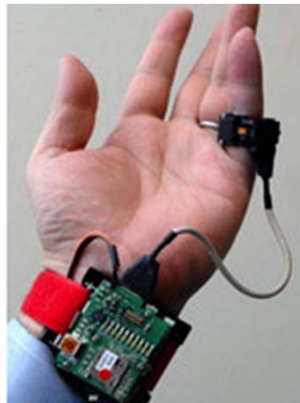
www.megaemg.com



www.imec.com



Pulse Oximeter
[Wikipedia]

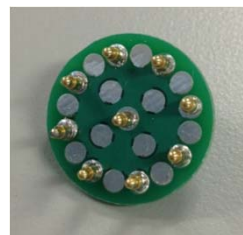


Blood Pressure
[MIT]

EEG



www.gtec.at

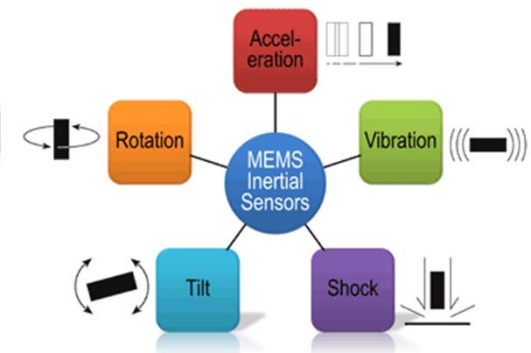


UTD

EEG Dry Electrode

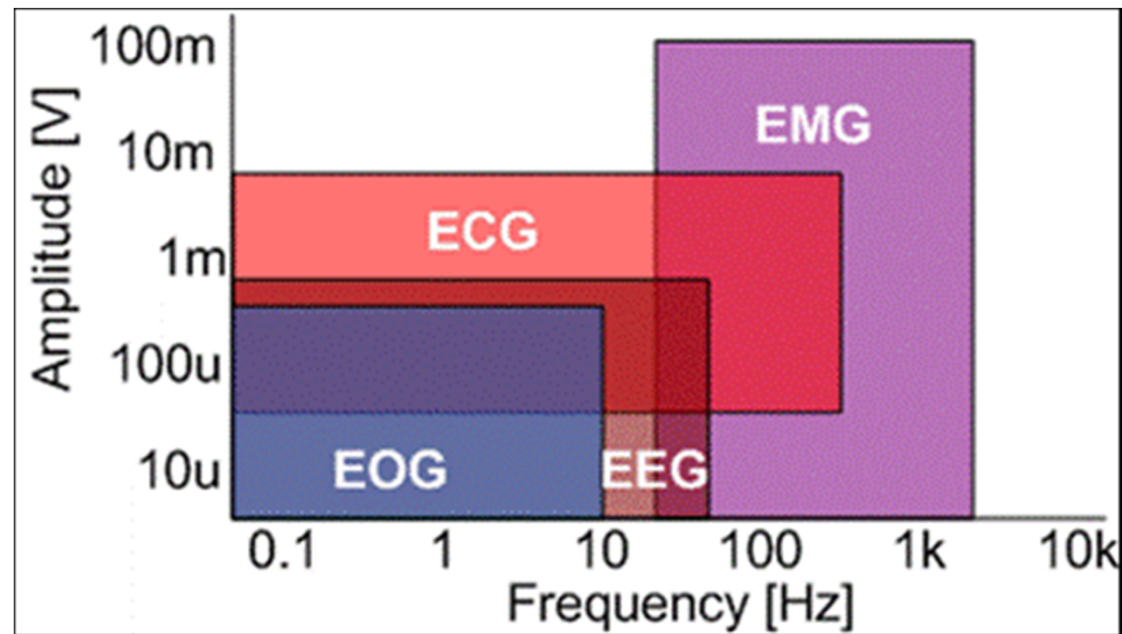


Acoustic Respiration Rate
www.masimo.com

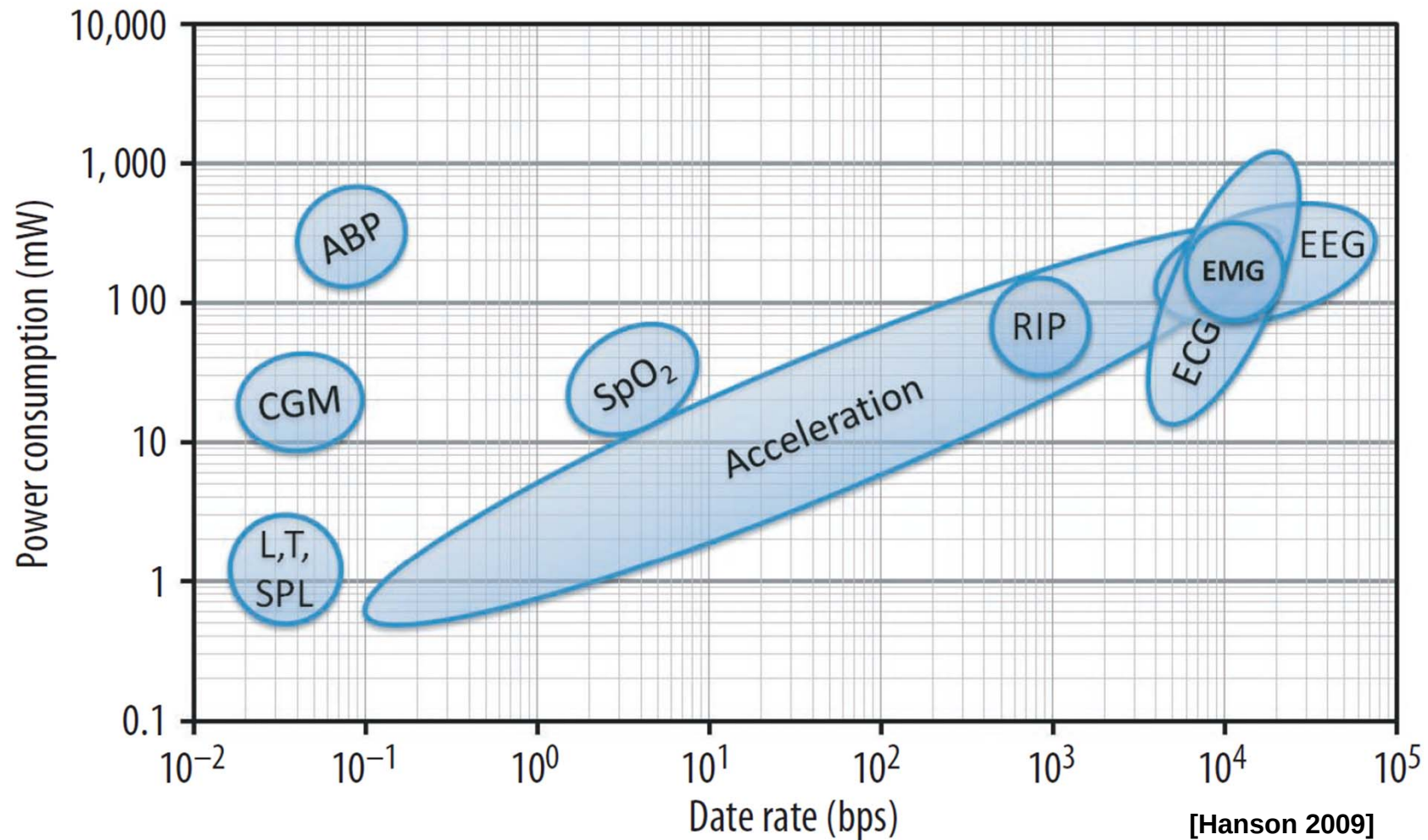


www.electronicproducts.com

Bio-potential Characteristics



Data Rate and Power Consumption

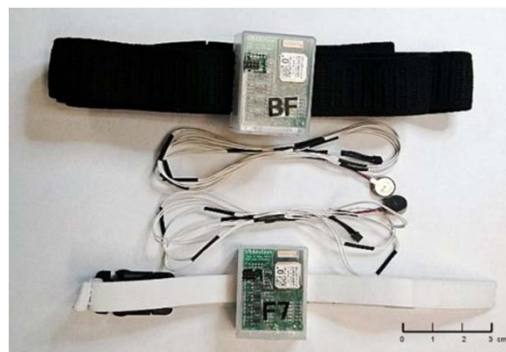


Needs

- Enhanced wearability
 - Dry-contact sensors for bio-potential monitoring
 - Can we use sensors that people are used to wearing (*e.g.*, a watch: PPG on wrist instead of fingers)
- Smaller and lower power consumption
 - Ultra-low power inertial sensors (*e.g.*, ADXL362, 6uW accelerometers)
- Non-invasive sensors (distance sensing)
- Quality-aware sensing

Actuators/Feedback

- Vibrotactile



UTD's biofeedback vibrotactile system for fall prevention



[Sensable Technologies]

- Haptic

- Sound/Voice



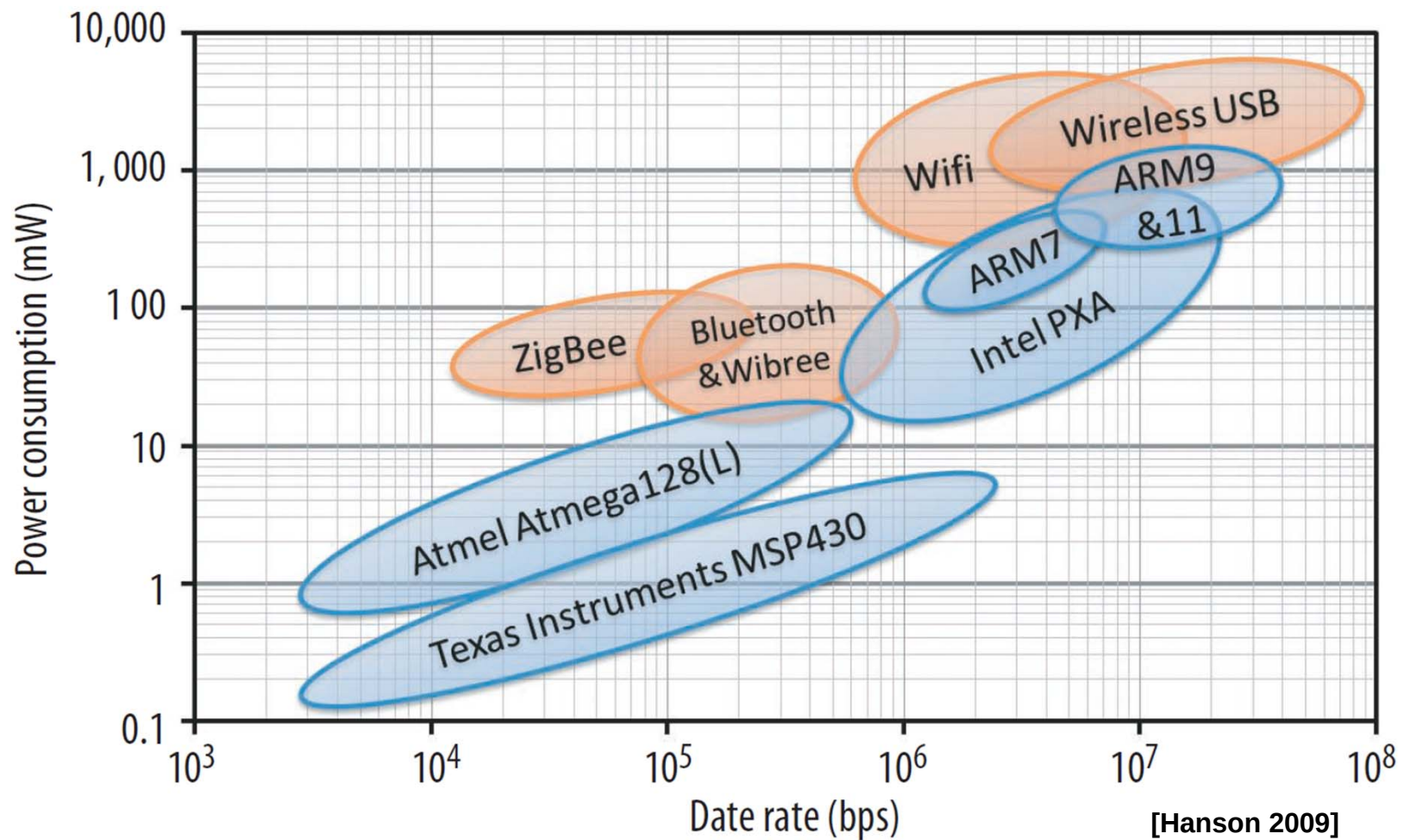
InerTouchHand
<http://mrl.isr.uc.pt>



Needs

- Easy-to-use and intuitive feedback
- Customization based on individual preferences
- Natural integration into our everyday clothing
- Flexible and skin-printed electronics for actuation

Processors/Transceivers

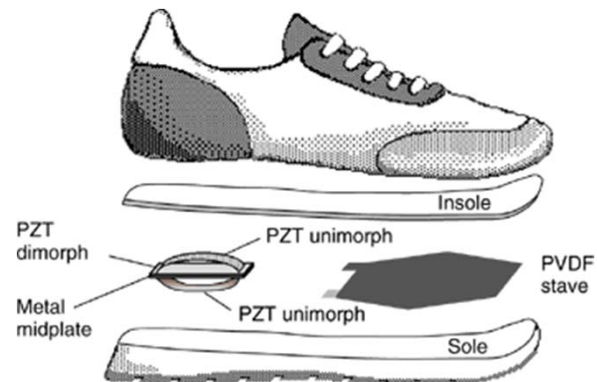


Needs

- Aggressive power optimization (μW range)
- Integration of hardware accelerators
- Aggressive sleep modes
- Sub-threshold operation to minimize the leakage (minimum energy operating point)
- New standards for wireless communication in body area networks (use body as the medium)

Energy Sources

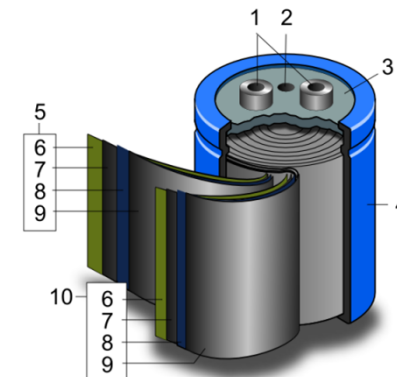
Piezo-electric Harvesting



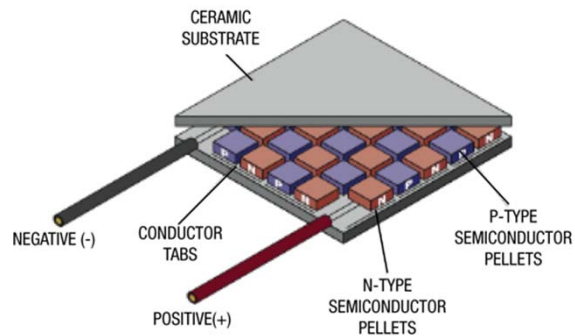
Conventional batteries



Super Capacitors



Thermo-electric Harvesting



Thin-film Batteries



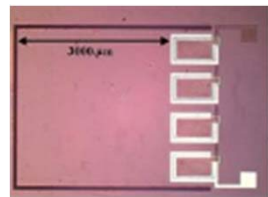
Energy Harvesting Sources

Energy Source	Characteristics	Efficiency	Harvested Power
Light	Outdoor	10~24%	100 mW/cm ²
	Indoor		100 µW/cm ²
Thermal	Human	~0.1%	60 µW/cm ²
	Industrial	~3%	~1-10 mW/cm ²
Vibration	~Hz–human	25~50%	~4 µW/cm ³
	~kHz–machines		~800 µW/cm ³
RF	GSM 900 MHz	~50%	0.1 µW/cm ²
	WiFi		0.001 µW/cm ²

Seiko watch
~5µW



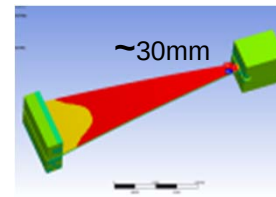
Holst Center
~40µW



2 channel EEG
~1mW



AdaptivEnergy
~10mW



Elastometer
~800mW



BigBelly
~40W



1uW

10uW

100uW

1mW

10mW

100mW

1W+

Energy Storage Options



	Li-Ion	Thin Film Rechargeable	Super Cap
Recharge Cycles	100s	5k-10k	Millions
Self Discharge	Moderate	Negligible	High
Charge Time	Hours	Minutes	Sec-Minutes
SMT & Reflow	Poor-None	Good	Poor
Physical Size	Large	Small	Medium
Capacity	0.3-2500mAHr	12-700uAHr	10-100uAHr
Environmental Impact	High	Minimal	Minimal

Needs

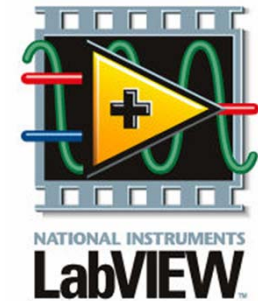
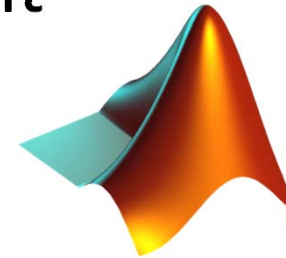
- Micro-power energy sources and storage
- Aggressive Power management techniques taking into account variable power supply and demand
- Harvesting techniques



