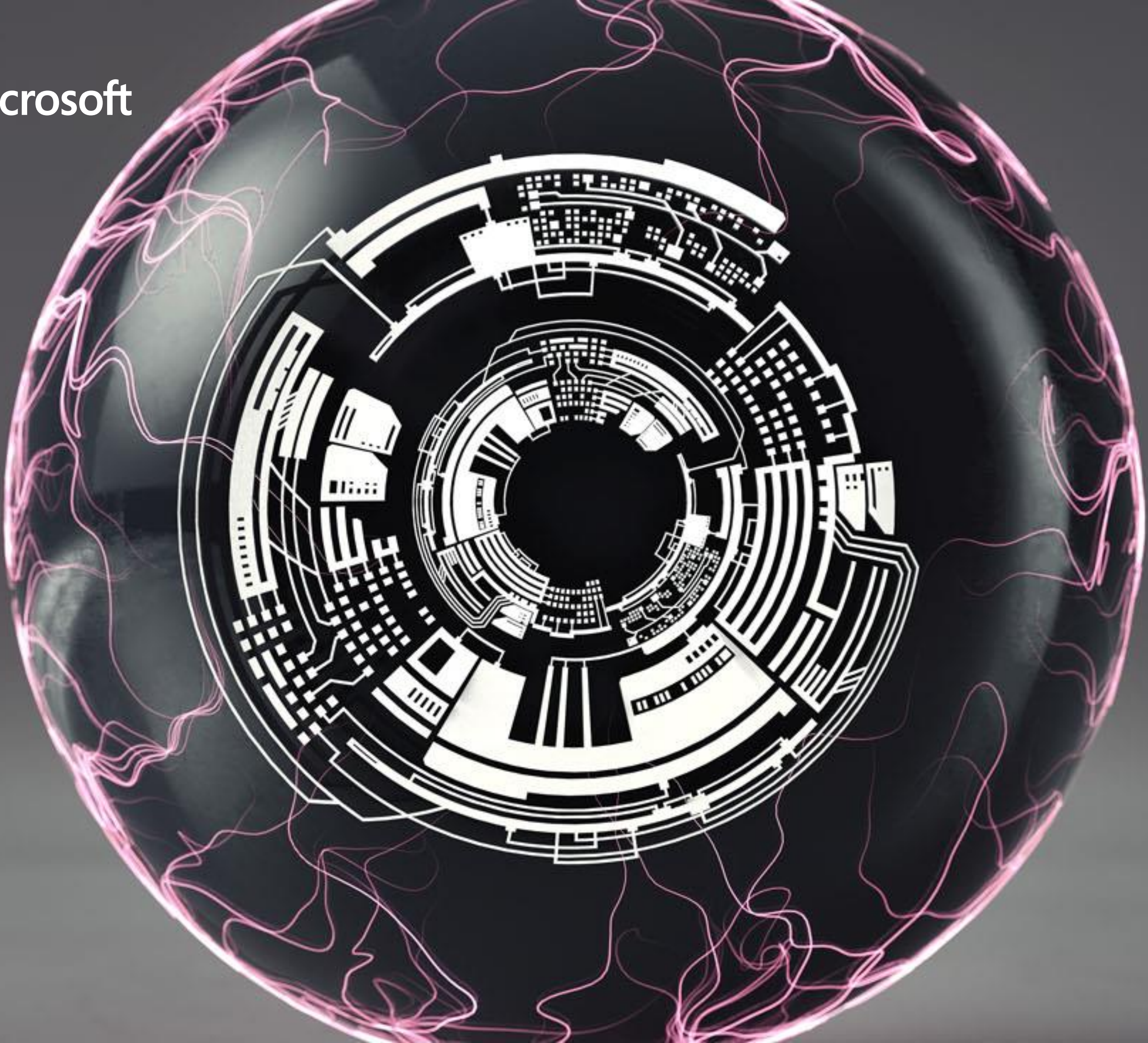
Microsoft



Microsoft Research Faculty Summit 2016

Wearable Computers on the Edge of Cloud

Roozbeh Jafari

Embedded Signal Processing Lab

http://jafari.tamu.edu

CENTER FOR REMOTE HEALTH TECHNOLOGIES & SYSTEMS
TEXAS A&M ENGINEERING EXPERIMENT STATION

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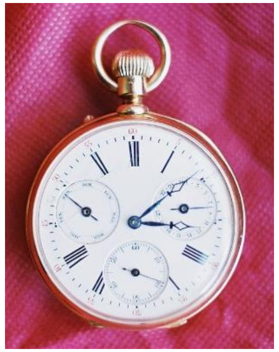
A Brief History

- What will drive the wearable market?
  - Driven by needs, fashion, or both?



Pocket watch, ca. 1876

Early wrist watch worn by soldiers in WWI

A Success Story

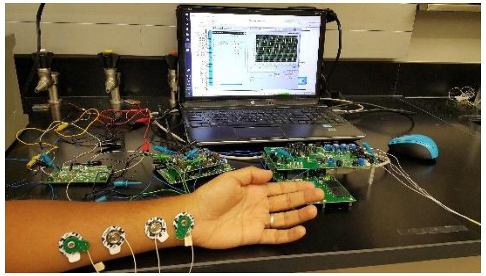
An open and programmable platform with

a user-centered design

Unique Characteristics

- In direct contact with human body
  - User is in the loop and can identify errors quickly
  - Must exhibit high degrees of robustness completing the assigned tasks
  - Power, computational resources and connectivity have unique requirements
  - High degrees of customization for individuals

