Body Area Sensor Networks I

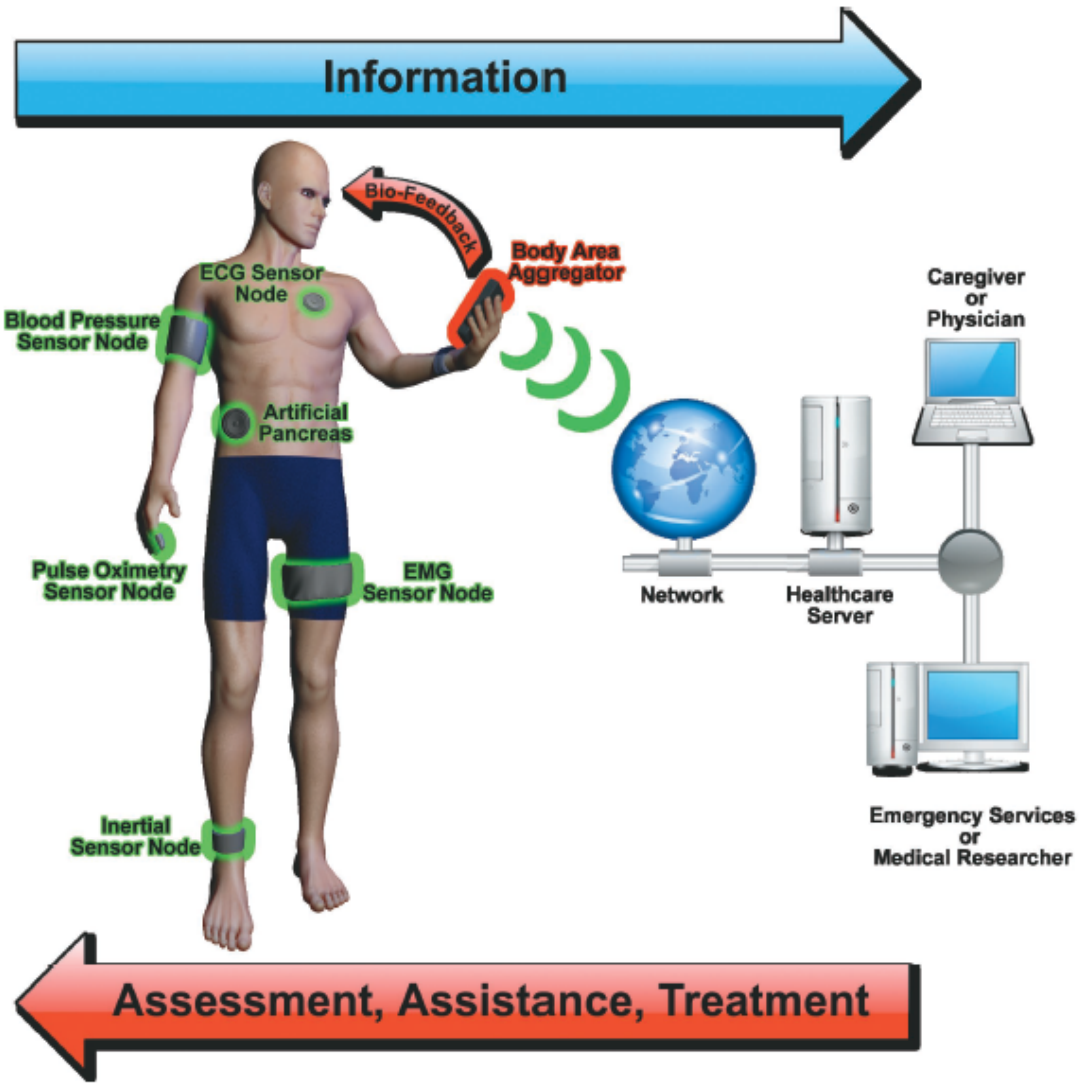
CSE 40437/60437-Spring 2015

Prof. Dong Wang

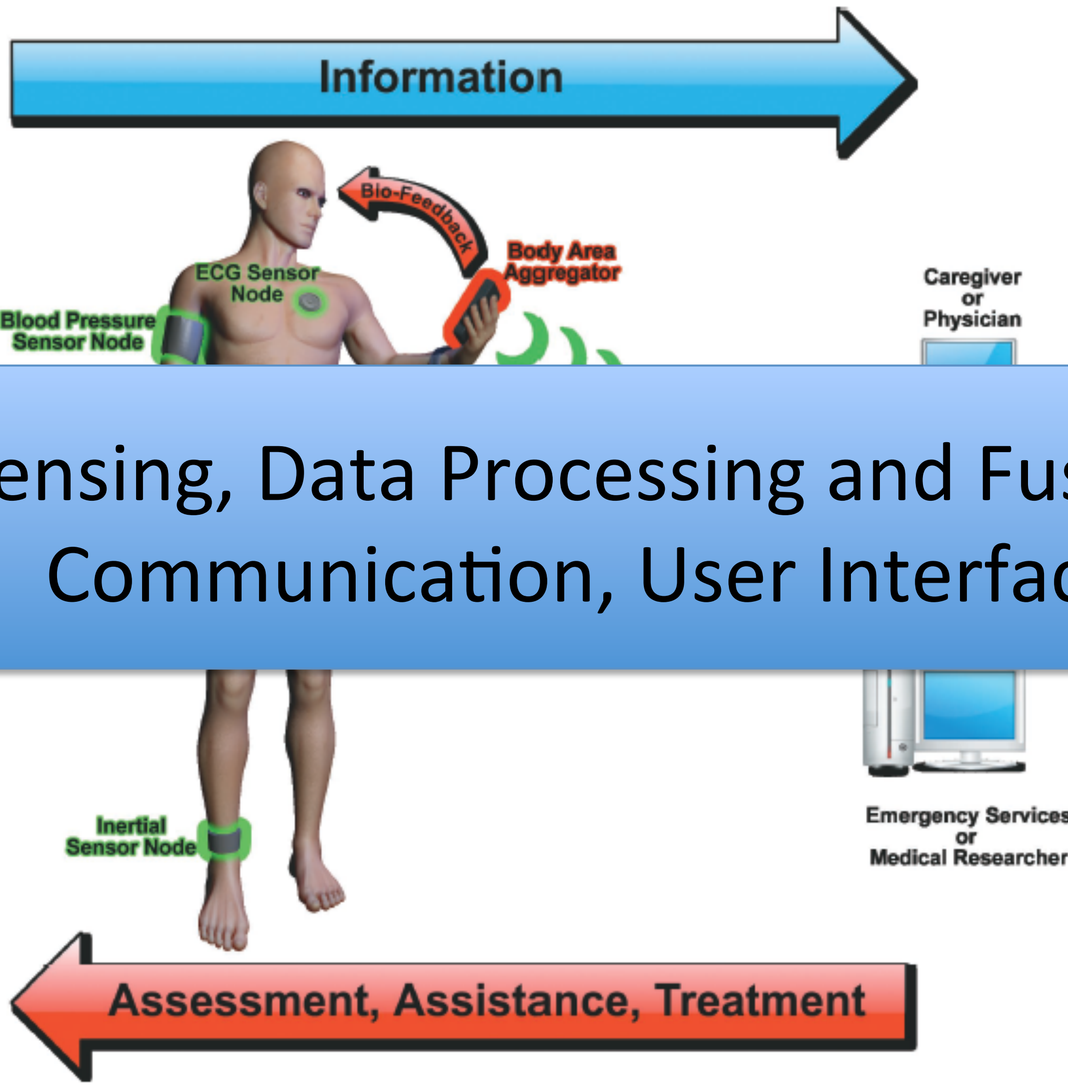
Outline

- Introduction to Body Area Sensor Network
  - "Body area sensor networks: Challenges and opportunities." Hanson, Mark A., et al. Computer 42.1 (2009): 58.
- Paper 1: Accurate caloric expenditure of bicyclists using cellphones." Zhan, Andong, et al. Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems. ACM, 2012.