SOFTWARE & SIGNAL PROCESSING

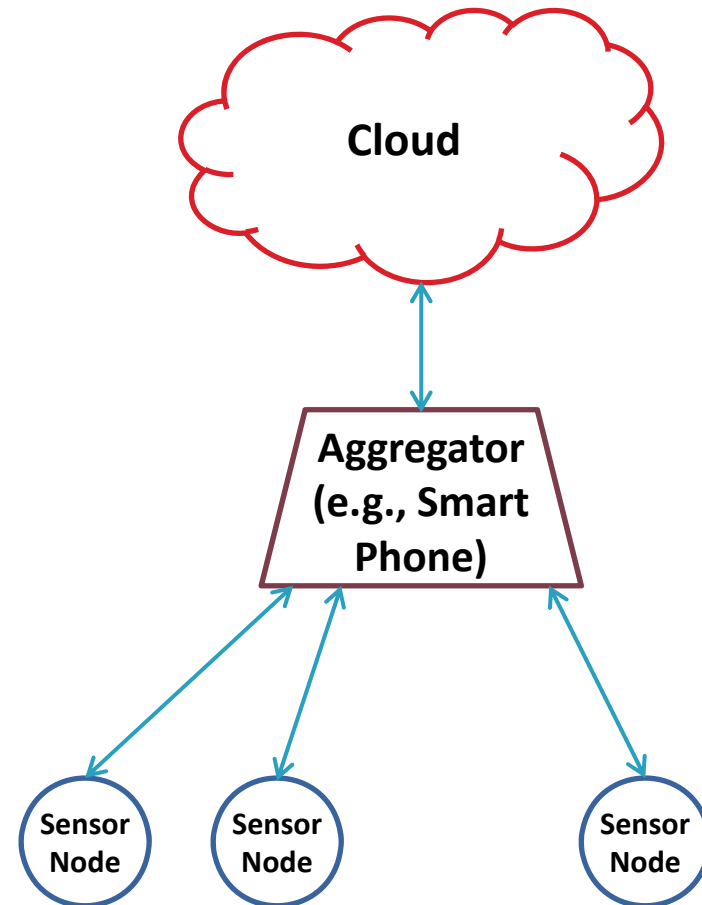
Signal Processing Prototyping

- Signal processing development
 - MATLAB
 - LabView
- On-node Processing
 - Firmware and mapping it onto wearable computers
 - Processor specific compiler tools
 - IAR Embedded Workbench
 - Available for various microcontrollers
 - TI Code Composer Studio



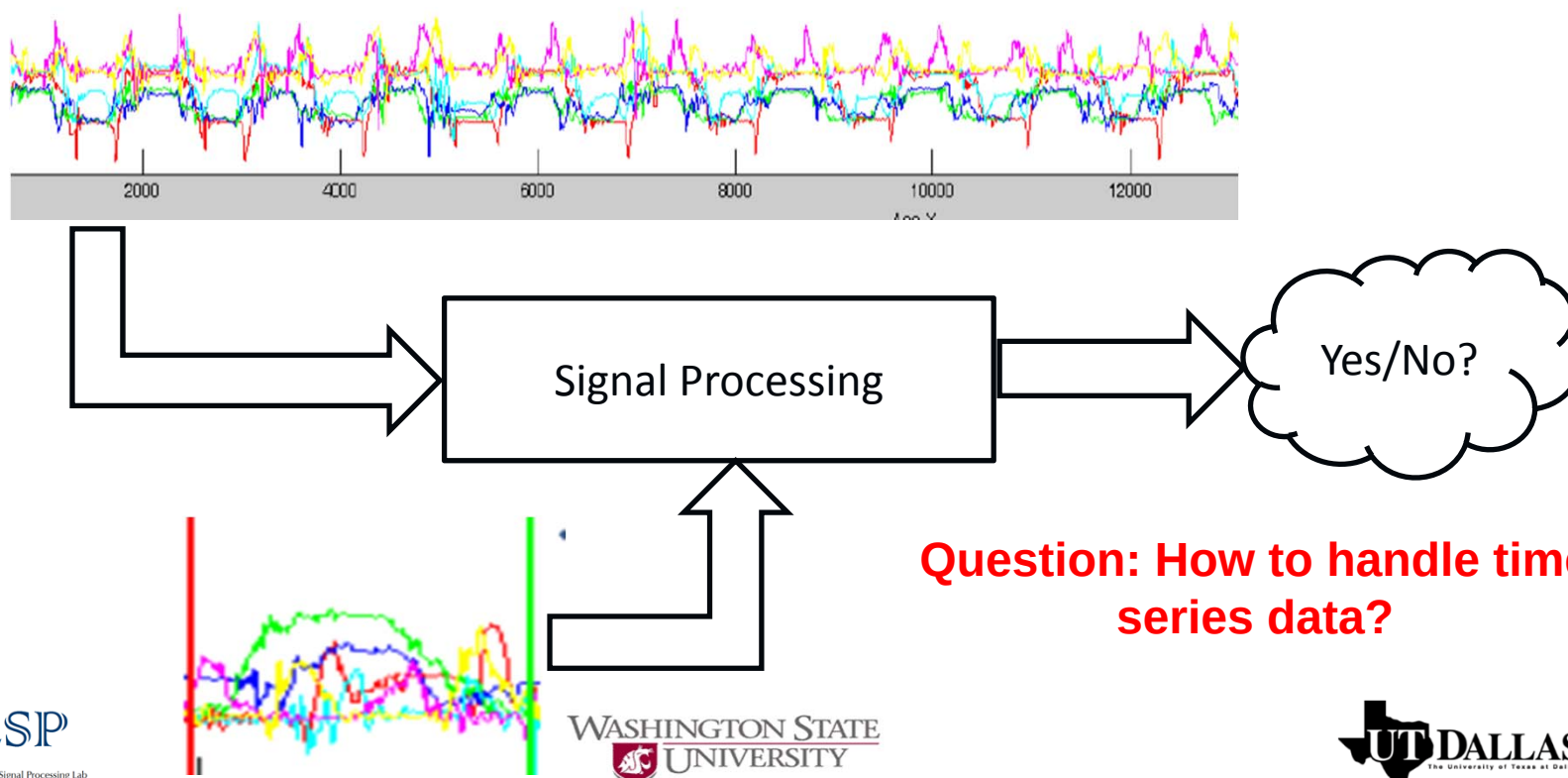
Aggregator and the Cloud

- Cloud-based processing
 - Some tasks may need a broader view to make a decision, *e.g.*, information from several sensor nodes
 - Processing power of the node may limit the development of the signal processing and decision support



Signal Processing

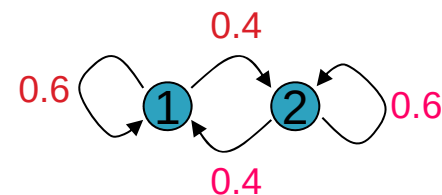
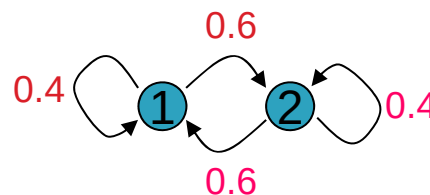
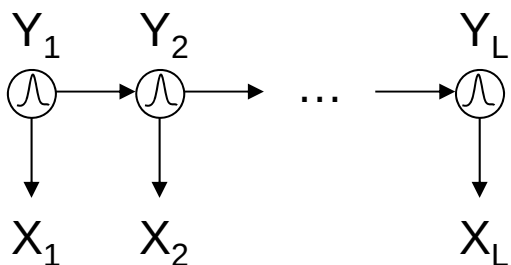
- To identify events of interest, *e.g.*, sit to stand or walking in activity monitoring



Hidden Markov Models (HMMs)

- Assumptions:
 - X_t is generated from certain probability distribution Y_t (called state)
 - Number of states is finite (*i.e.* finite sources of data)
 - State transition follows Markov property

$$P(Y_t | Y_{t-1}, \dots, Y_1) = P(Y_t | Y_{t-1})$$

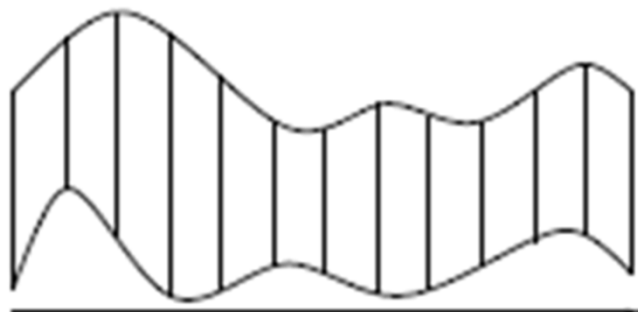


Hidden Markov Models (HMMs)

- Parameters to estimate:
 - Transition probabilities
 - Distribution parameters in each state
- Estimation procedure:
 - Initialization: k-means, Viterbi training
 - Iterative training: forward-backward procedure (EM algorithm)

Dynamic Time Warping

- Allows acceleration-deceleration of signals along the time dimension
- Widely used in speech recognition
- Find optimal match between two given sequences

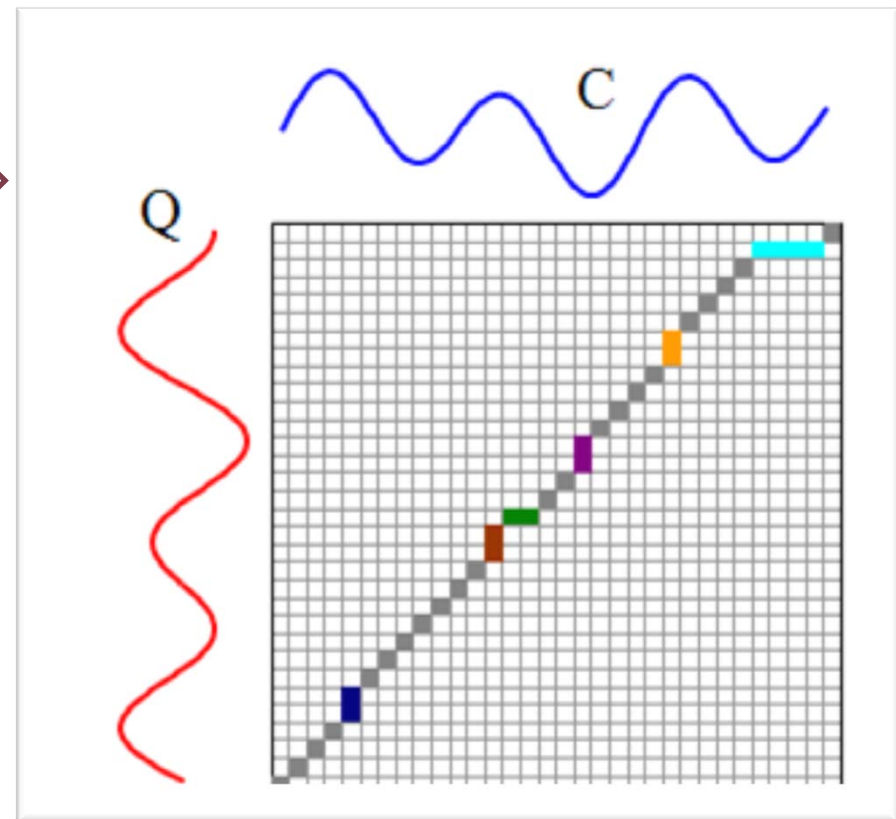
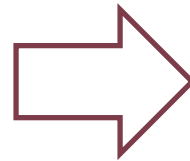
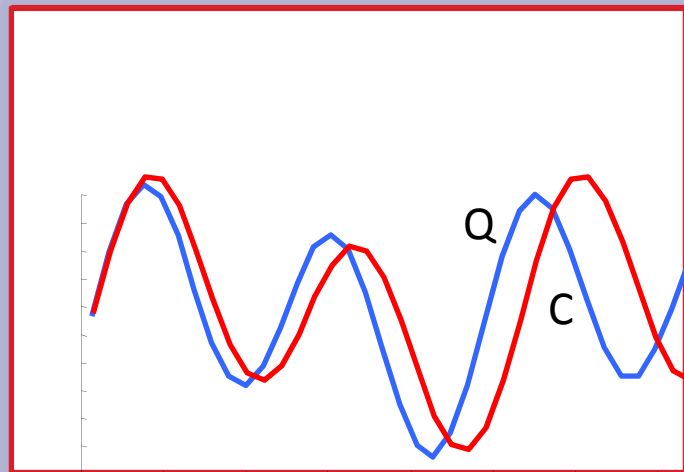


Naïve Alignment

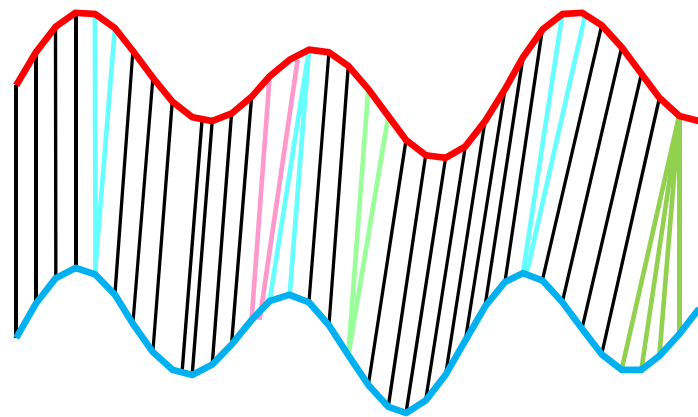


DTW Alignment

Time Warping



Warping Path

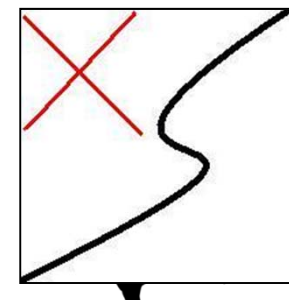
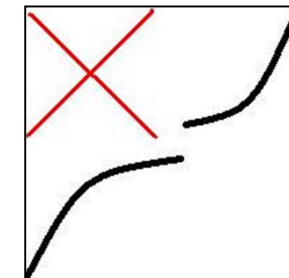
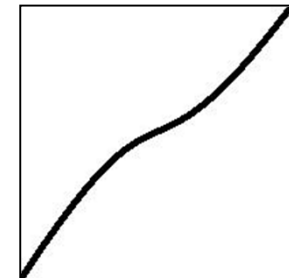


Dynamic Time Warping

- $\gamma(i,j) = d(q_i, c_j) + \min\{ \gamma(i-1,j-1) , \gamma(i-1,j) , \gamma(i,j-1) \}$



- Three Basic Constraints of Time Warping
 - Path should include beginning and ending
 - Path should not have any jumps
 - Path cannot go back in time



Trade-offs

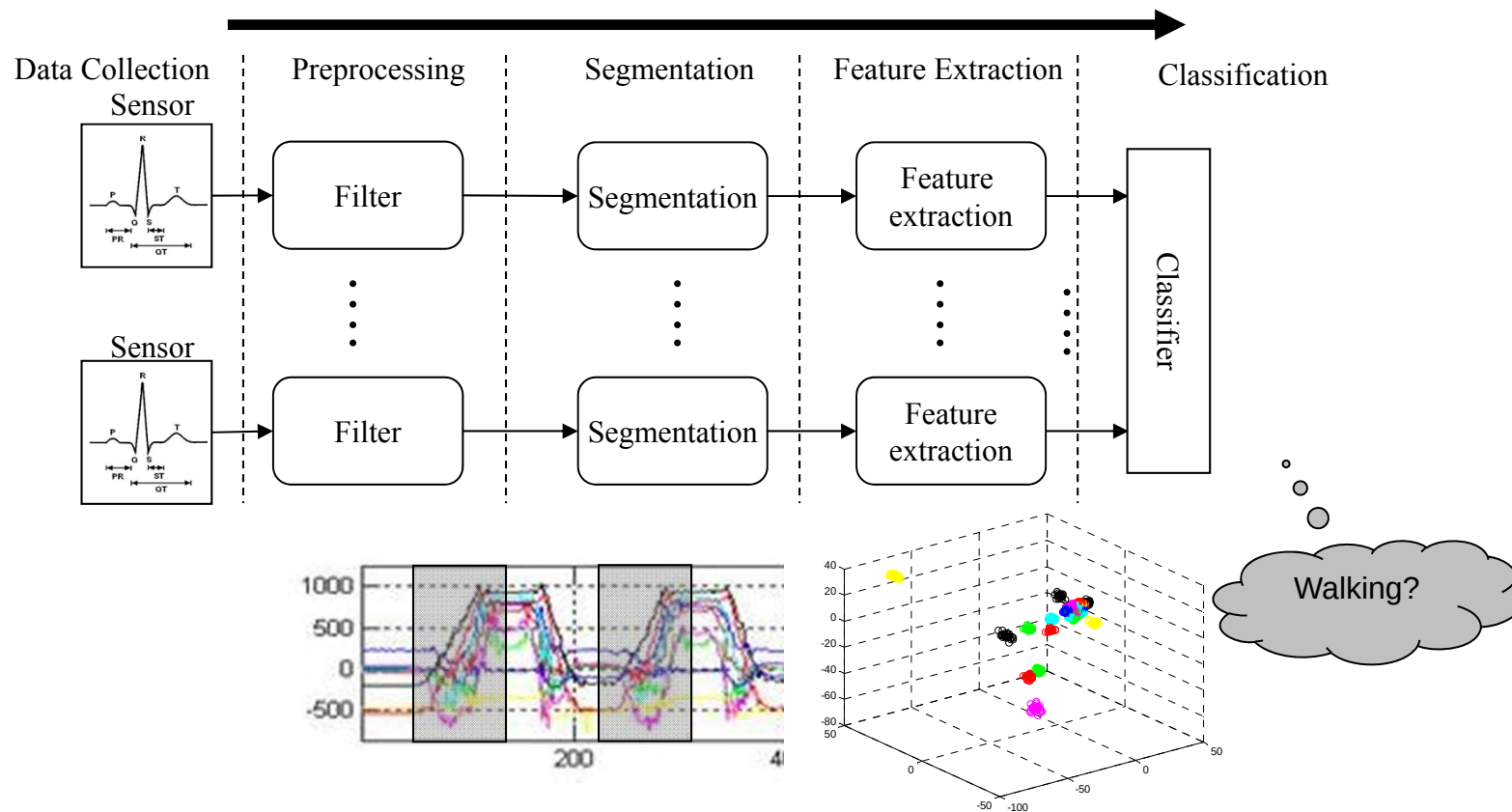
- Computational complexity
 - DTW: fixed-point arithmetic
 - HMM: floating point to compute model parameters
- Training and retraining
 - DTW: simply replace a new template in memory
 - HMM: requires training a new HMM model

SIGNAL PROCESSING

(FEATURE EXTRACTION)

Typical Event Classification

- Example: detect what action the patient is performing!
 - Actions: sit-to-stand, stand-to-sit, walk, jump, ...