Embedded Signal Processing Laboratory



Vision: Enhance wearability and usability

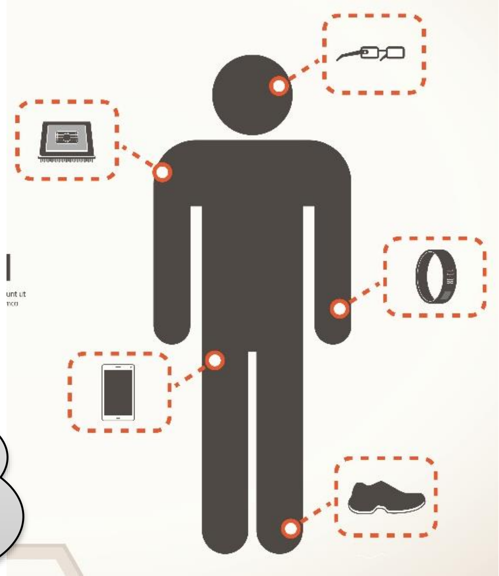
Wearable Technology

Sensor and System Design: Power and New Sensing Paradigms

Dry-contact EEG, wrist-worn blood pressure

Robust Signal Processing

Orientation-independent activity recognition, motion artifact rejection techniques

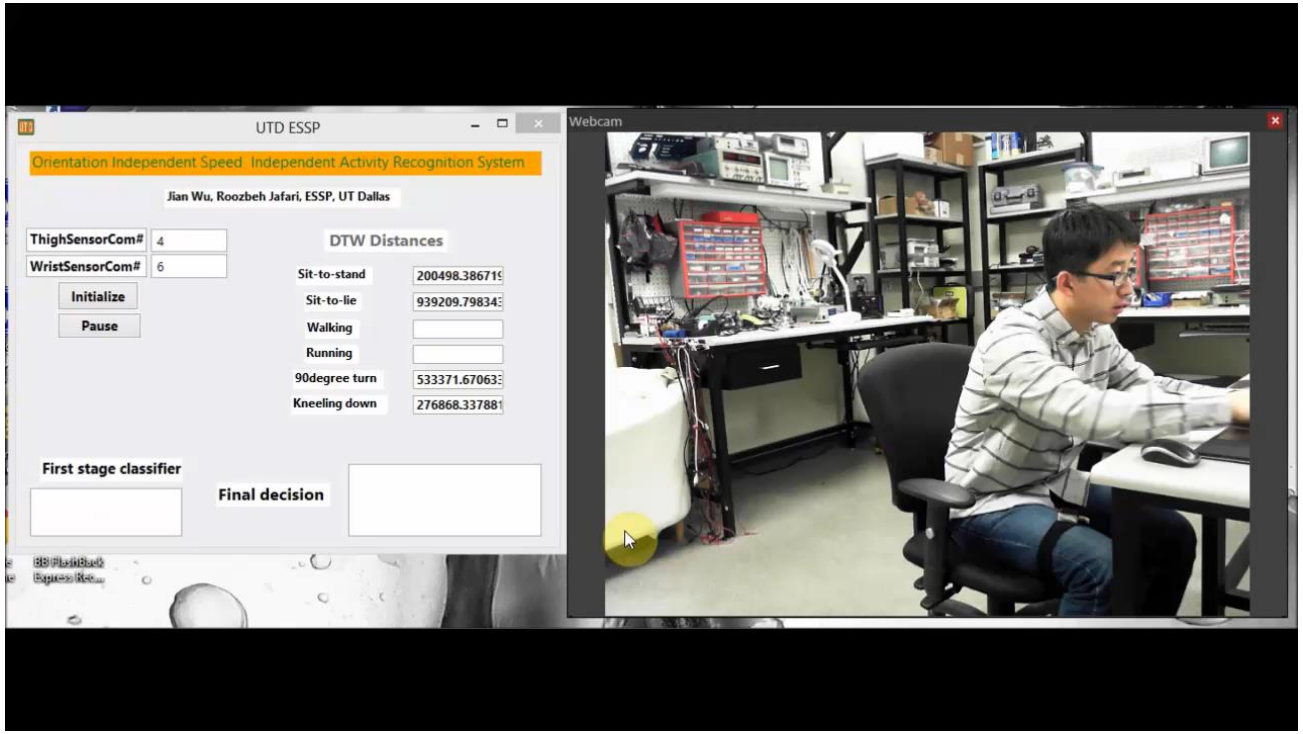


Anomaly detection, repository and quality framework

Analytics in the Cloud

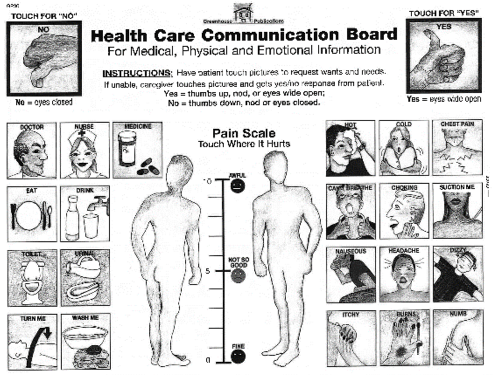
Monitoring Motor Functions

Neurological disorders, activities of daily living (ADLs), gait monitoring and fall prevention

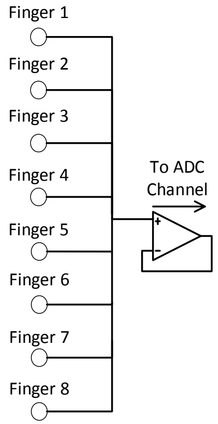


Brain Computer Interface

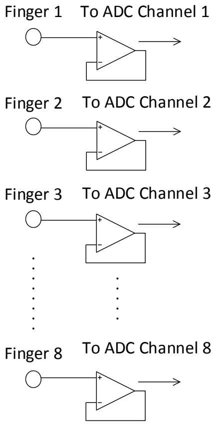
Assist locked-in individuals to communicate, used for gaming, facilitate care-giver/patient communication in ICU units