Body Area Sensor Network (BASN)

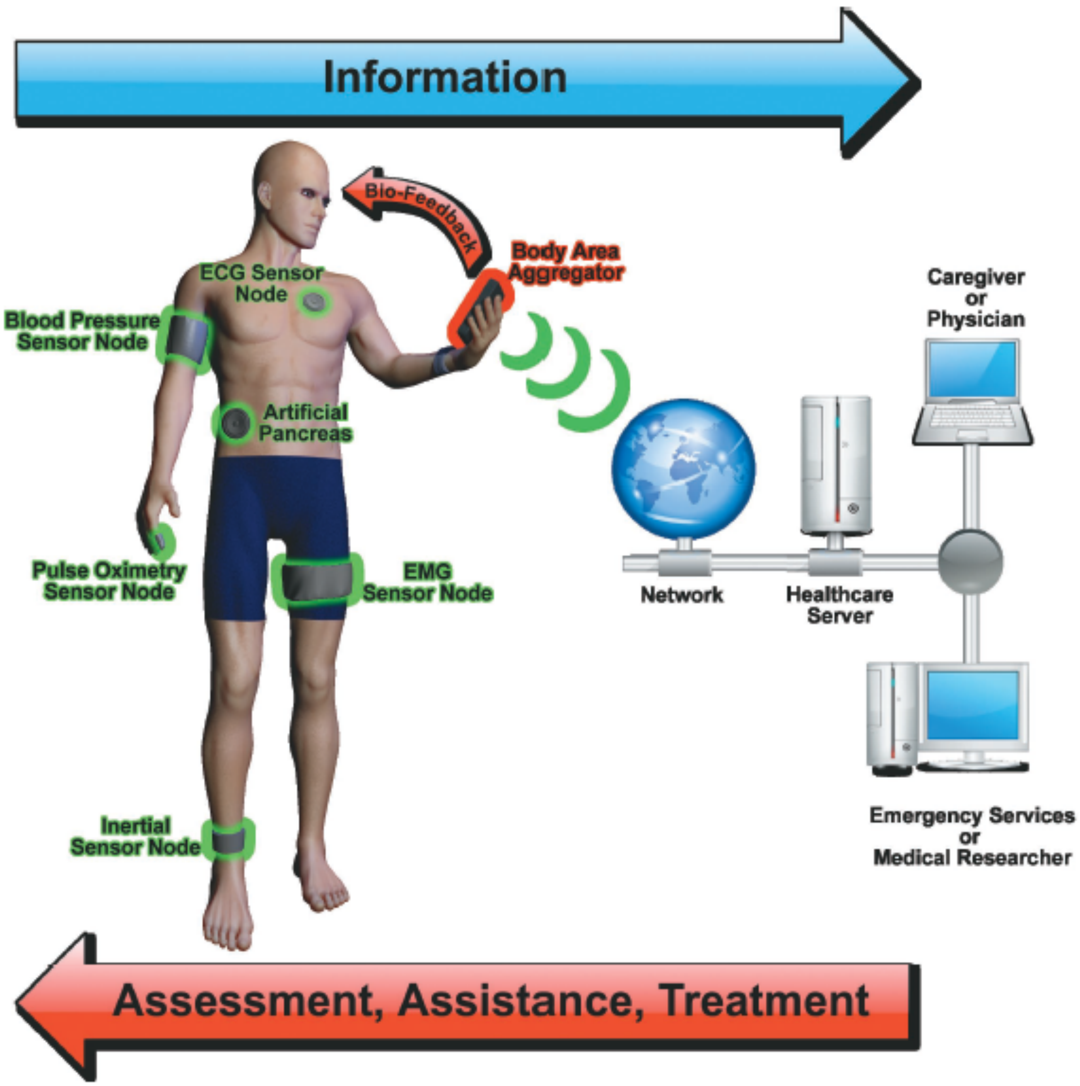


What are the key components of BASN?