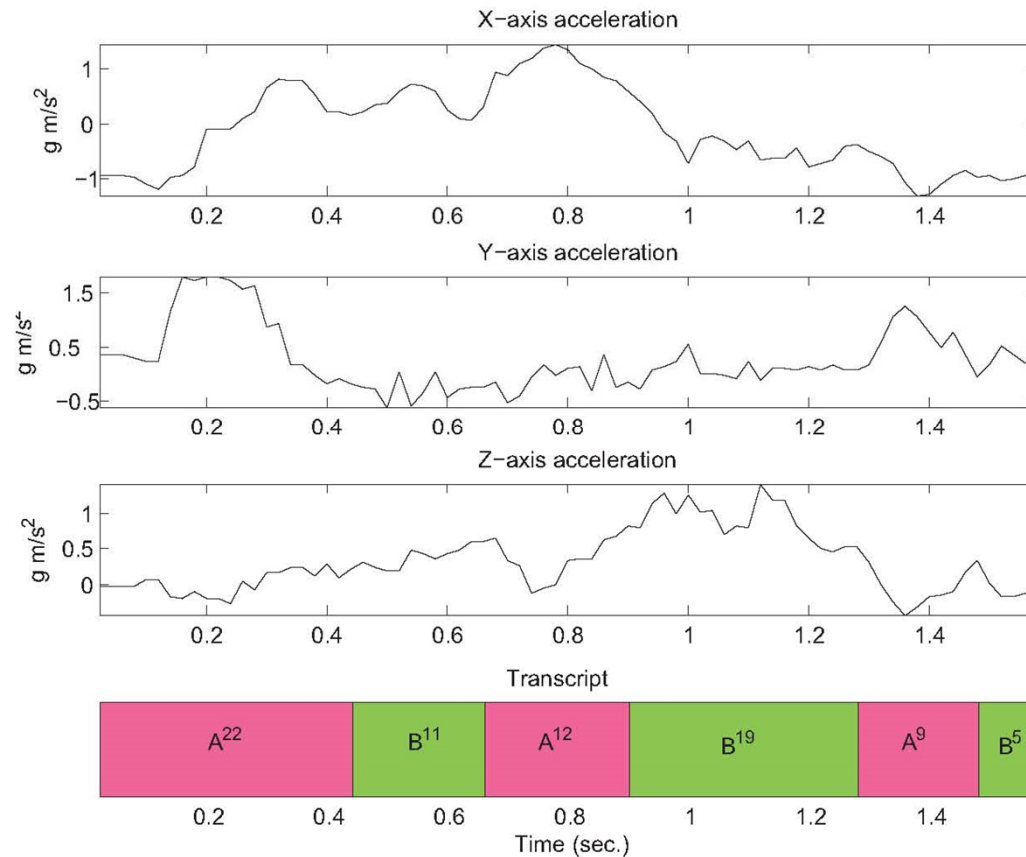
Feature Extraction Approaches

- Statistical features
 - Time-domain features
 - mean value, variance, signal energy, zero crossing rate and correlation between different sensors
 - Frequency domain features
 - Geometric subspace
 - Use of information-theoretic measures, PCA, ICA for feature extraction
- Structural features
 - Physical model
 - Fitting observations to a model (e.g. human body)
 - Unsupervised structural model
 - Extracting underlying structure of the signals using clustering algorithm

Feature Extraction

Category	Approach / Feature Type	Ref.	Application
Statistical	Time-domain	[Gao, 2014]	Activity recognition
Statistical	Time-domain	[Forster, 2009]	Activity & gesture recognition
Statistical	Time-domain	[Shi, 2009]	ECG biometric detection for key distribution (security)
Statistical	Frequency-domain	[Lie, 2005]	Gait analysis
Statistical	Frequency-domain	[Zheng, 2014]	Activity recognition
Statistical	Frequency-domain	[Atallah, 2009]	Gait analysis
Statistical	Frequency-domain	[Lester, 2005]	Activity tracking
Statistical	Geometric subspace	[Hild, 2006]	ECG arrhythmia detection
Statistical	Geometric subspace	[Hanson, 2009]	Gait classification
Statistical	Geometric subspace	[Ibaida, 2009]	ECG arrhythmia detection
Structural	Physical model	[Blanke, 2010]	Activity recognition
Structural	Physical model	[Zhang, 2012]	Activity monitoring
Structural	Unsupervised	[Ghasemzadeh, 2010]	Activity recognition
Structural	Unsupervised	[Stiefmeier, 2007]	Activity recognition
Structural	Unsupervised	[Huynh, 2008]	Activity monitoring

Unsupervised Approach

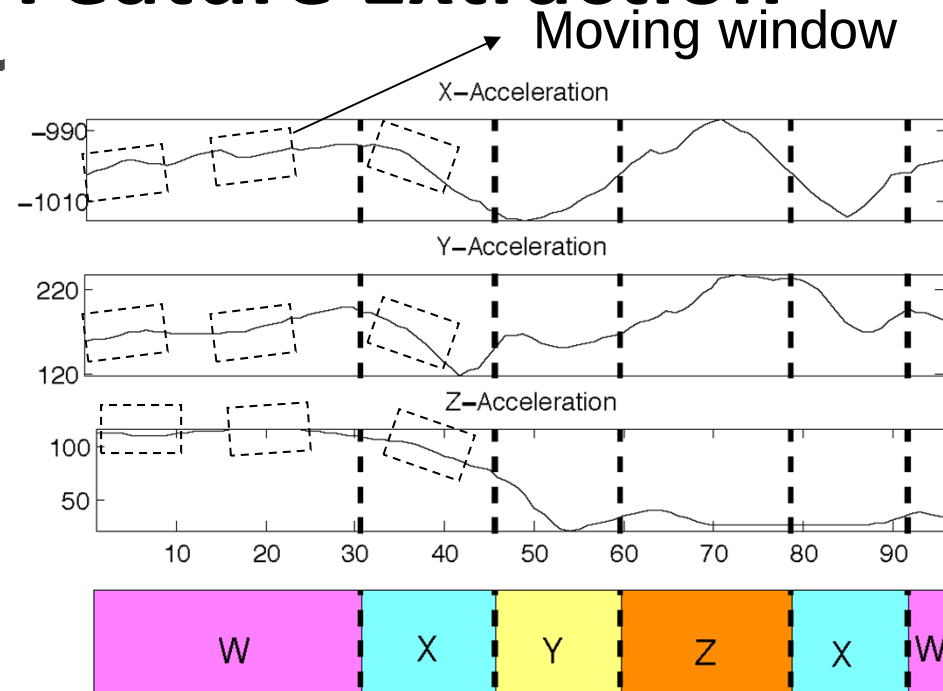


A clustering approach (e.g. GMM) is used to group similar data samples over a sliding window

Structural Feature Extraction

Sensor readings from
“wrist” node for action
“Bend & Grasp”

Symbolic Representation



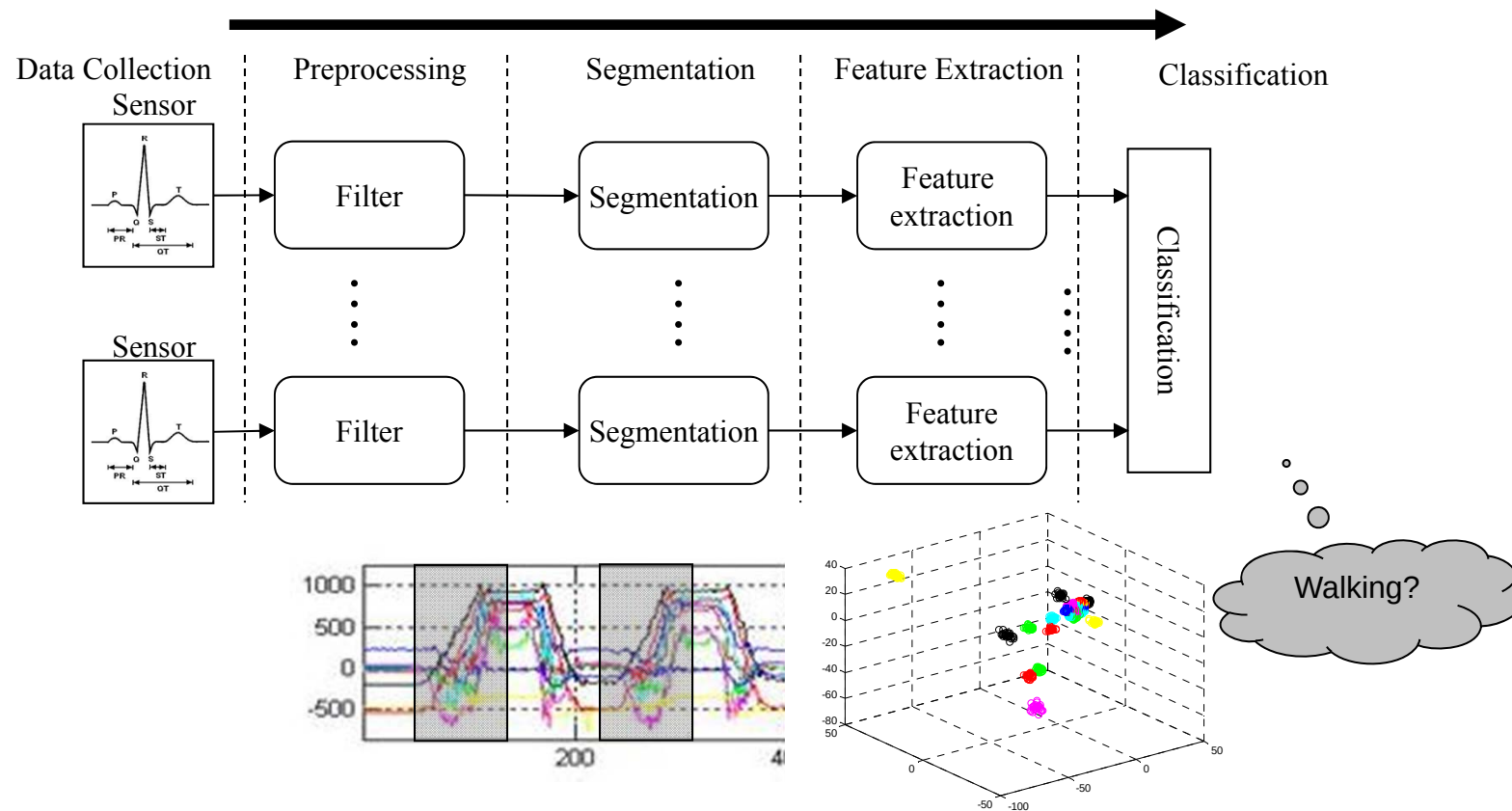
- Clustering (e.g. GMM)
 - Group similar samples on a set of statistical features (e.g. mean, 1st derivative, 2nd derivative, ...) from moving windows
- Labeling
 - Assign each cluster a label (W, X, Y, Z, ...)

SIGNAL PROCESSING

(EVENT CLASSIFICATION)

Movement Classification

- Detect what action the patient is performing!
- Actions: sit-to-stand, stand-to-sit, walk, jump, ...



Movement Classification

- Sensors
 - Accelerometers, gyroscopes, magnetometers
- Algorithms
 - kNN (k-Nearest Neighbor)
 - SVM (Support Vector Machines)
 - HMM (Hidden Markov Models)
 - Decision Trees
 - Naïve Bayes
- Parameters affecting accuracy
 - Number of sensors
 - Location of sensors
 - Movements to classify
 - Algorithm used

Movement Classification (1)

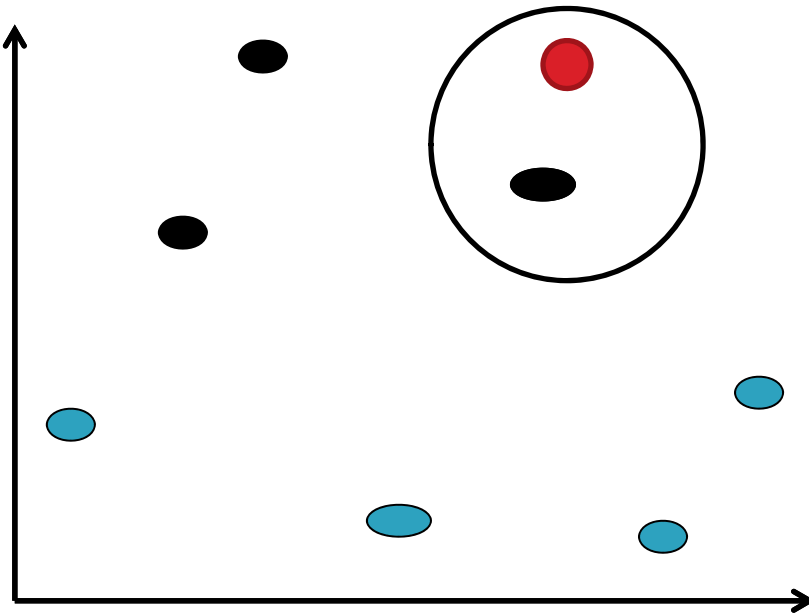
Classifier	#Nodes	#Movements	Accuracy	Location of nodes
kNN	6	7	91%	Shoulder, Chest, Waist, Back, Wrist, Ankle
kNN	1	4	84%	Chest
kNN	8	25	97%	Waist, L-wrist, R-wrist, L-arm, R-thigh, L-thigh, R-ankle, L-ankle
kNN	5	25	96%	L-wrist, R-wrist, L-thigh, R-ankle, L-ankle
kNN	2	25	92%	Active nodes are detected dynamically
kNN	1	4	85%	Pocket
kNN	1	4	86%	Necklace
kNN	1	4	87%	Belt
kNN	1	4	87%	Wrist
kNN	1	4	89%	Shirt
kNN	1	4	92%	Bag
HMM	19	10	98%	R-arm (10 nodes), L-arm (9 nodes)
HMM	3	10	97%	R-forearm, L-forearm, L-arm
HMM	1	10	80%	Active nodes are detected dynamically
HMM	3	8	90%	Shoulder, Waist, Wrist

Movement Classification (2)

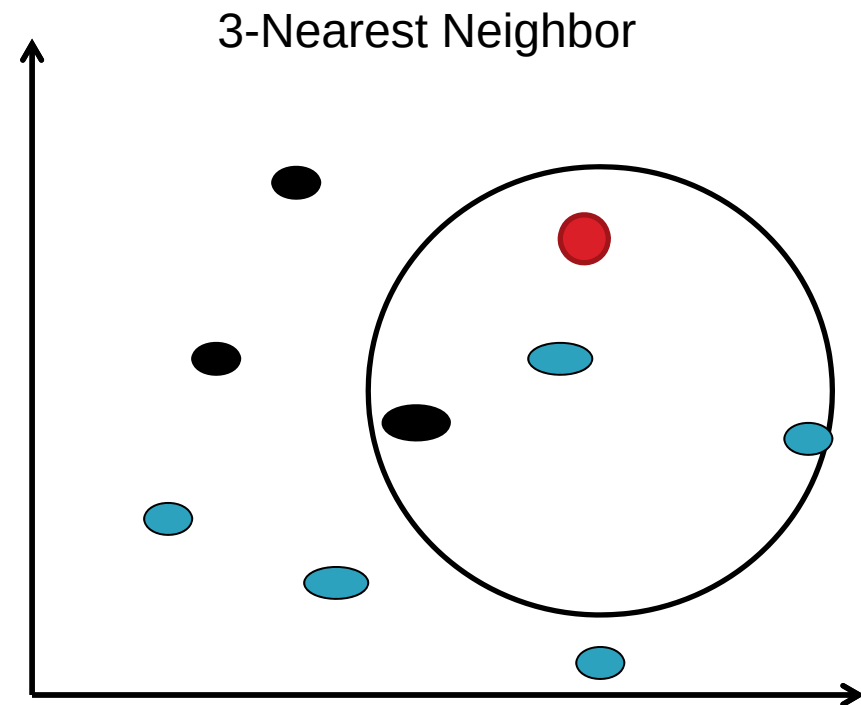
Classifier	#Nodes	#Movements	Accuracy	Location of nodes
HMM	3	19	92%	Waist, Wrist, Thigh
HMM	8	25	93%	L-wrist, R-wrist, L-arm, R-arm, R-thigh, L-thigh, R-ankle, L-ankle
SVM	6	6	95%	Shoe (1 accelerometer & 5 pressure sensors)
SVM	2	9	79%-97%	Hip (accelerometer), Chest (2 ECG electrodes)
SVM	1	8	84%	Waist (mobile-phone)
Decision Tree	14	14	89.9%	Head, Chest, Elbows, Wrists, Pockets, Knees, Ankles, Toes
Decision Tree	1	6	86.6%	Ankle
Naïve Bayes	3	3	99.5%	Knees, Chest
Naïve Bayes	3	5 (while sitting)	96.5%	Knees, Chest

[Maurer,2006; Lester,2006; Lombriser,2009; Jafari,2007; Zappi,2008; He,2008]; [Guenterberg,2009; Sazonov,2011; Li,2010; Zhao,2011; Zheng,2014; Chieh, 2012; Parkka, 2010; Ruchansky,2011]

K-Nearest Neighbor (kNN)



1-Nearest Neighbor



3-Nearest Neighbor

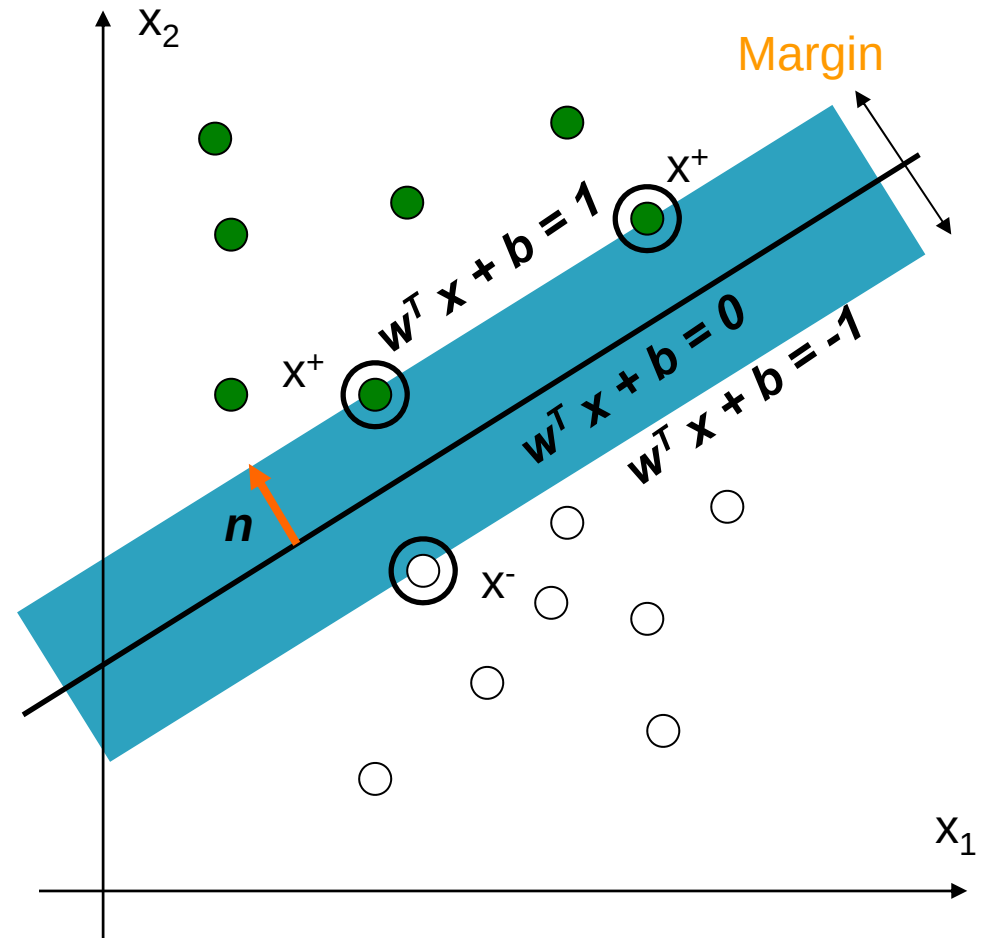
Support Vector Machines (SVM)