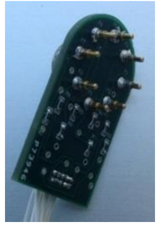


EEG Dry-Contact Electrode Characterization

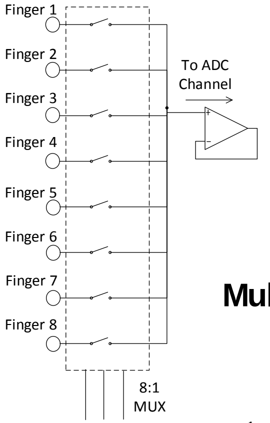


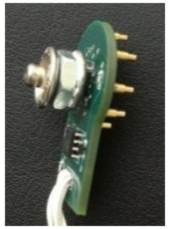
Classic Electrode



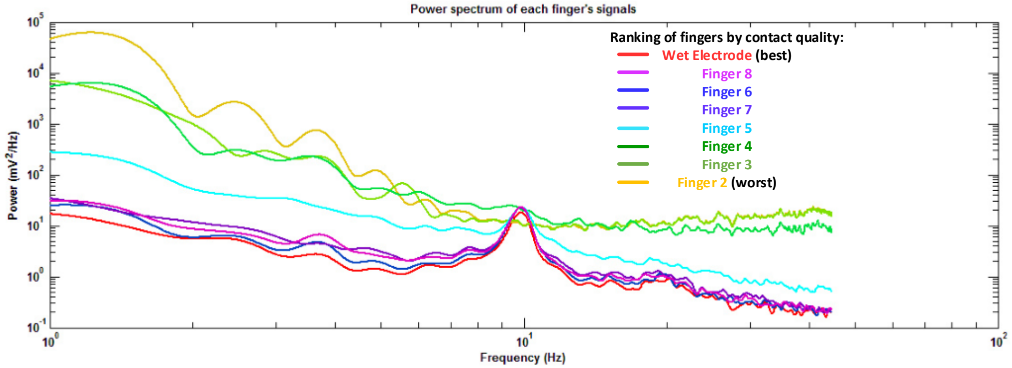


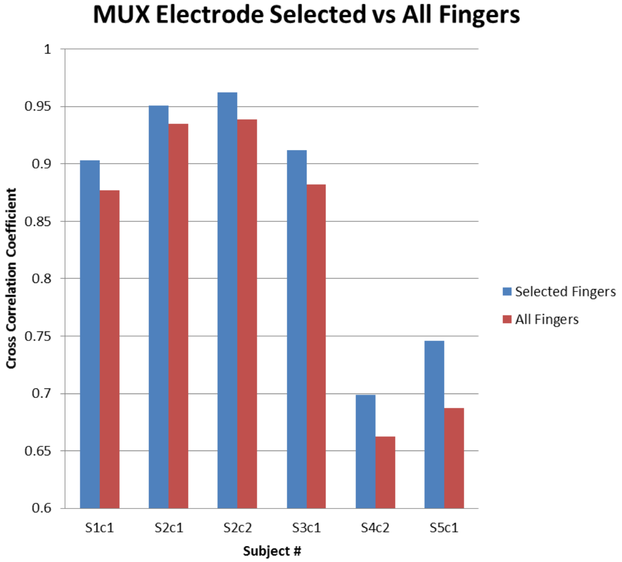
Individual Finger Channel (IFC) Electrode