- Optimization

$$\text{maximize } \frac{2}{\|\mathbf{w}\|}$$

such that

$$y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1$$



SVM Training & Test

- Training
 - Quadratic optimization

Find $\alpha_1 \dots \alpha_N$ such that

$Q(\alpha) = \sum \alpha_i - \frac{1}{2} \sum \sum \alpha_i \alpha_j y_i y_j \mathbf{x}_i^T \mathbf{x}_j$ is maximized and

(1) $\sum \alpha_i y_i = 0$

(2) $0 \leq \alpha_i \leq C$ for all α_i

- Test
 - Involves inner product

$$f(\mathbf{x}) = \sum \alpha_i y_i \mathbf{x}_i^T \mathbf{x} + b$$

SVM Parameters

- Using kernel function for non-linear SVM
 - Map data points to higher dimensional space in order to make them linearly separable.
- Choosing appropriate kernel parameters
- Adoption for wearable computers
 - Incremental learning
 - Adaptively updating the model as new observations become available
 - Enhancing memory usage

Naïve Bayes Classification

- Uses Naïve Bayes rule

$$P(Y|X_1, \dots, X_n) = \frac{P(X_1, \dots, X_n|Y)P(Y)}{P(X_1, \dots, X_n)}$$

- Assumes features are independent given the class label

$$P(X_1, \dots, X_n|Y) = \prod_{i=1}^n P(X_i|Y)$$

- This makes computation of likelihood probability easy

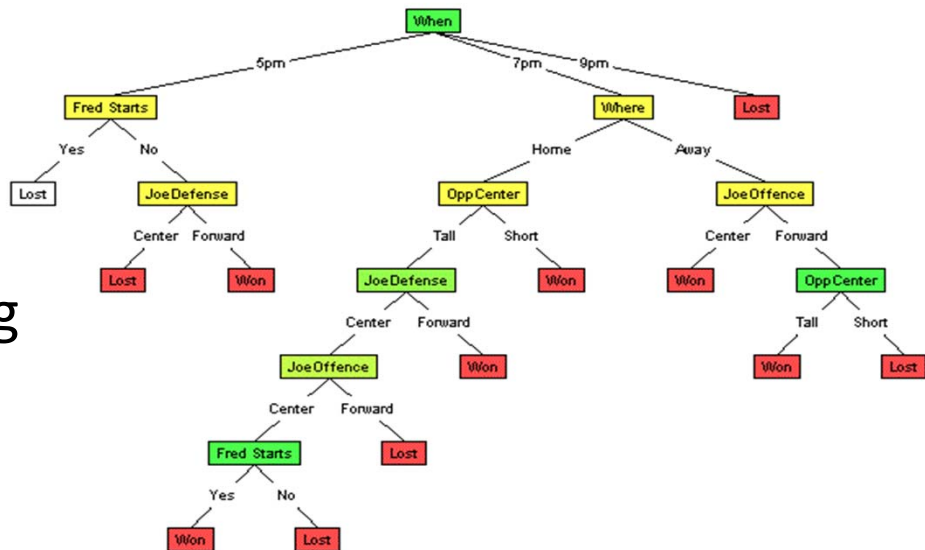
- Training involves counting

$$P(X_i = u|Y = v) = \frac{\text{Count}(X_i = u \wedge Y = v)}{\text{Count}(Y = v)}$$

Decision Tree Classifier

- Criterion
 - Selection of a feature to test at each node
 - choosing the most useful attribute for classifying examples

- Information gain
 - Measures how well a given feature separates the training examples according to their target classification
 - Used to select among the candidate features at each step while building the tree



Trade-offs

- Computational complexity
 - kNN: a function of # of training examples
 - SVM: a function of # of support vectors
 - Naïve Bayes: a function of # of classes
 - Decision Tree: a function of # of features
- Training and retraining
 - kNN: add new instances to the feature space
 - SVM: requires training a new SVM model
 - Naïve Bayes: requires recalculation of probabilities
 - Decision Tree: requires rebuilding the tree

Impact of Validation on Accuracy

Classifier	Setting1	Setting2	Setting3	Setting4
Naive Bayes(NB)	98.86	96.69	89.96	64.00
Boosted NB	98.86	98.71	89.96	64.00
Bagged NB	98.58	96.88	90.39	59.33
SVM	98.15	98.16	68.78	63.00
Boosted SVM	99.43	98.16	67.90	73.33
Bagged SVM	98.15	98.53	68.78	60.00
kNN	98.15	99.26	72.93	49.67
Boosted kNN	99.15	99.26	72.93	49.67
Bagged kNN	99.15	99.26	70.52	46.67
Decision Tree(DTr)	97.29	98.53	77.95	57.00
Boosted DTr	98.15	98.35	77.95	57.00
Bagged DTr	97.29	95.22	78.82	63.33

Setting1: Cross validation, same subject, multiple days

Setting2: Cross validation, multiple subjects, multiple days

Setting3: Same subject, day1 data for training, day2 data for test

Setting4: Subject1 on day1 for training, subject2 on day2 for test

SIGNAL PROCESSING

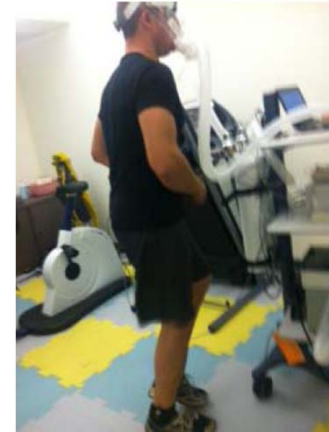
(MET CALCULATION)

Need

- Physical activity is a critical component of many chronic conditions [Haas, 2013; Colberg, 2010; ADA, 2013]
- Interventions require monitoring of physical activity goals
 - Example: perform 30 minutes of moderate physical activity 3 times a week [Lokken, 2007]
- Activity intensity estimation
 - Physical activities can be low, moderate, or intense
 - MET (Metabolic Equivalent of Task) is the standard measure
 - MET can be transformed into caloric expenditure values

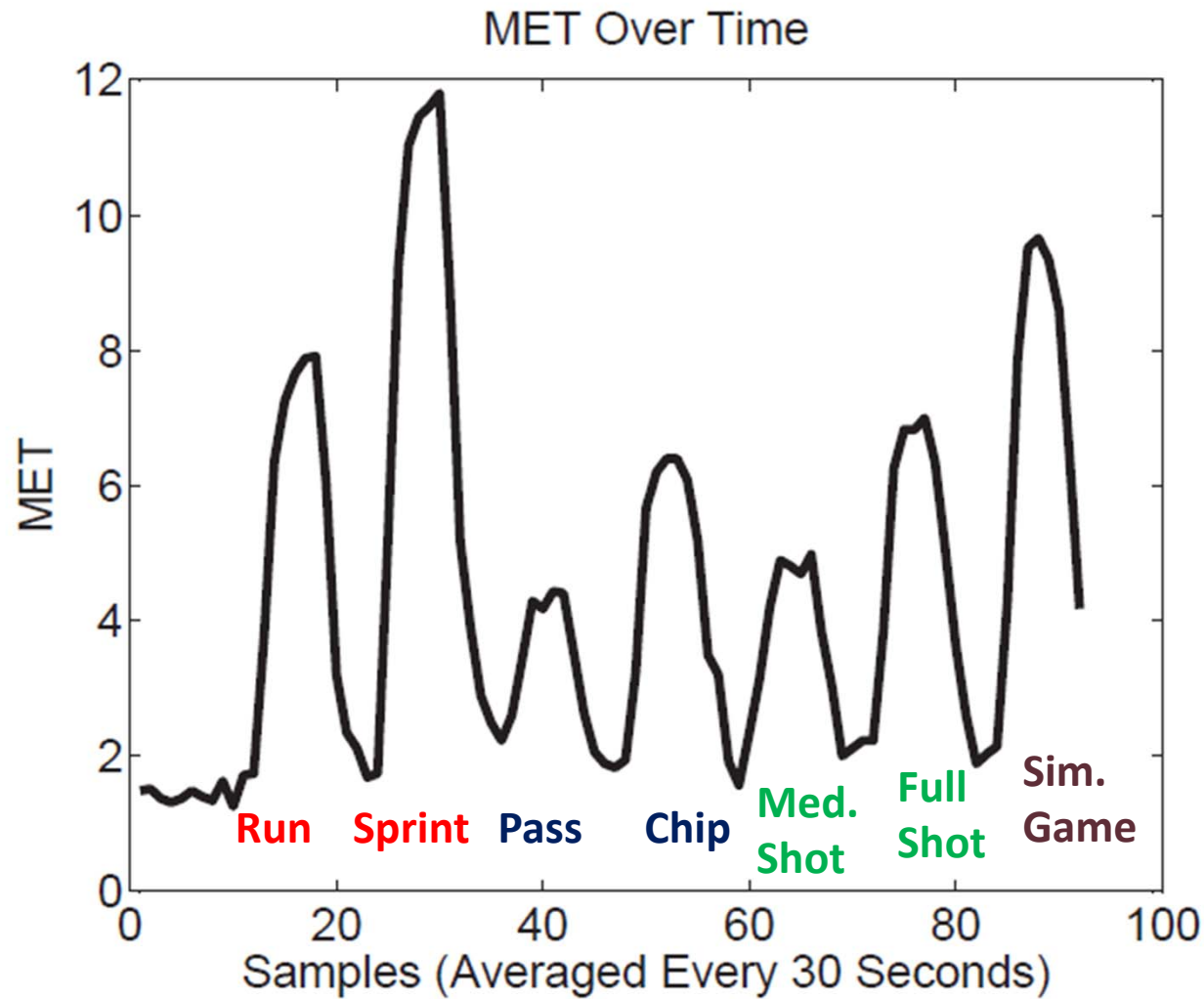
MET Calculation

- Ground truth $MET = \frac{VO_2}{3.5 * m}$
 - Measured using metabolic cart
- Goal
 - Find a mathematical model that converts sensor readings to MET values
 - Use data from motion sensors (e.g. accelerometers) attached to various body segments
- Method
 - Regression models have been the most common approach



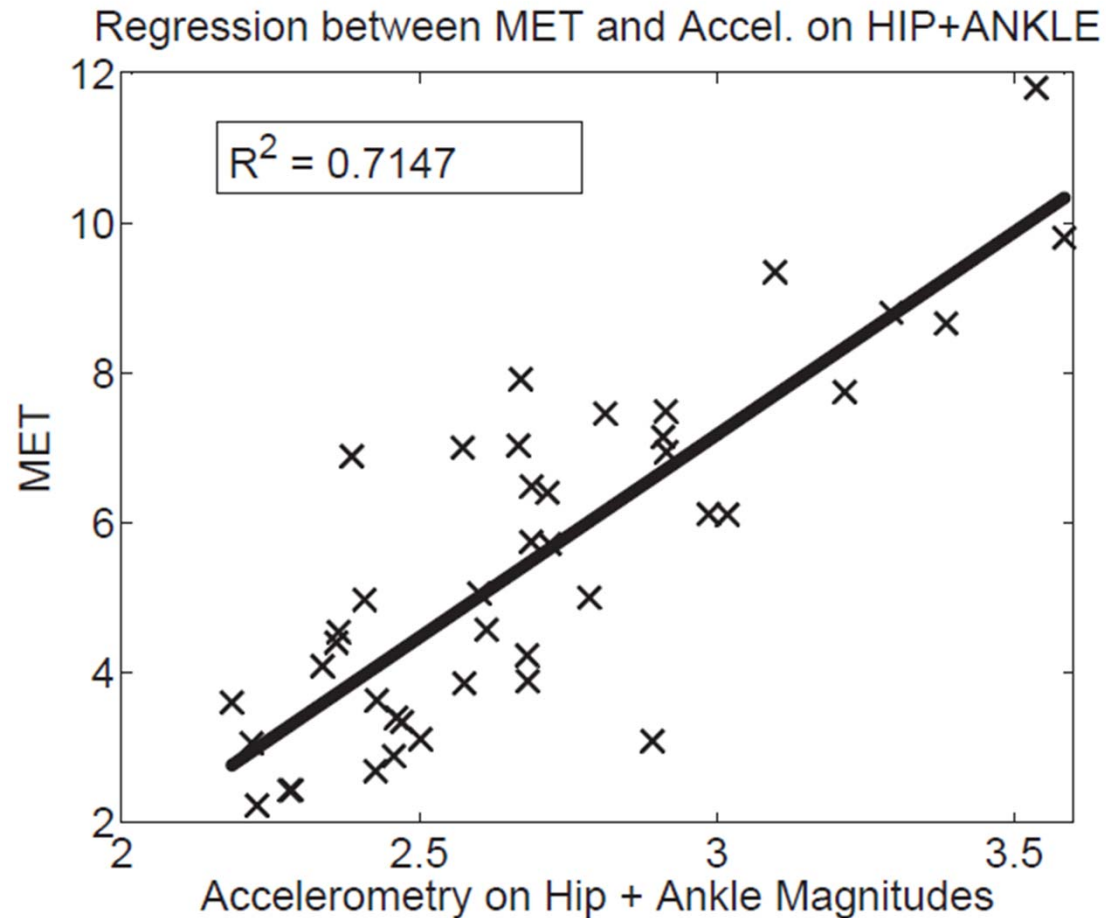
[Mortazavi, 2013]

Changes in MET



Courtesy of B. Mortazavi

Regression Model: Example



$$MET = 5.289 * (MAG_{hip} + MAG_{ankle}) - 8.5548$$

Courtesy of B. Mortazavi

MET Calculation Approaches

Ref.	Single vs. Multidomal	Sensors	Model
[Crouter, 2006]	Single	Accelerometer	Single model
[Ceesay, 1989]	Single	Heart rate	Single model
[Hees, 2009]	Single	Skin conductance	Single model
[Altini, 2013]	Single	Skin humidity	Single model
[Rothney, 2007]	Single	Accelerometer	Single model
[Freedson, 2011]	Single	Accelerometer	Single model
[Bonomi, 2009]	Single	Accelerometer	Activity-specific model
[Rumo, 2011]	Single	Accelerometer	Activity-specific model
[Bonomi, 2012]	Single	Accelerometer	Unsupervised clustering
[Chen, 2013]	Single	Accelerometer	Unsupervised clustering
[Smolander, 2008]	Multimodal	Heart rate & respiration rate	Single model
[Altini, 2013]	Multimodal	Heart rate and accelerometer	Activity-specific model
[Kalantarian, 2013]	Multimodal	Heart rate and accelerometer	Single model

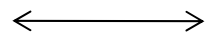
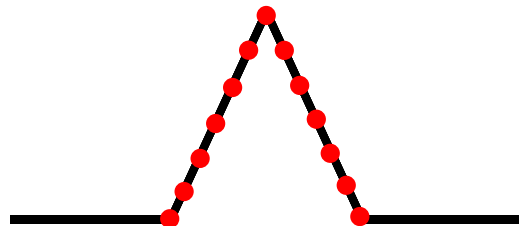
HARDWARE OPTIMIZATION

Optimization in Digital

- Only certain events are of interest
 - **Walking** in fall monitoring
 - **Tremors** in Parkinson's disease
 - Restless **leg movements** in sleep apnea
 - **ECG abnormalities** in cardiac assessment
- Events of interest are
 - Sparse (*e.g.*, <1-5% duty cycle)
 - Slow
 - Governed by physics of human body

An Example

Signal of interest

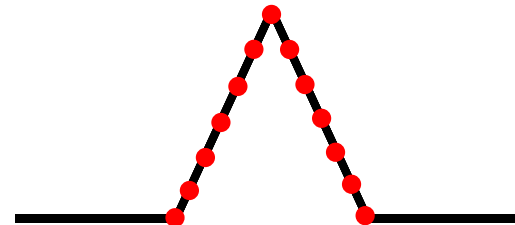
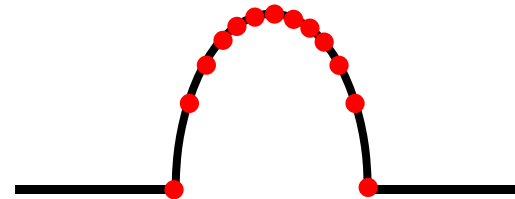


2 seconds

50 Hz @ 12 bits

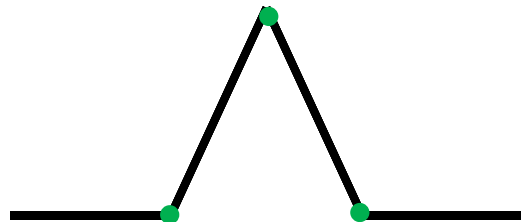
100 samples @ 12 bits

Sensor readings

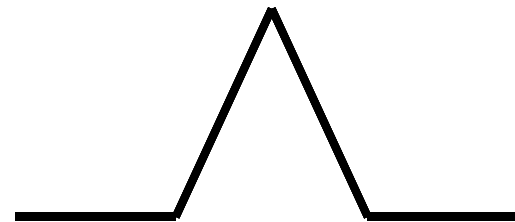
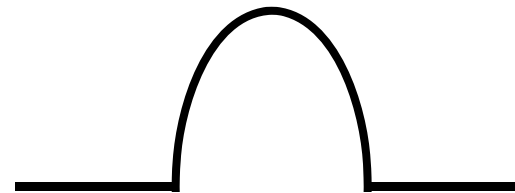