Multiplexed (MUX) Electrode

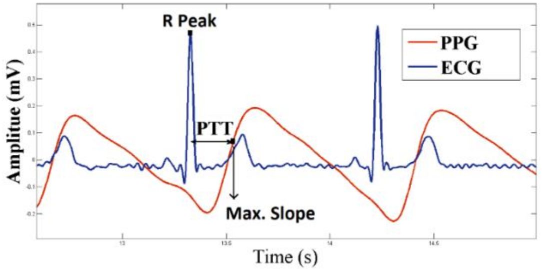


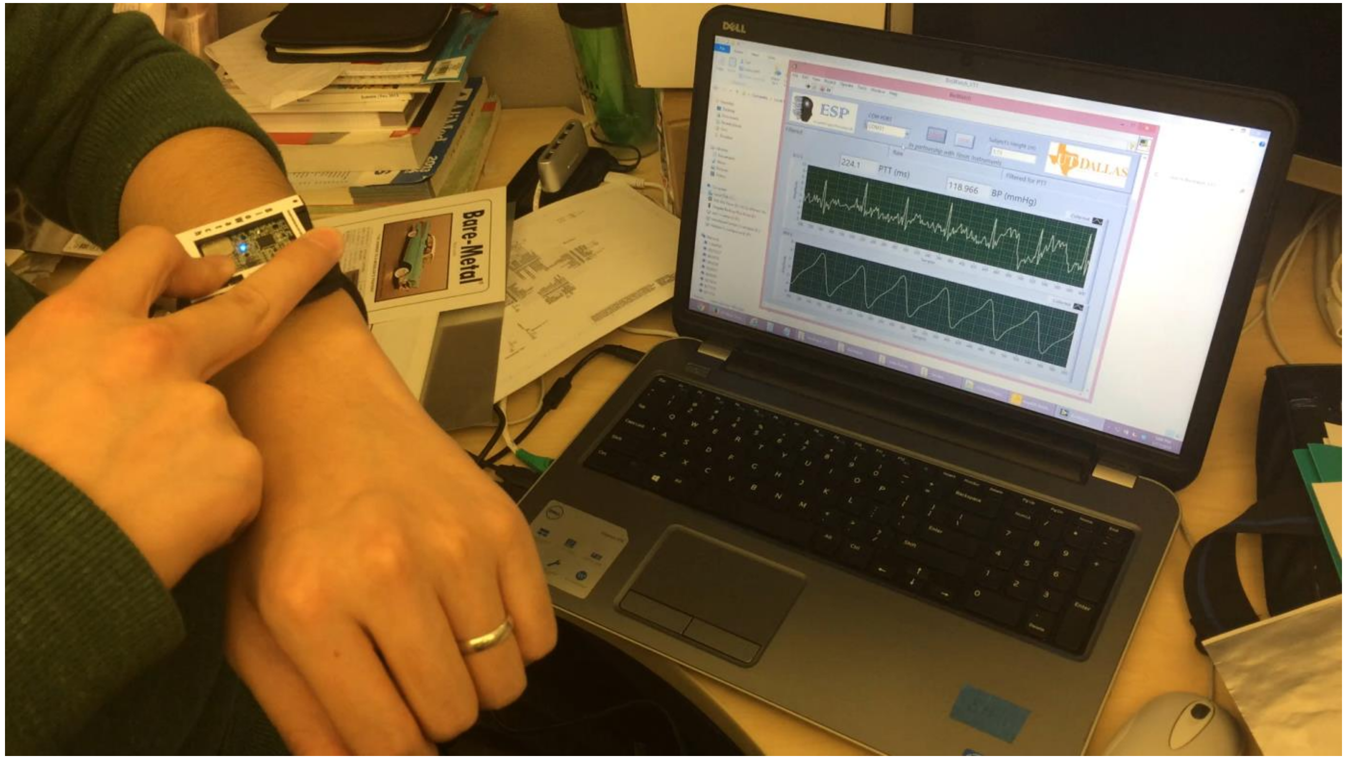


Using the best combination of fingers reduces this noise level by about 40% on average

Wrist-worn Physiological Monitoring Systems

BioWatch capable of measuring ECG, PPG and Blood Pressure





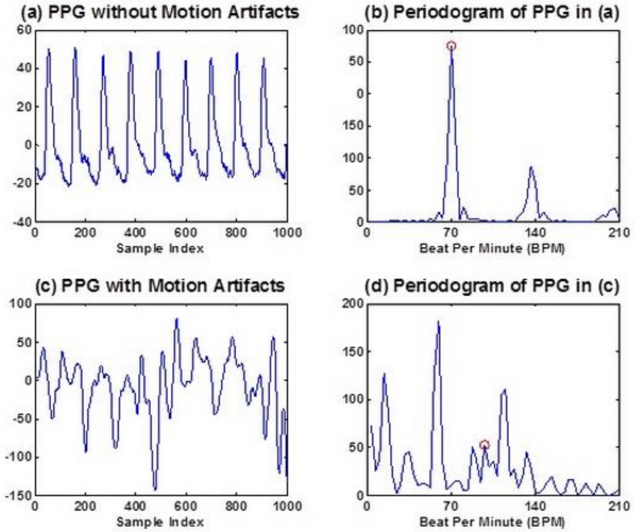
Case Study: Heart Rate Tracking

http://w ww.dailymail.co.uk/sciencetech/article-2415943/Now -NISSAN-jumps-smartw atch-bandw agon-Wearable-tech-monitors-performance-car-driver.html

http://w ww.wareable.com/smartw atches/sony-smartw atch-vs-samsung-gear

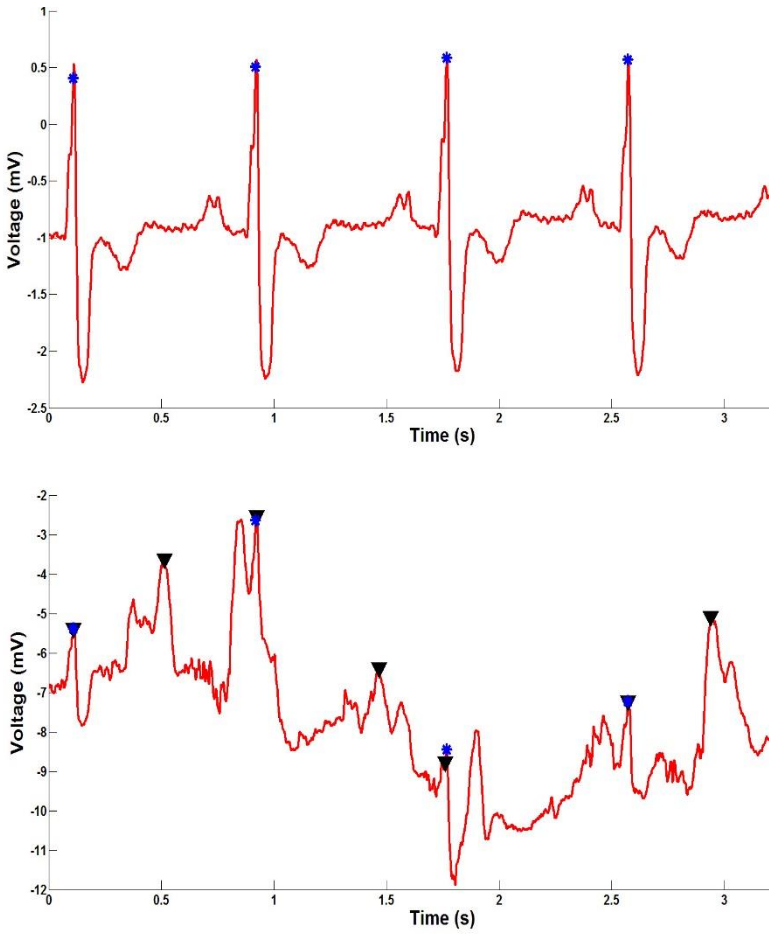
http://w ww.mensjournal.com/health-fitness/articles/get-in-tennis-shape-5-drills-one-serious-w orkout-w 204391

http://w ww.amazon.com/Epson-PULSENSE-PS-500-Activity-Tracking/dp/B00MUKZDO6



Noise Sources

- Comfort => Noisier interface (*e.g.* wet vs dry electrodes)
- Motion Artifacts
- Errors in usage/placement of sensors
- Need to adapt to changing conditions over long periods



Multiple Sensors

- Multiple sensors simultaneously measuring same phenomenon
- Fusion of sensor streams