An Example

Signal of interest



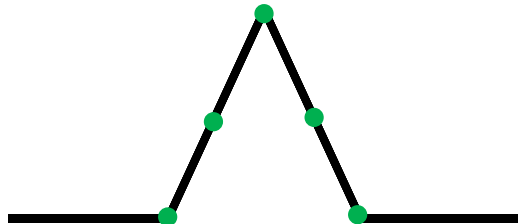
Sensor readings



@ 2 bits

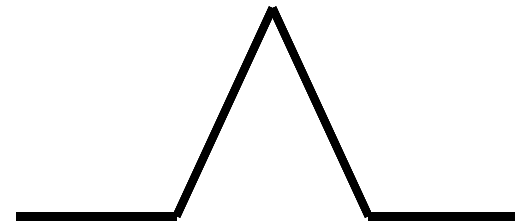
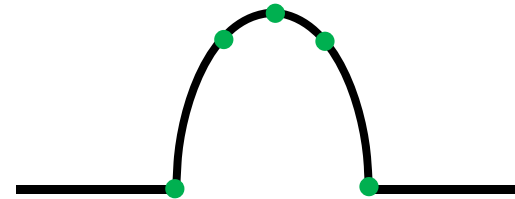
An Example

Signal of interest



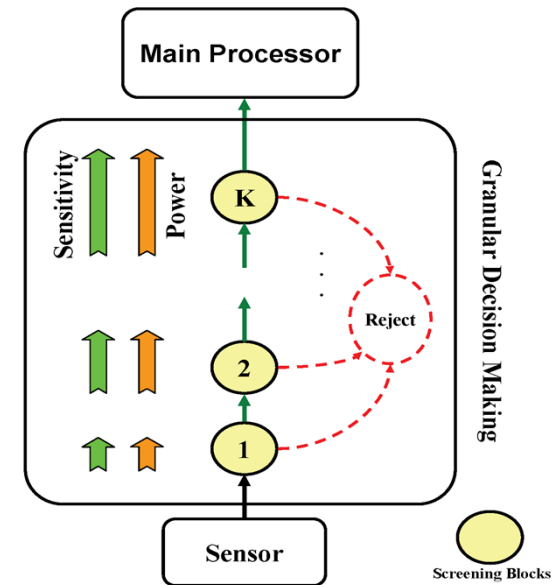
@ 10 bits

Sensor readings



Power Optimization

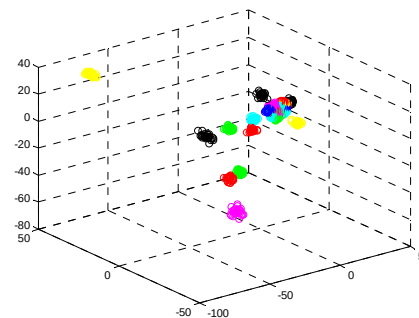
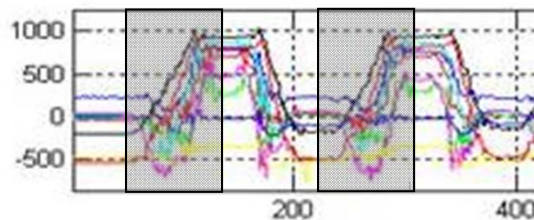
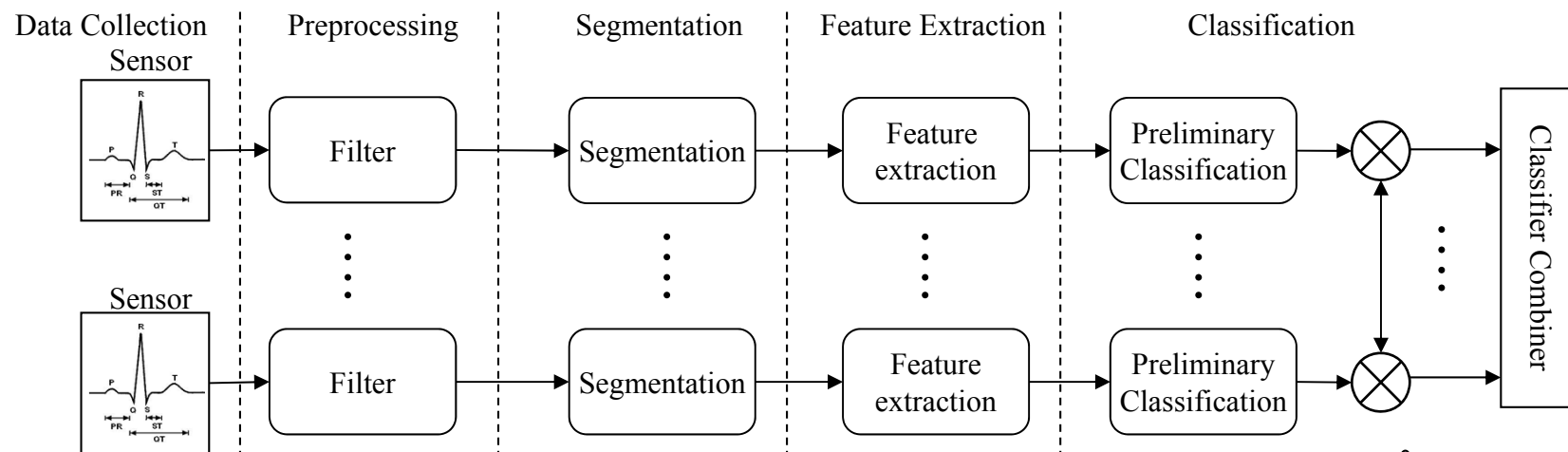
- Optimal decision path
 - Tunable parameters (sampling frequency, bit resolution, size and location of processing windows, # of templates)
 - Choose from millions of instances
 - Many variations NP-complete or NP-hard
 - Real-time reconfiguration and customization



M. Bidmeshki, R. Jafari, Low Power Programmable Architecture for Periodic Activity Monitoring, ACM/IEEE International Conference on Cyber-Physical Systems (ICCPs) 2013, Philadelphia, PA.
R. Lotfian, R. Jafari, An Ultra-Low Power Hardware Accelerator Architecture for Wearable Computers Using Dynamic Time Warping, IEEE/ACM Design, Automation and Test in Europe (DATE) 2013, Grenoble, France.

SIGNAL PROCESSING OPTIMIZATION: (POWER-AWARE FEATURE SELECTION)

Distributed Event Classification



Feature Selection

- Choosing a subset of prominent features for classification
 - Done during system training and on training dataset



Feature Selection Approaches

- Filter
 - Ranks features as a pre-processing step prior to the learning algorithm, and select those features with higher ranking scores. [Yu, 2003 & 2004]
- Wrapper
 - Scores features using the learning algorithm that will eventually be employed. [Kohaviand, 1997]
- Hybrid
 - Combines feature selection with learning algorithm and hence, they are specific to a model. [Grumer,2007]

Feature Selection Criteria

- Regardless of feature selection method, we need criteria for selection of the best feature set.
- Common criteria for feature selection include:
 - Relevance
 - Redundancy
- Example
 - Original feature set: $\{f_1, f_2, \dots, f_5\}$
 - Classification rule: $C = g(f_1, f_2)$
 - Assume: $f_2 = f_3$ and $f_4 = f_5$
 - Relevance analysis: eliminate f_4 & f_5
 - Redundancy analysis: eliminate one of f_2 or f_3
 - Final feature set: $\{f_1, f_2\}$ or $\{f_1, f_3\}$

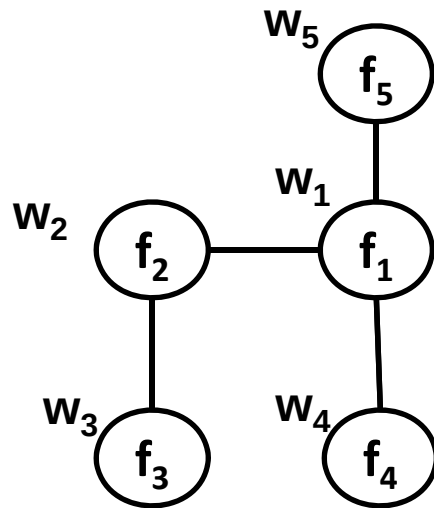
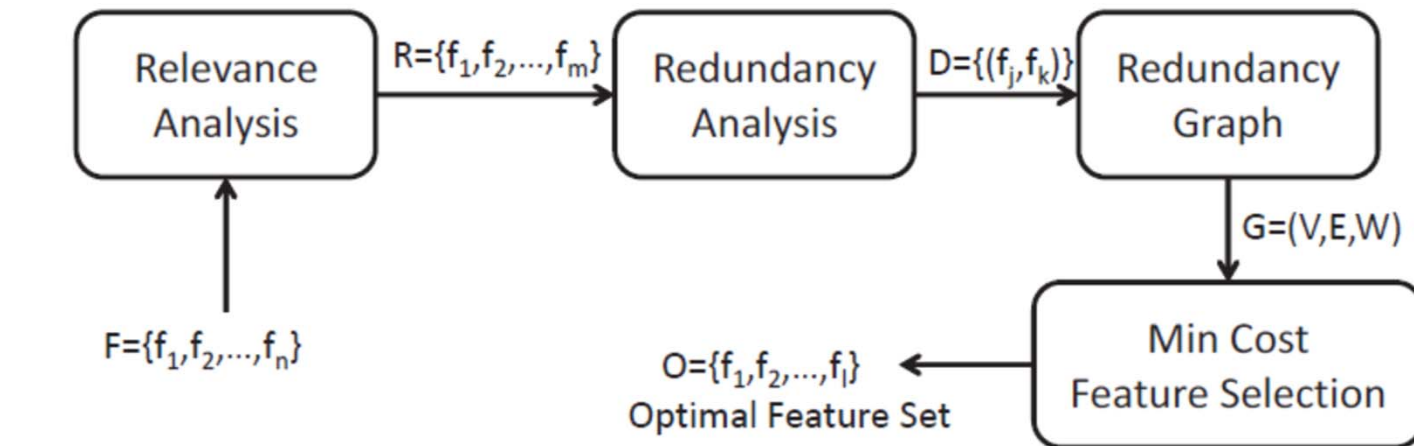
Power-Aware Feature Selection

- Wearable monitoring systems have limited battery lifetime
- Computing complexity of features must be taken into consideration to select features
- Complex features can lead to quick battery depletion

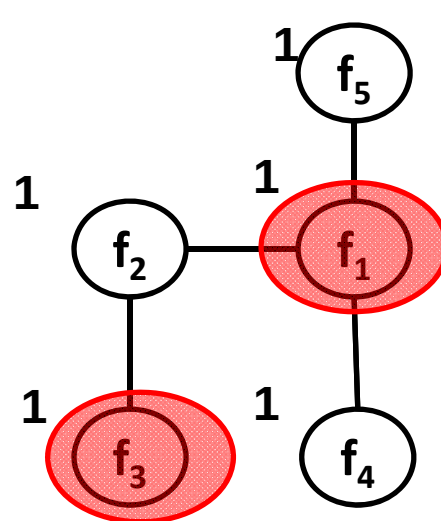
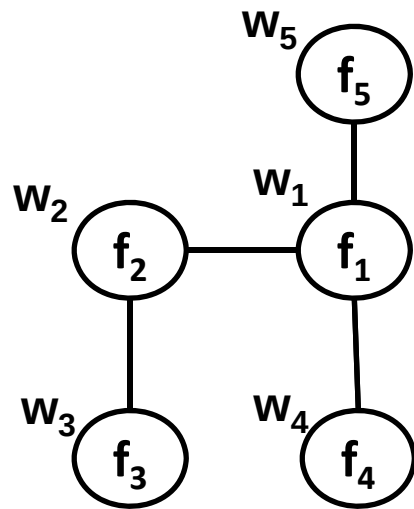
No.	Feature	Description	Energy (nJ)	
1	Amp	Amplitude of signal segment (Max - Mean)	16386	
2	Med	Median of signal segment	405159	405 uJ
3	Mean	Mean value of signal segment	8126	
4	Max	Maximum amplitude of signal segment	8103	
5	P2P	Peak to peak amplitude (Max - Min)	16291	.
6	Var	Variance of signal segment	38846	.
7	Std	Standard deviation	40431	.
8	Rms	Root mean square power	29705	
9	S2E	Start to end value	83	83 nJ

[Ghasemzadeh, 2012 & 2014]

Modeling Power-Awareness

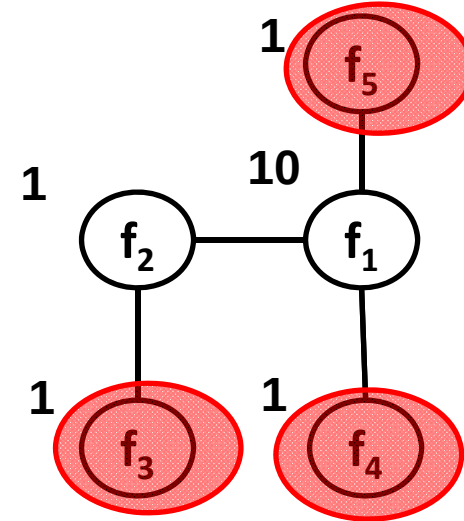


Finding Minimum Cost Feature Set



Case A

$W = \{1, 1, 1, 1, 1\}$
 Optimal set = $\{f_1, f_3\}$
 Total cost = 2



Case B

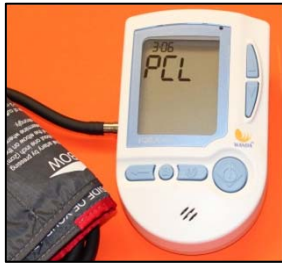
$W = \{10, 1, 1, 1, 1\}$
 Optimal set = $\{f_3, f_4, f_5\}$
 Total cost = 3

Minimum Cost Dominating Set

SIGNAL PROCESSING OPTIMIZATION: (SENSOR SELECTION)

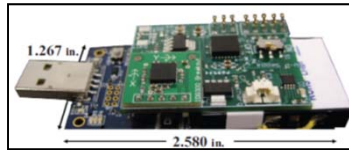
Why Sensor Selection?

- No strong clinical evidence
 - Remote monitoring is emerging
 - Contextual information (e.g. activity) is important in interpreting physiological data

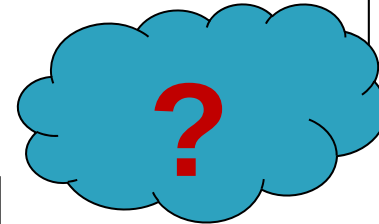


BP

+



Activity



Maybe!

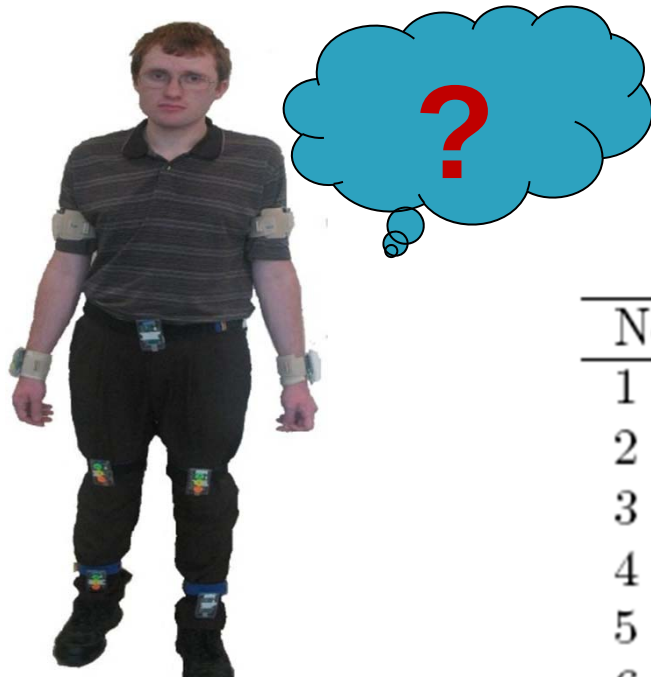
We don't know!

What Sensors To Use?

- Currently
 - Domain knowledge
- Open research question
 - Inter-sensor relationship/correlation
- Let us focus on Activity Monitoring
- Why **Activity Monitoring**
 - Important for clinical assessment in many medical conditions
 - Other physiological signals are highly correlated with the level/type of activity
 - Systolic BP increases (e.g. from 120 mmHg to 200 mmHg during exercise)

Sensor Selection for Activity Monitoring

- **How many sensors to use?**
- **Where to place them on the body?**

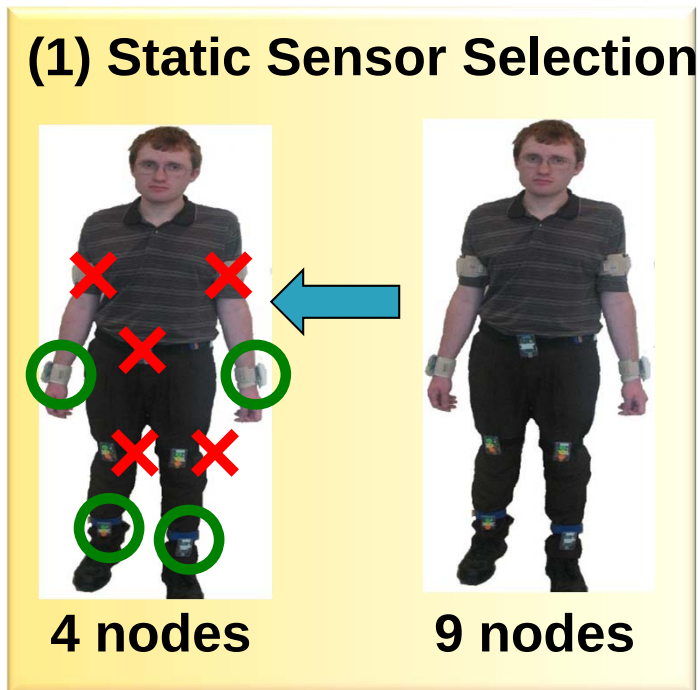


No.	Description
1	Stand to sit
2	Sit to stand
3	Stand to sit to stand
4	Sit to lie
5	Lie to sit
6	Sit to lie to sit

Static Sensor Selection

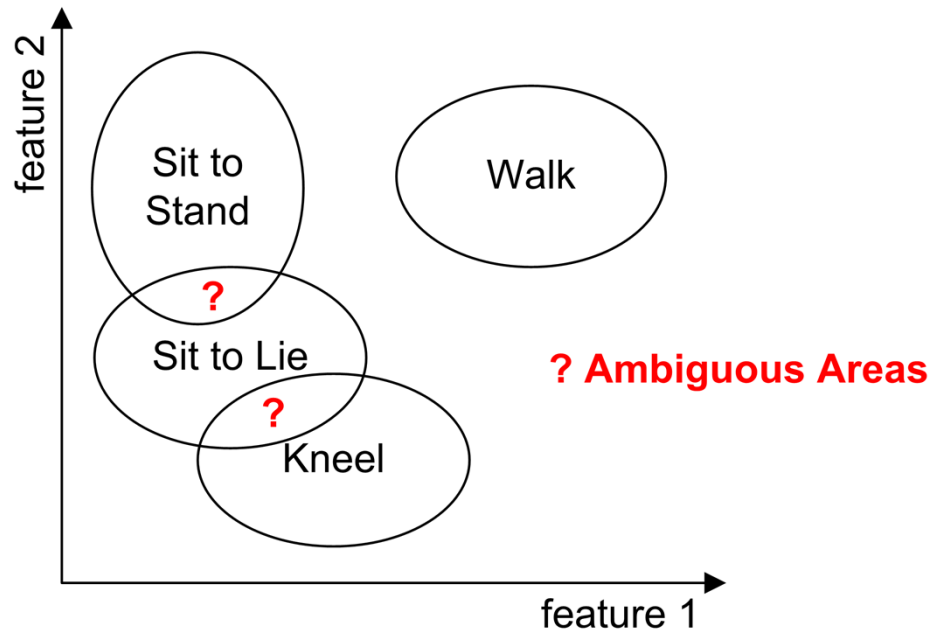
Objective

- Find **smallest subset** of nodes required for monitoring activities



Motivation

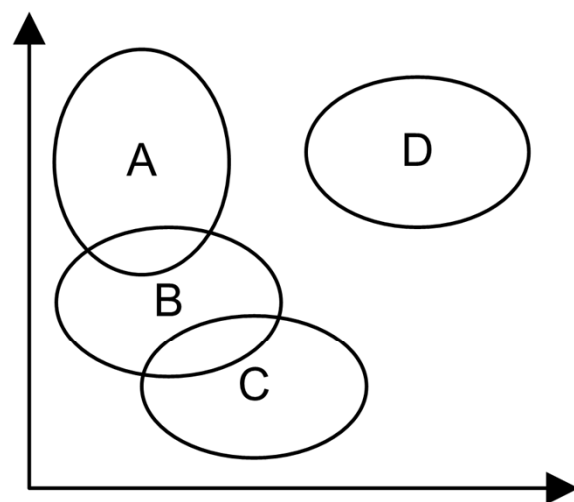
- Each node can reliably detect some actions



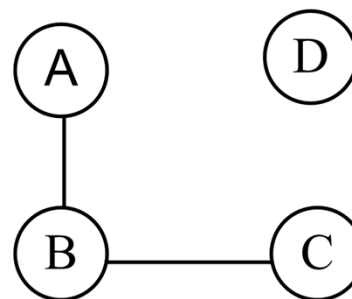
- How to represent knowledge of each node about actions?

Compatibility Graph

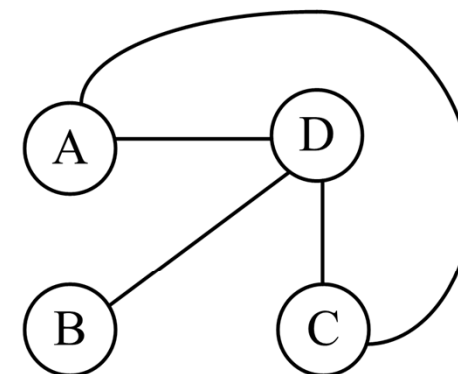
- Vertices represent actions
- Edge represent action separations



Class Distribution



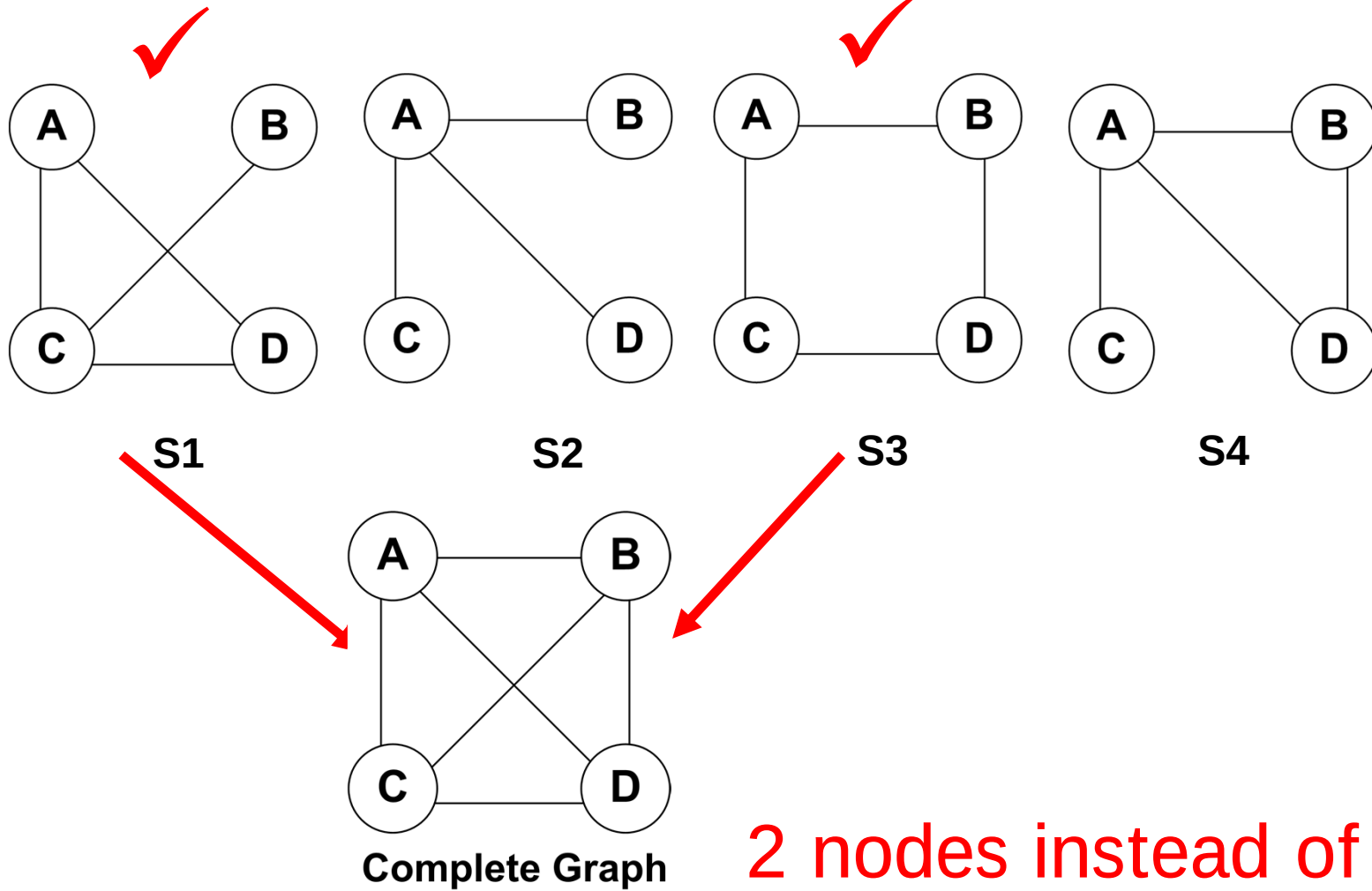
Conflict Graph



Compatibility Graph



How To Select Active Nodes?



Problem Complexity

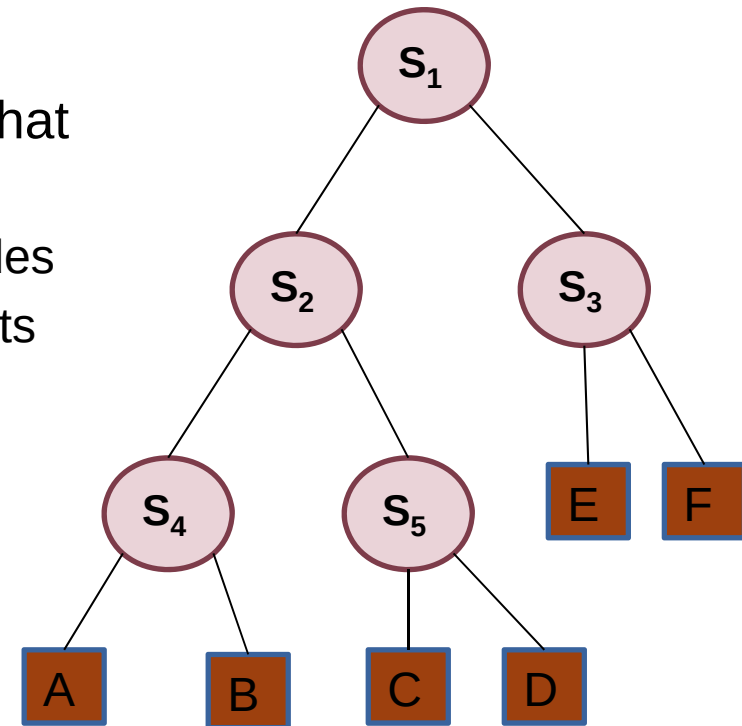
- It is a **Set Cover** problem
- It is an **NP-hard** problem
- Best approximation factor **$O(\log n)$**
- ILP Formulation $x_i = \begin{cases} 1 & \text{if graph } G_i \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$

Objective:
$$\text{Min} \sum_{i=1}^n x_i$$

Subject to:
$$\sum_{i: e_j \in G_i} x_i \geq 1 \quad \forall e_j \in E$$

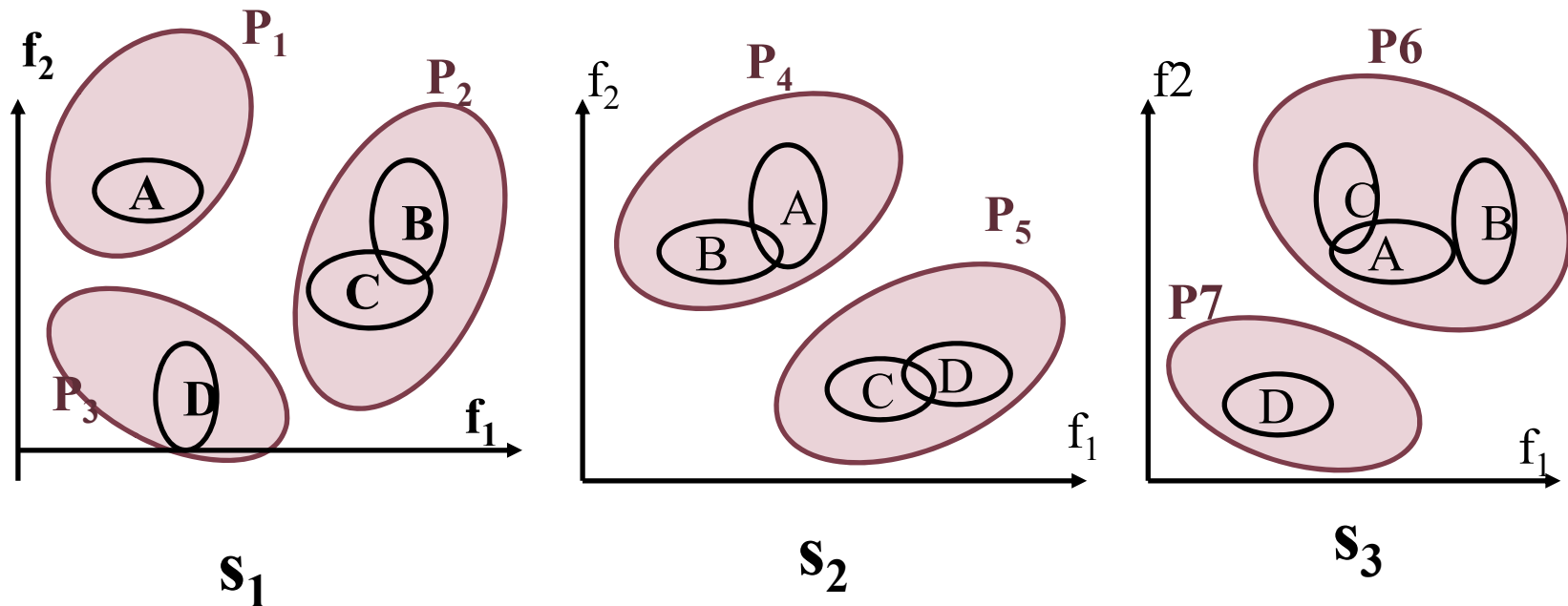
Pseudo-dynamic Sensor Selection

- Problem
 - Construct an optimal decision tree that classifies actions of interest
 - Internal nodes represent sensor nodes
 - Terminal nodes represent movements
- Minimize average number of active nodes
 - Depth of the tree



Spatial Primitives

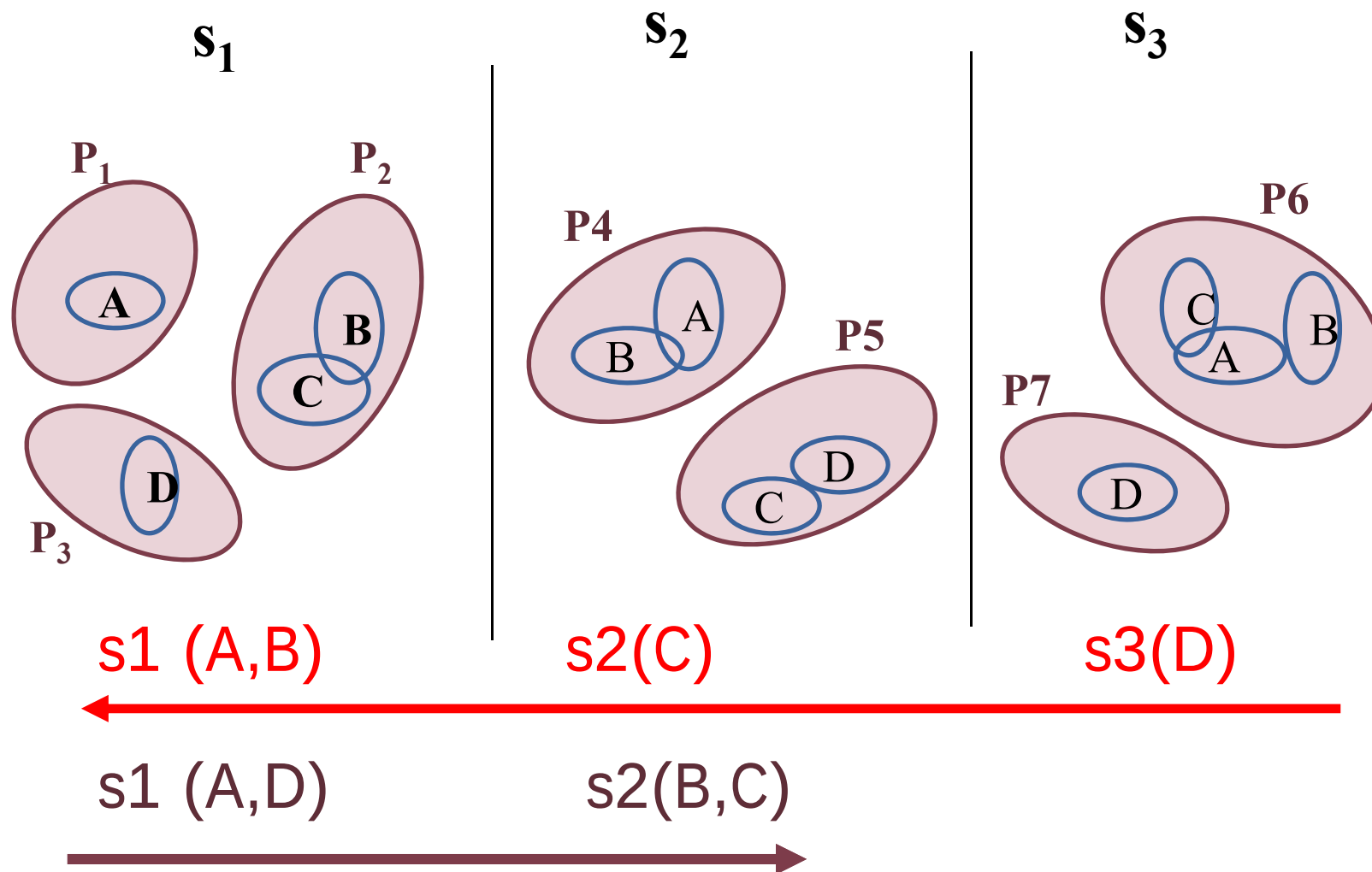
- Actions are grouped at each node using clustering techniques.
- Actions may fall into different clusters at different nodes.



- Each action is represented by a set of primitives:

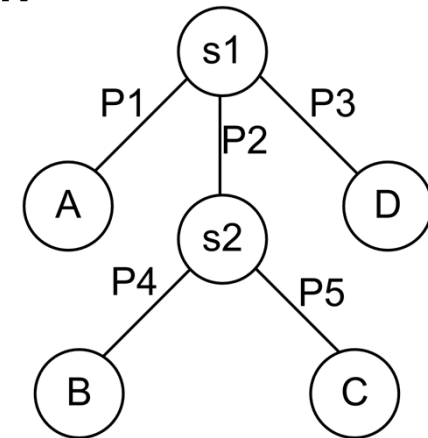
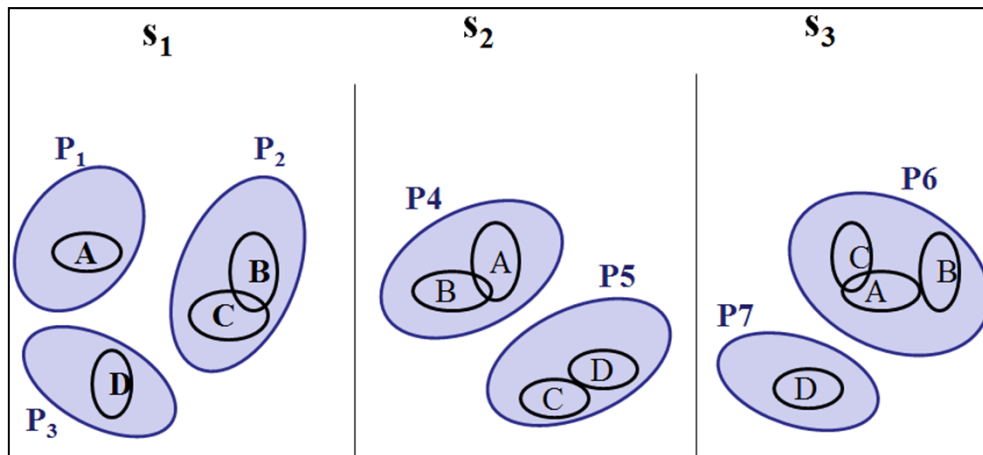
$$\begin{aligned}
 A &= \{P_1, P_4, P_6\} & B &= \{P_2, P_4, P_6\} \\
 C &= \{P_2, P_5, P_6\} & D &= \{P_3, P_5, P_7\}
 \end{aligned}$$

Action Recognition (example)



Decision Tree

- How to construct optimal tree?
 - Tree with minimum average depth!