Particle Filter

- Probabilistic state estimation
- Sequential Monte Carlo with numerous ‘particles’ representing possible states
- Observations of system update particle weights
- Particles converge to posterior probability distribution

$$\mathcal{X}_t \sim Uniform(HR_{min}, HR_{max})$$

$$W_{X_t^p} \propto p(Z_t | X_t^p) = \sum_{n=1}^{O_t} p\left(Z_t^n \middle| X_t^p\right)$$

$$= \sum_{n=1}^{O_t} N(\, Z_t^n, X_t^p, \sigma_z)$$

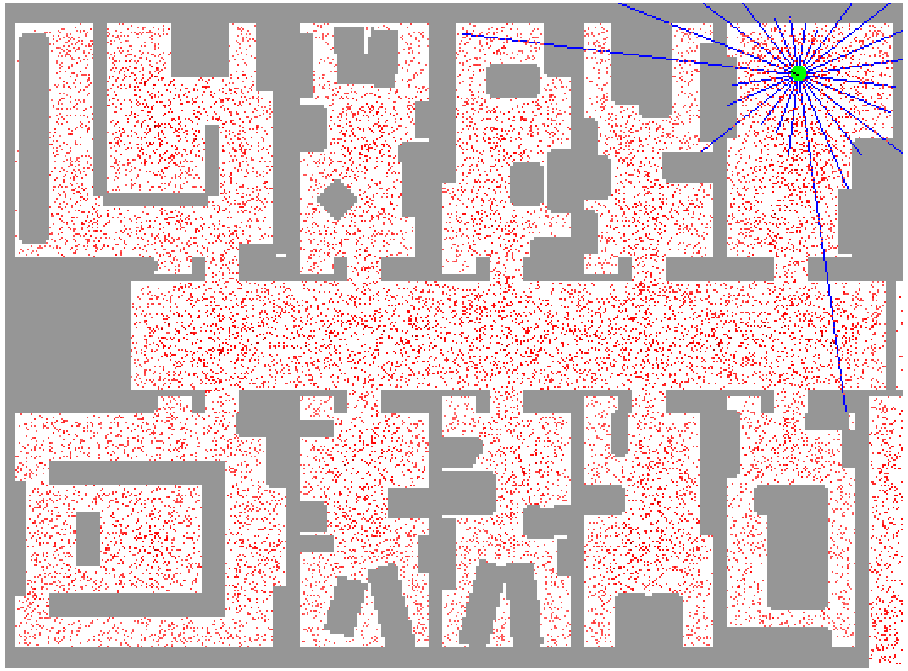
$$WNorm_{X_t^p} = W_{X_t^p} / \sum_{r=1}^{N_p} W_{X_i^r}$$

$$HREst_t \sim Maximum\ a\ posteriori\ (MAP) estimate$$

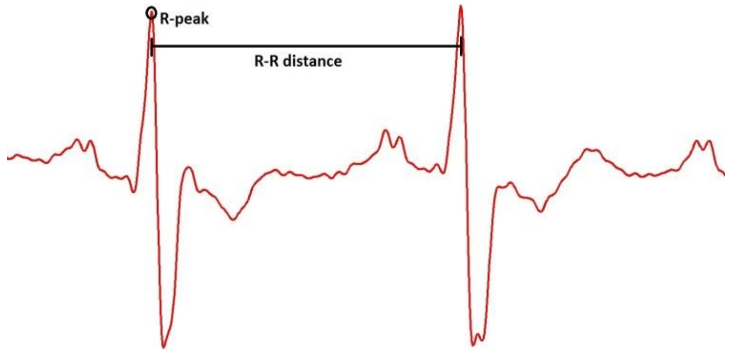
Particle Filter Applications

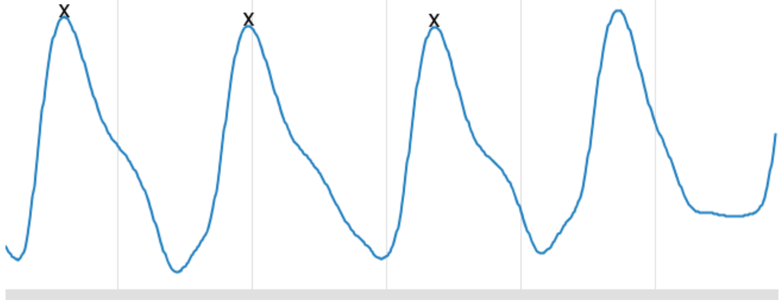
- Computer vision
- Speech Recognition
- **Target Localization**
- … and many more