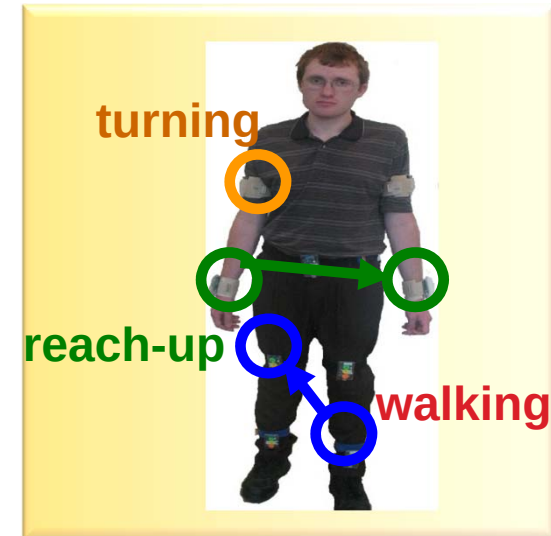
Optimal Decision Tree

Decision Path

- Optimal Decision Tree is equivalent to a linear ordering of sensor nodes s.t. cost of recognition is minimized
- Equivalently, number of sensor nodes in linear ordering must be minimized
- Problem is **NP-hard** (by reduction from **Min. Sum Set Cover**)
- Best approximation factor is 4
 - (U. Feige and, P. Tetali, “Approximating min sum set cover”, Algorithmica, vol. 40, no.4, pp. 219–234, 2004.)

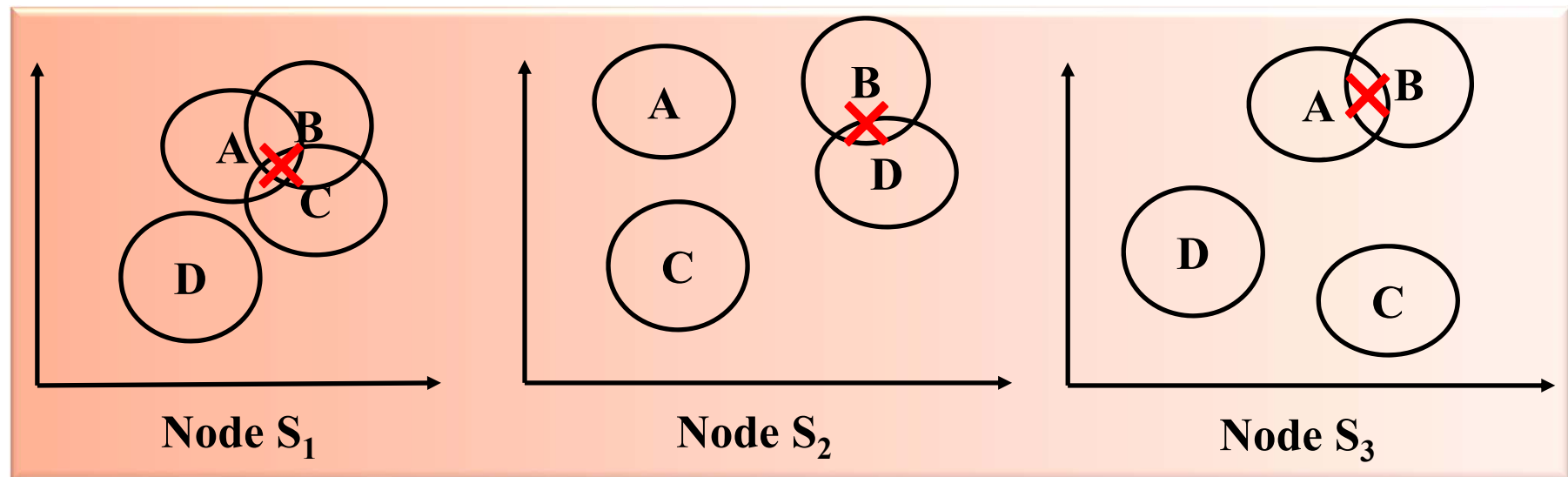
Dynamic Sensor Selection

- A decision path is determined dynamically in real-time
- No prior ordering/path is known
- Incremental classification
- Intuition
 - Each node makes a local classification
 - Most reliable node transmits to others
 - Other nodes combine results and do classification
 - Again only most reliable node transmits data

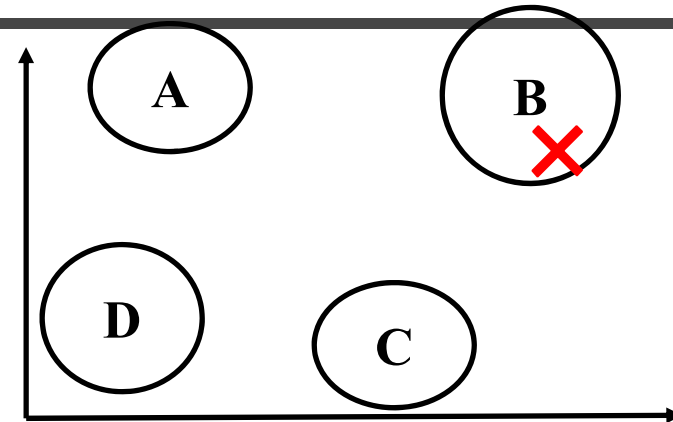
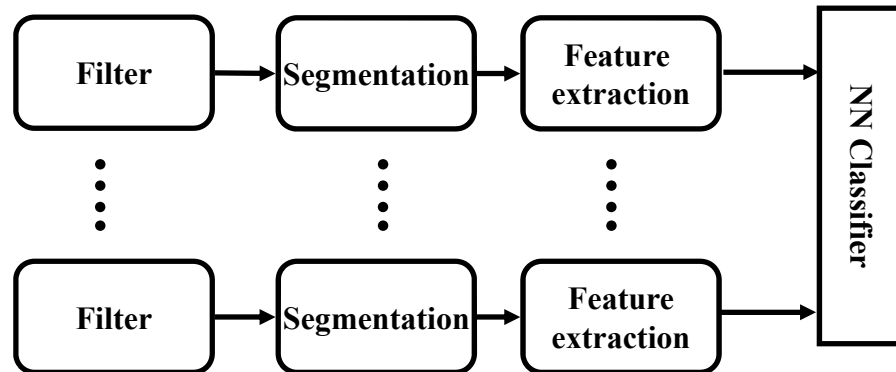


Motivation

- A node alone may **not** reliably **classify** actions
- However, each node **can** reliably **reject** some actions



Intuition



Classification

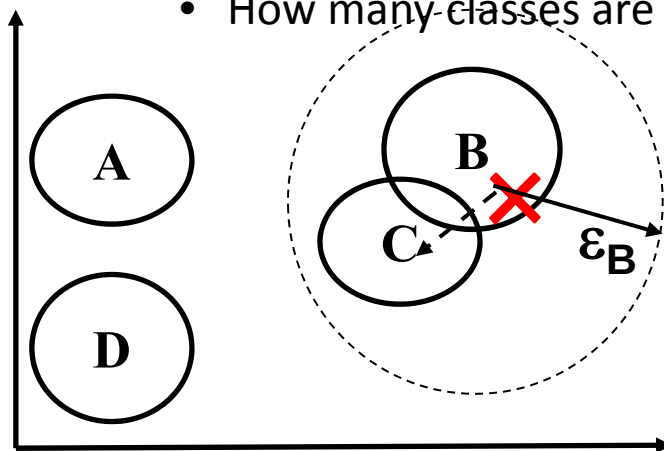
$$\begin{aligned} D_A &= d_{1A} + d_{2A} + \dots + d_{nA} \\ D_B &= d_{1B} + d_{2B} + \dots + d_{nB} \\ D_C &= d_{1C} + d_{2C} + \dots + d_{nC} \\ D_D &= d_{1D} + d_{2D} + \dots + d_{nD} \end{aligned}$$

$$x = \operatorname{argmin} D_x$$

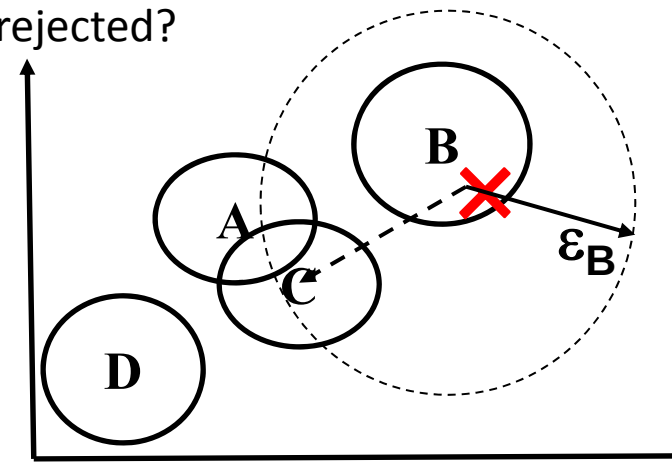
If $d_{ix} \gg \varepsilon_x$ reject 'x'

Which Node Starts Communication?

- Criteria
 - Classification accuracy
 - Confidence is the distance to second closest class
 - Convergence
 - How many classes are going to be rejected?



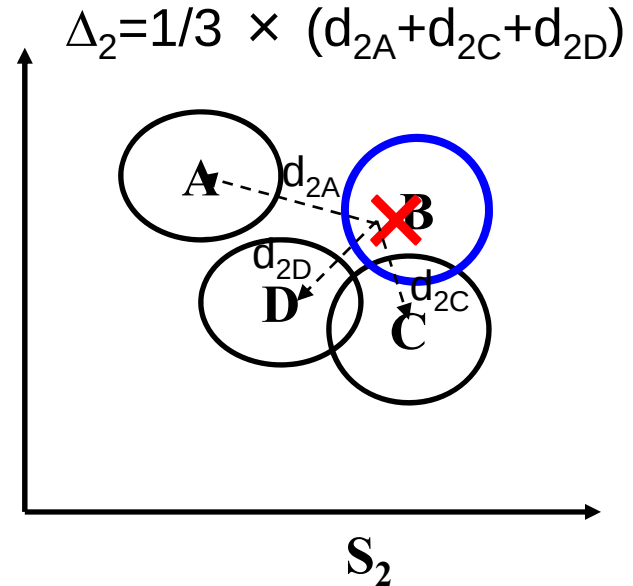
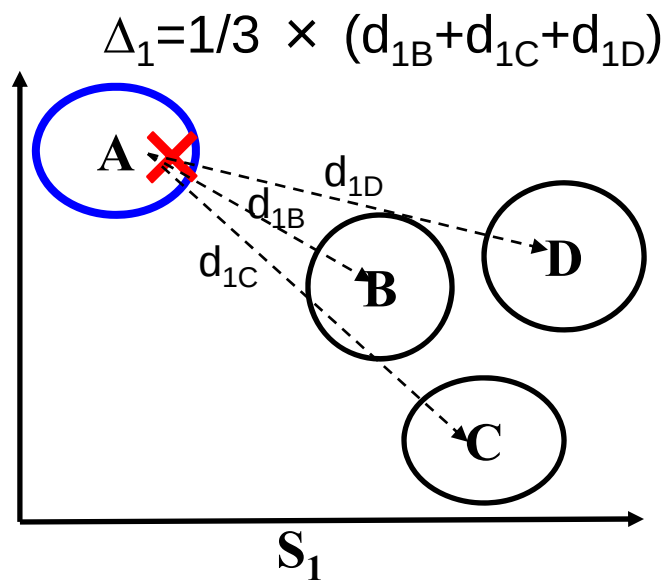
Low Confidence (distance to C)
Good pruning (rejects both A & D)



Higher Confidence (distance to C)
Poor pruning (rejects only D)

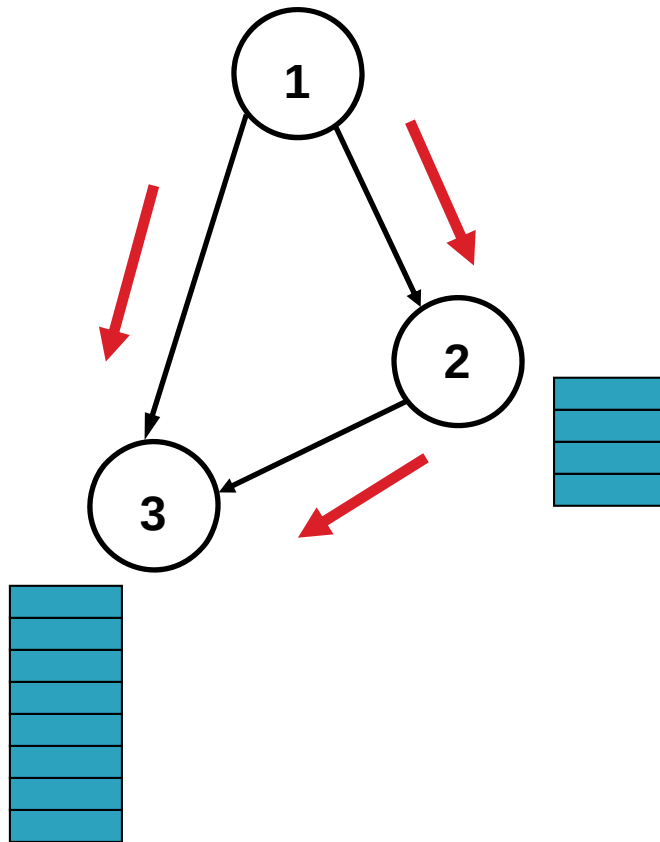
Intuition

- The node with most reliable classification decision starts communication
 - Reliability is defined as average distance to other classes than target class (Δ_i) .
- All nodes set their timers to $\tau_i \propto \frac{1}{\Delta_i}$, the first node transmits, it turns off and all other nodes reset their timers.

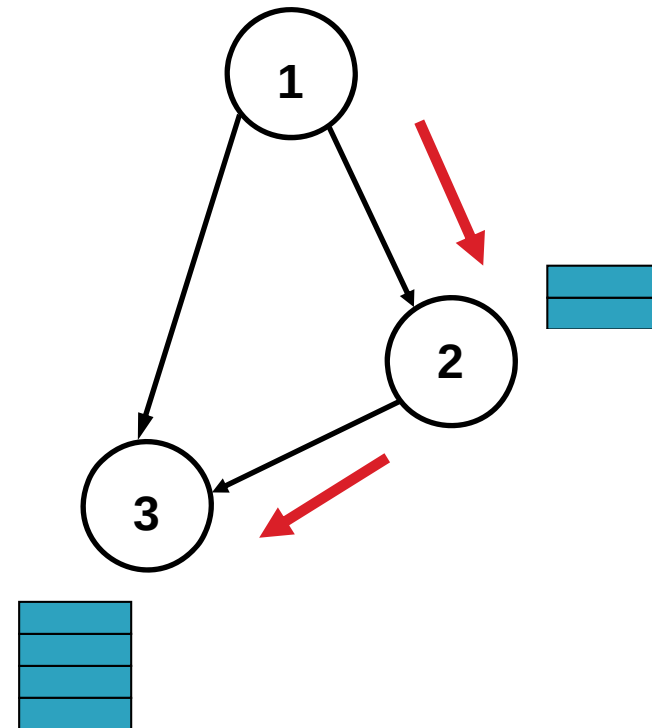


COMMUNICATION OPTIMIZATION

Approaches



Buffer Allocation



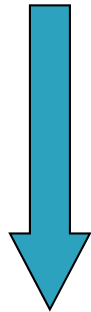
Data Aggregation

Motivation

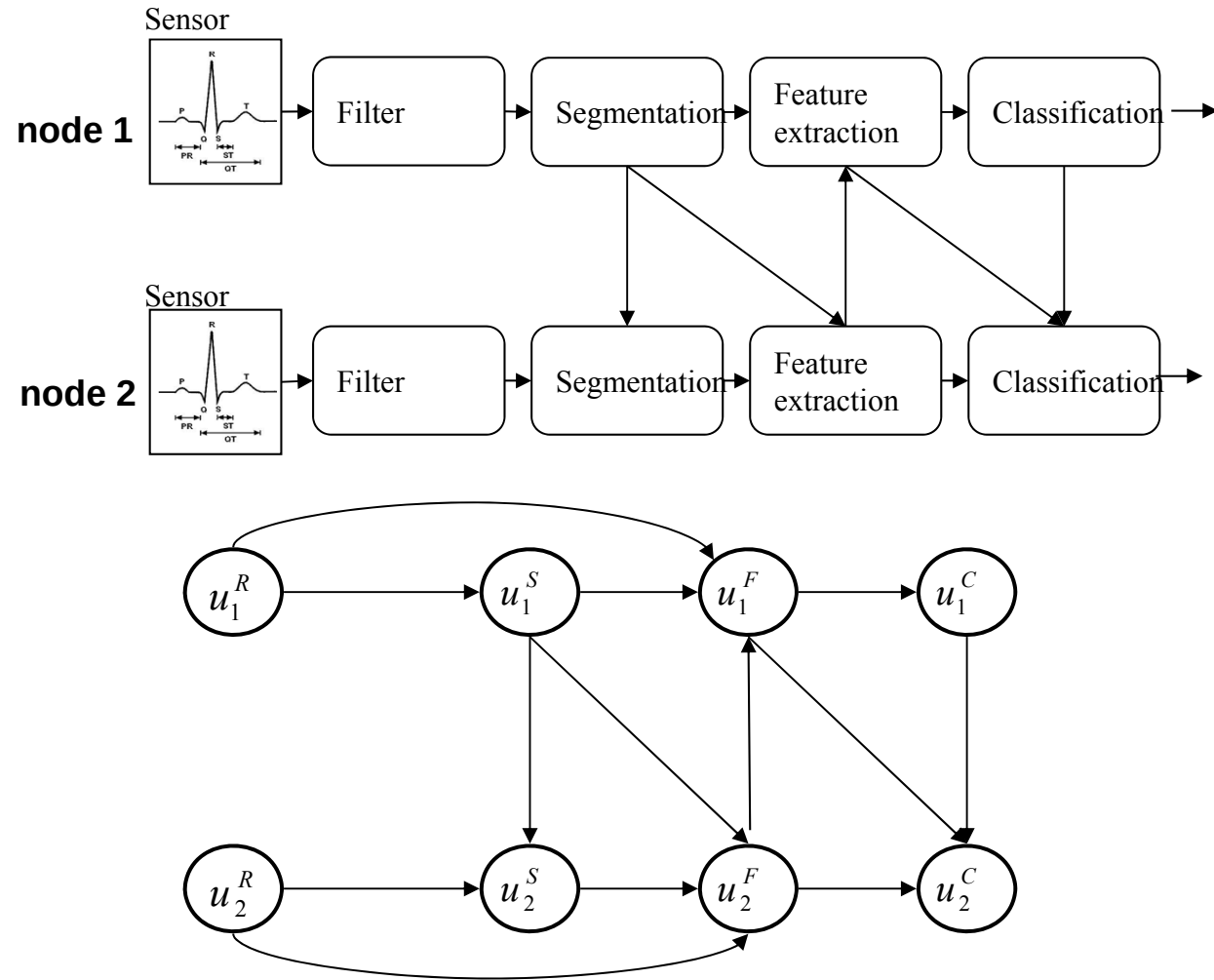
- Intensive inter-node communication is required in case of real-time response
- In many applications, **no immediate deadline** is necessary
 - Physicians may need **periodic reports** (e.g. at the end of each day)
- Can we **store data locally** before transmission?
 - This would reduce total number of transmissions

Signal Processing Model

Signal Processing



Task Graph



Buffer Allocation

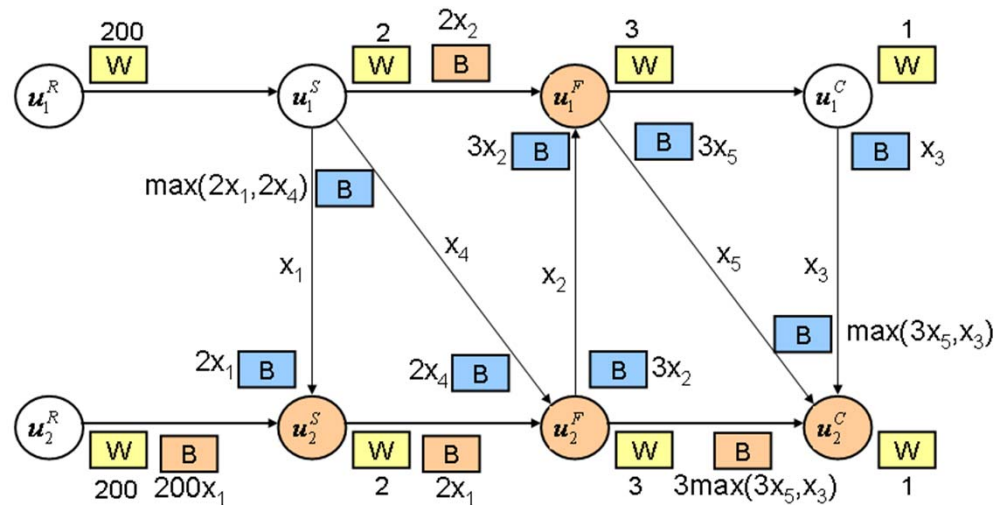
- Assume 'A' is number of actions to detect
- Number of transmissions per link is A/x_i
- Minimize total number of transmissions subject to memory constraints on each node
- It turns into following **Convex Optimization Problem**

$$\text{minimize} \left(\frac{A}{x_1} + \frac{A}{x_2} + \frac{A}{x_3} + \frac{A}{x_4} + \frac{A}{x_5} \right)$$

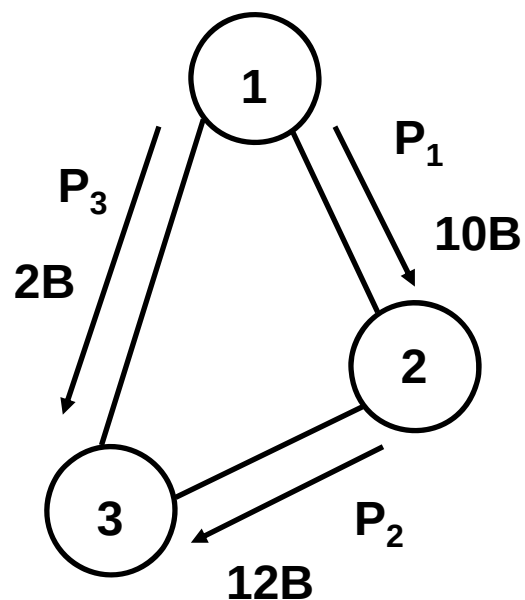
subject to :

$$\sum B + W \leq \text{Memory}$$

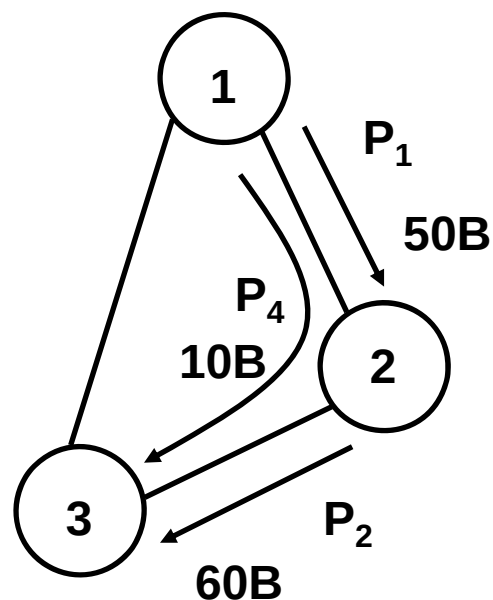
$$x_i \geq 1$$



Data Aggregation

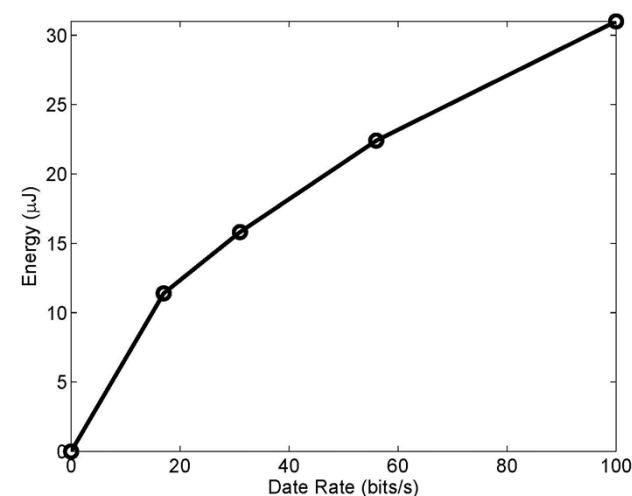


Direct Transmission
340 μJ



Path Sharing
223 μJ
34% saving

Energy (ZigBee)



EVALUATION

Evaluation Features

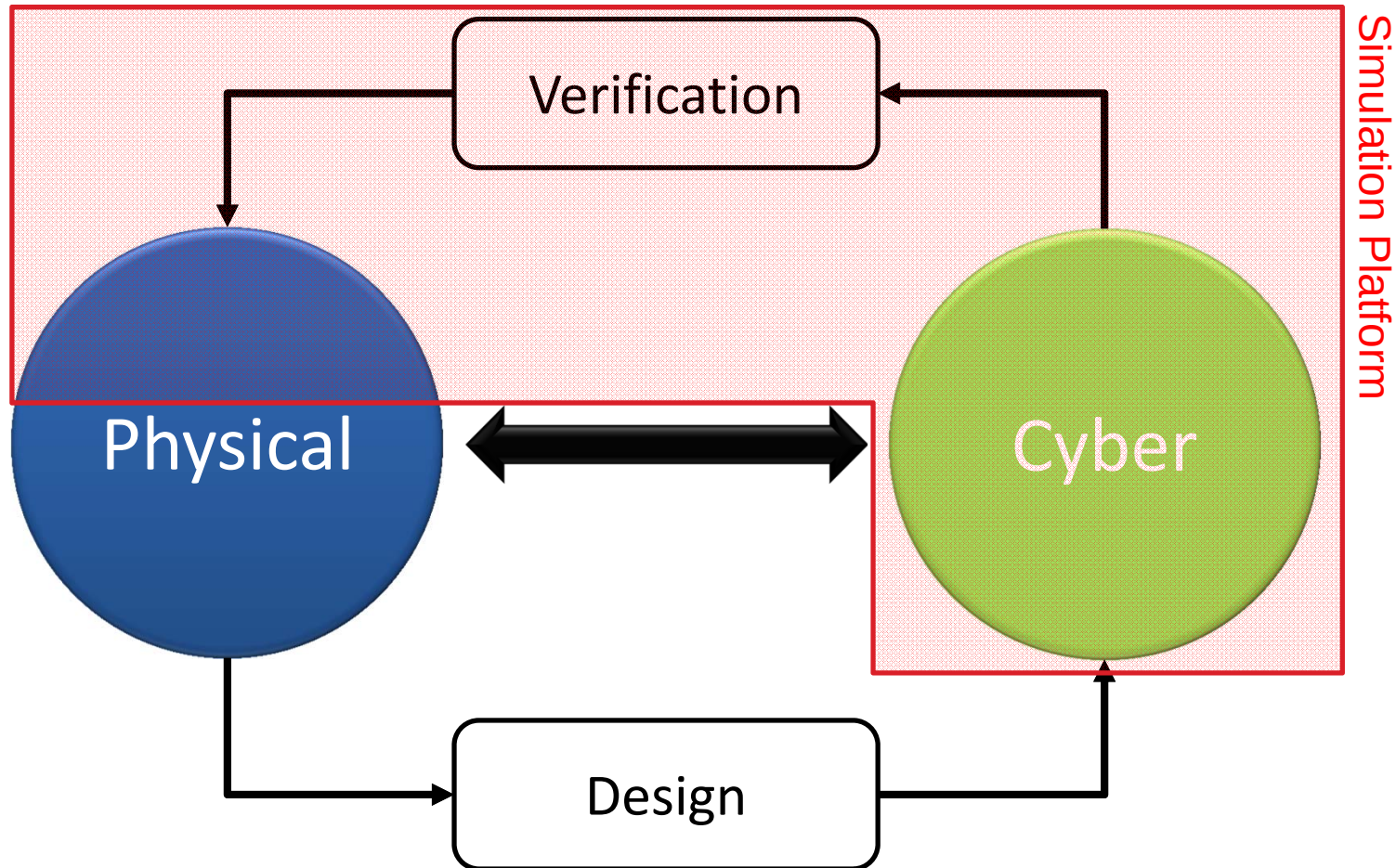
Feature	Description
Wearability	The system must have low weight and size
Appropriate placement on the body	The system has to be unobtrusive and comfortable, in order to not to interfere with the user's movements and daily activity
Aesthetic issues	The system should not affect the user's appearance
Data encryption and security	Encrypted transmission of measured signals and authentication requirement for private data access
Operational lifetime	Ultra low power consumption for long-term, maintenance-free health monitoring
Real application	The developed system is applicable (and useful) to real-life scenarios/health condition
Computational and storage requirements	The computational and storage resources required or utilized by the system to achieve desirable results
Ease of use	The system incorporates a friendly, easy-to-use and easy-to-learn user interface

Evaluation Features (2)

Feature	Description
Performance and test in real cases	Sufficient results and performance statistics are provided to verify the system's functionality in real cases
Reliability	The system produces reliable and accurate results
Cost	The amount of money required to produce and purchase the proposed wearable system
Interference robustness	Availability and reliability of wirelessly transmitted physiological measurements
Fault tolerance	The system produces reliable results under any circumstances, such as various kinds of patient's movements
Scalability	Potentiality of upgrading, enhancing and easily incorporating additional components to develop system
Decision support	The implemented system includes some type of diagnosis /decision mechanism or an algorithm/pattern recognition system for context aware sensing of parameters

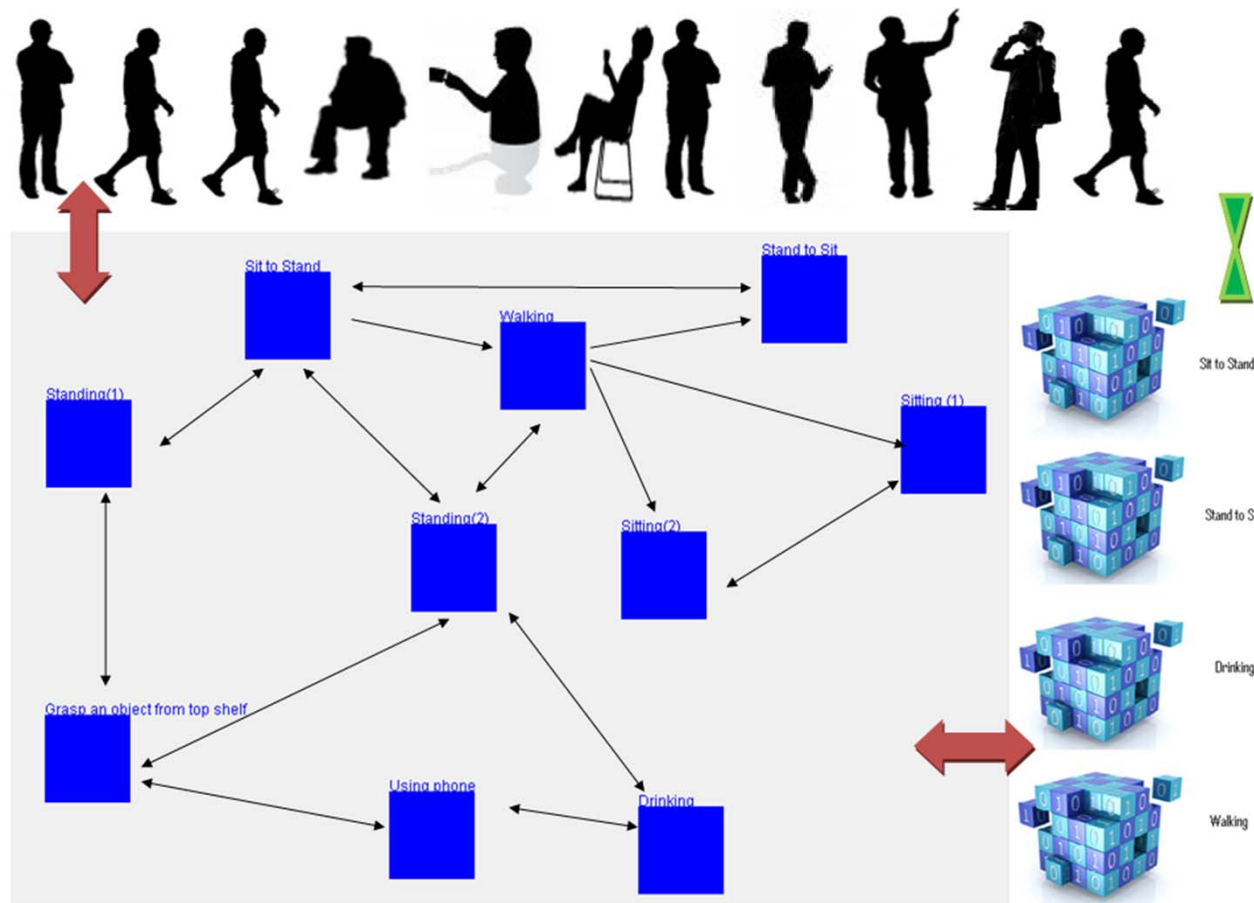
- Not all evaluation features have the same importance from the user, physician and manufacturer perspective

Data Centric Verification



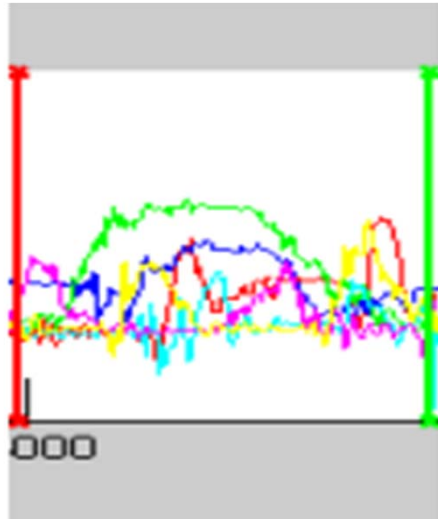
Data Synthesis

Synthesize data based on user defined diaries



Data Synthesis

- A data set for ADL is under development
- Simulation platform representing architecture in C



Success Stories



Conclusions



Programmability, new paradigms for human-computer interface, and aggressive cross-layered power optimization techniques

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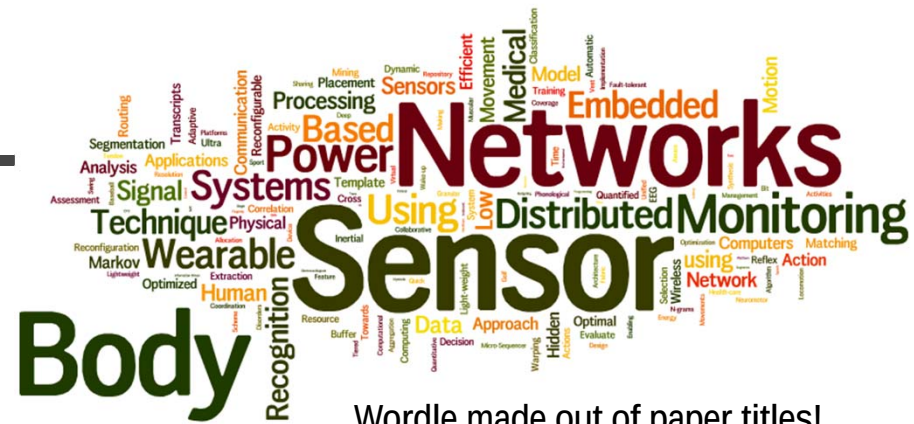
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