Using measurements from range sensor, robot localizes itself in environment



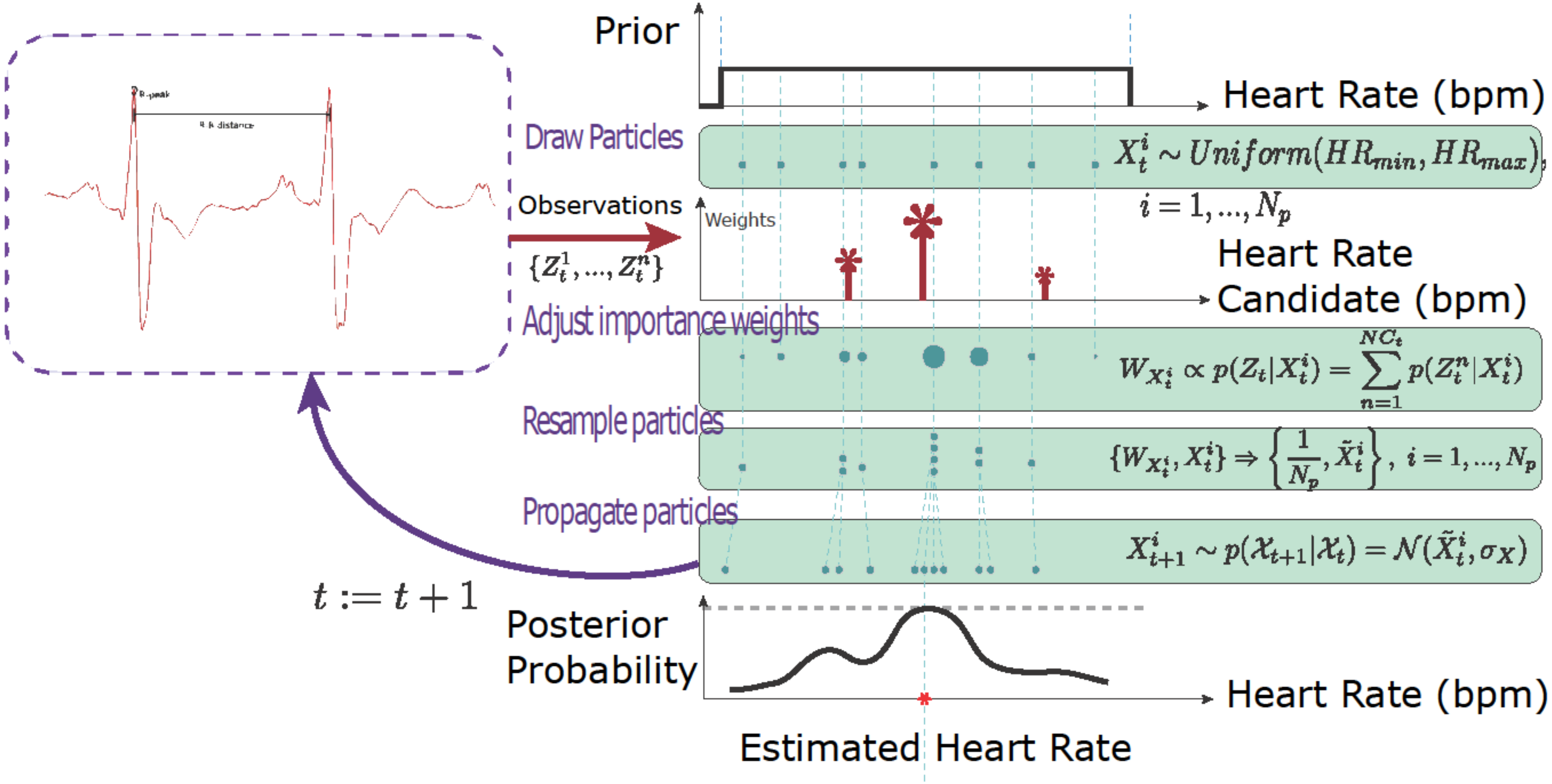
Case Study: Heart Rate Tracking



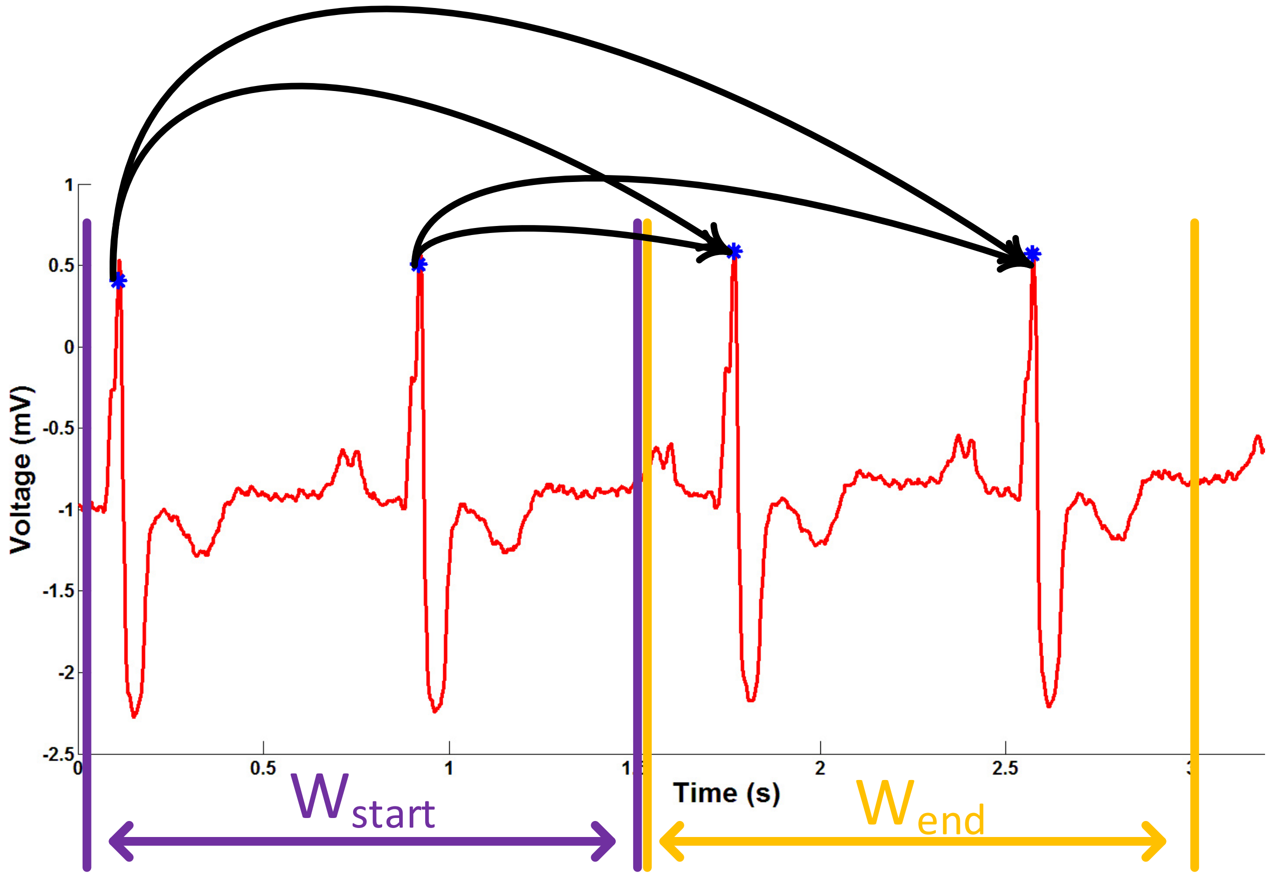


- Each particle represents a possible heart rate
- Observations with suitable ‘operators’ made in windows
  - Not tied down to any particular type of operator
  - R-R distance for ECG, max slope point for PPG etc.
- Observations guide update of weights of particles
- Particles redistributed according to weights
- Particles converge to posterior probability distribution of true state

Overall Flow



ECG Observation

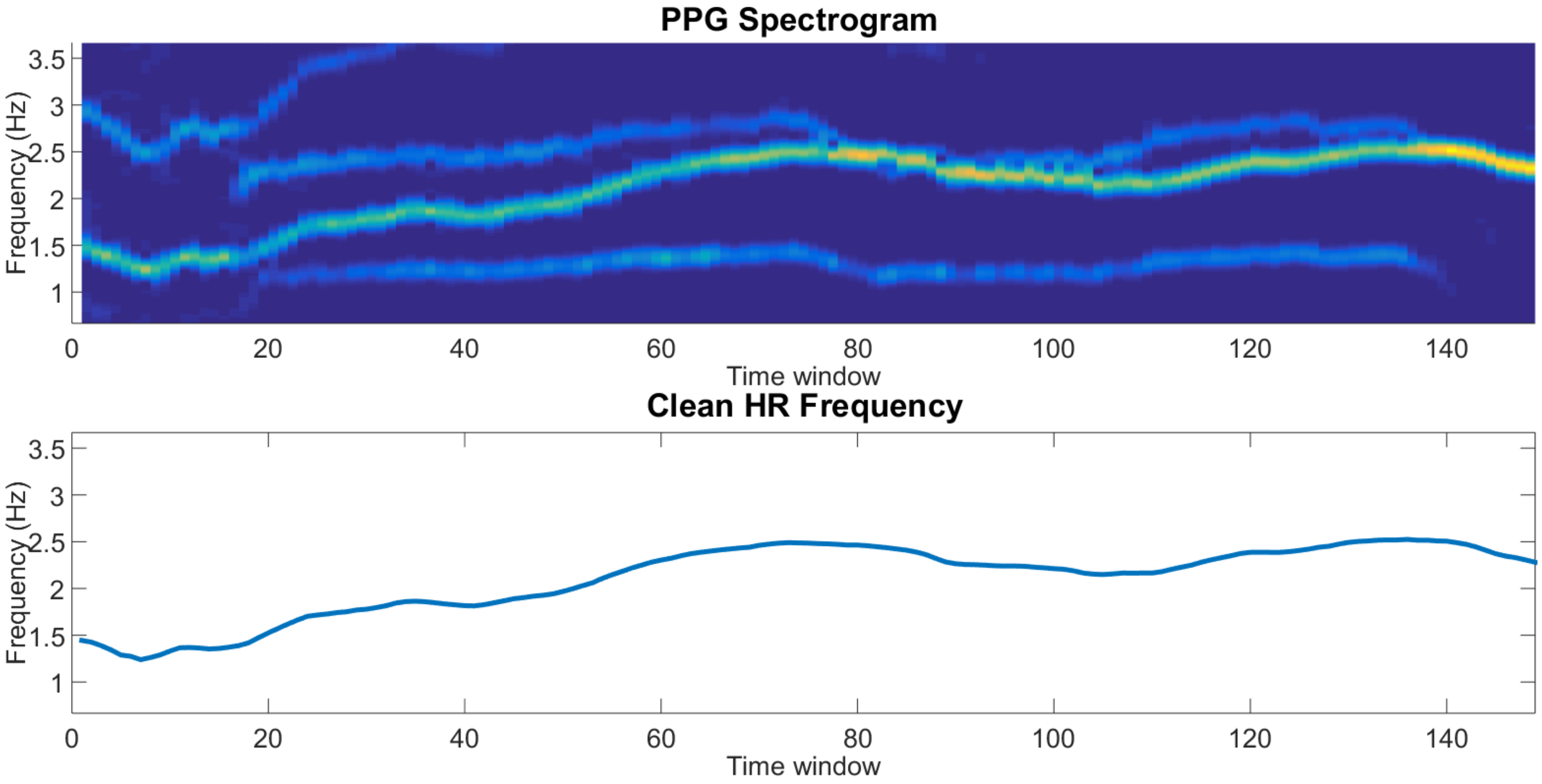


Back-to-back moving, non-overlapping windows W_{start} and W_{end}

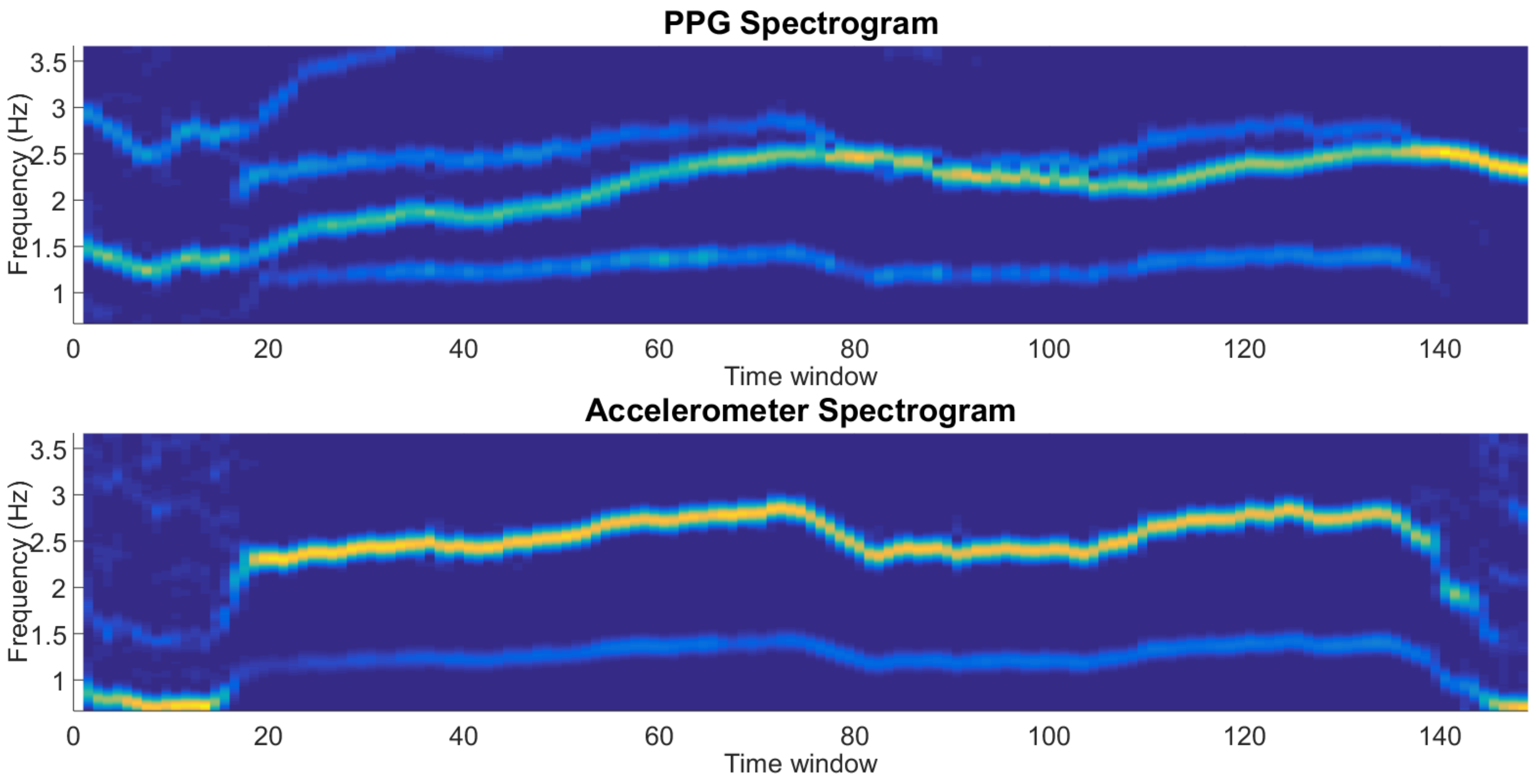
We only consider R-R intervals that begin with a peak in W_{start} and end with a peak in W_{end}

The R-R intervals correspond to observations of the heart rate

PPG Observation



Accelerometer Observation



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Particle Weighting

$$W_{X_t^p} \propto p(Z_t|X_t^p) = \begin{cases} \left(\sum_{n=1}^{O_t} N(Z_t^n, X_t^p, \sigma_z)\right) \times \beta, for\ ECG \\ \varphi_t^d \times \left(1 - \tilde{\varphi}_t^d\right), for\ PPG \end{cases}$$
$$\forall p \in \left(1, N_p\right)$$

Where,

X_t^p is the p^{th} particle of window t,

$W_{X_t^p}$ is the weight of particle X_t^p,

$N(Z_t^n, X_t^p, \sigma_z)$ is the value of a Gaussian distribution with mean X_t^p and standard deviation σ_z evaluated at Z_t^n,

β is a constant biasing factor,

φ_t^d is the probability of the event that the frequency corresponding to X_t^p represents the true heart rate.

$\tilde{\varphi}_t^d$ is the probability of the event that the frequency corresponding to X_t^p is not the heart rate, which for our purposes means it is noise

Sensor Fusion

$$W_{X_t^p}^{fusion} = \prod_{s=1}^{S} p(Z_t^s | X_t^p)$$

Where,

$W_{X_t^p}^{fusion}$ is the weight assigned to particle X_t^p when fusing the information from multiple sources of observation

S is the total number of observation sources under consideration

Z_t^s is the set of observations in time window t from source s

Case Study: HR Sensor Fusion

$$W_{X_t^p}^{fusion} = p\left(Z_t^{ECG} \middle| X_t^p\right) \times p\left(Z_t^{PPG+ACC} \middle| X_t^p\right)$$

$$p\left(Z_t^{ECG} \middle| X_t^p\right) = \left(\sum_{n=1}^{O_t} N(Z_t^n, X_t^p, \sigma_z)\right) \times \beta$$

$$p\left(Z_t^{PPG+ACC} \middle| X_t^p\right) = \varphi_t^d \times \left(1 - \tilde{\varphi}_t^d\right)$$

Results – HR Estimation Error

PPG Particle Filter Estimation Error

Subject #	1	2	3	4	5	6	7	8	9	10	11
HR Error (bpm)	4.35	43.7	3.82	1.52	1.01	1.97	0.87	0.96	0.88	7.10	11.3

ECG Particle Filter Estimation Error

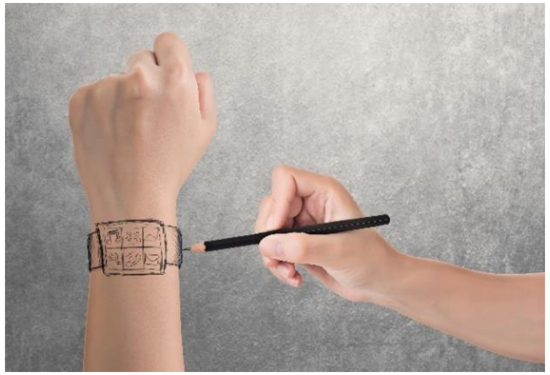
Subject #	1	2	3	4	5	6	7	8	9	10	11
HR Error (bpm)	2.19	2.89	2.12	1.93	1.24	5.84	4.32	2.04	1.54	1.39	1.64

PPG+ECG Particle Filter Estimation Error

Subject #	1	2	3	4	5	6	7	8	9	10	11
HR Error (bpm)	1.38	1.63	1.18	1.67	1.08	1.18	1.26	1.37	1.15	1.40	1.87

Concluding Remarks

- Robustness of sensing is of paramount importance.
- Context and sensor fusion can empower many new application paradigms.
- Wearables know quite a bit their users, and could potentially enable application development beyond the rate that we have observed with Smart Phones.
- Very personal! Requiring deep user customization capabilities.
- Empower students and researchers with the tools, hardware and know-how’s.



Thanks & Questions

Roozbeh Jafari, rjafari@tamu.edu
http://jafari.tamu.edu

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