Sensing, Data Processing and Fusion, Communication, User Interface

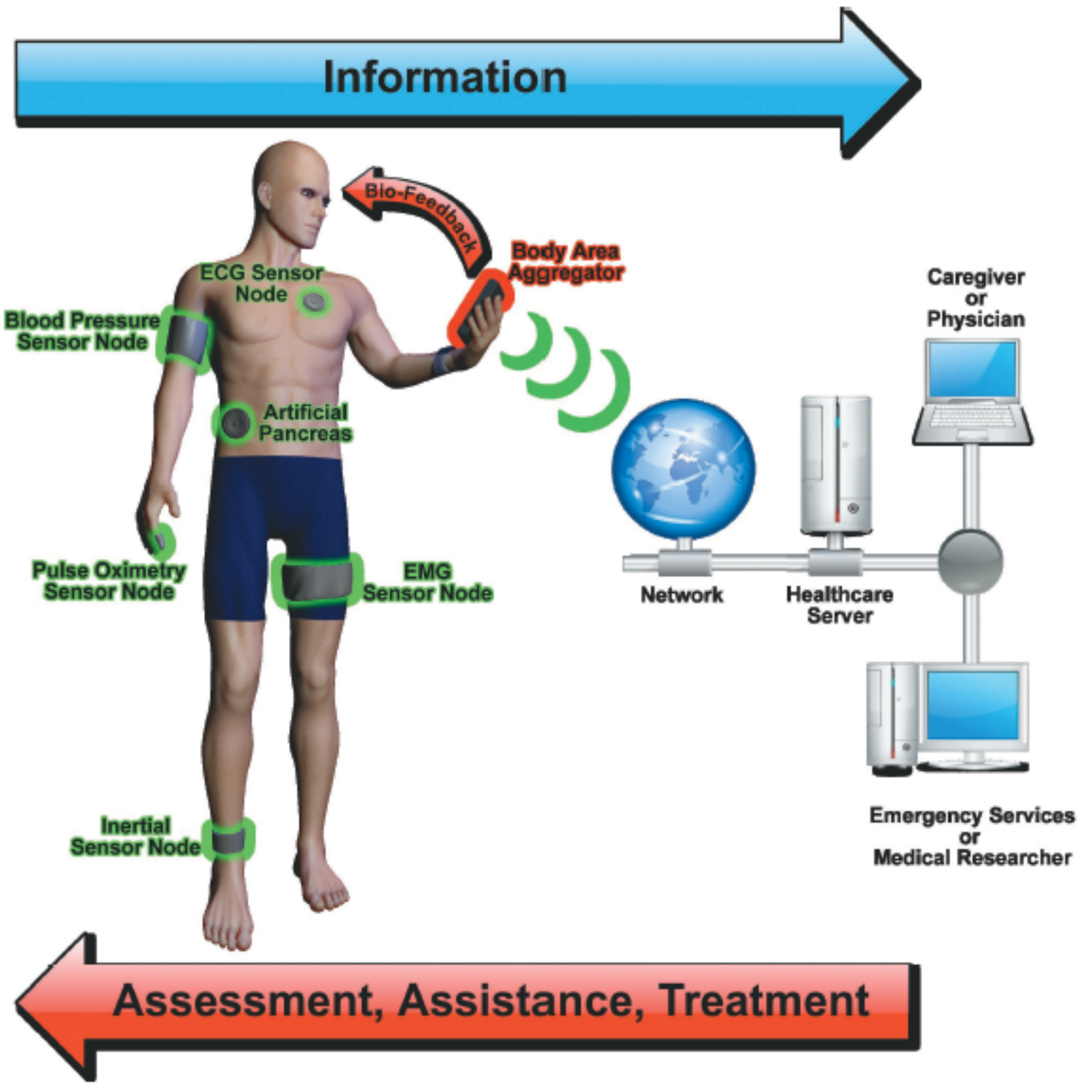
What are the key features of BASN?



BASN Features

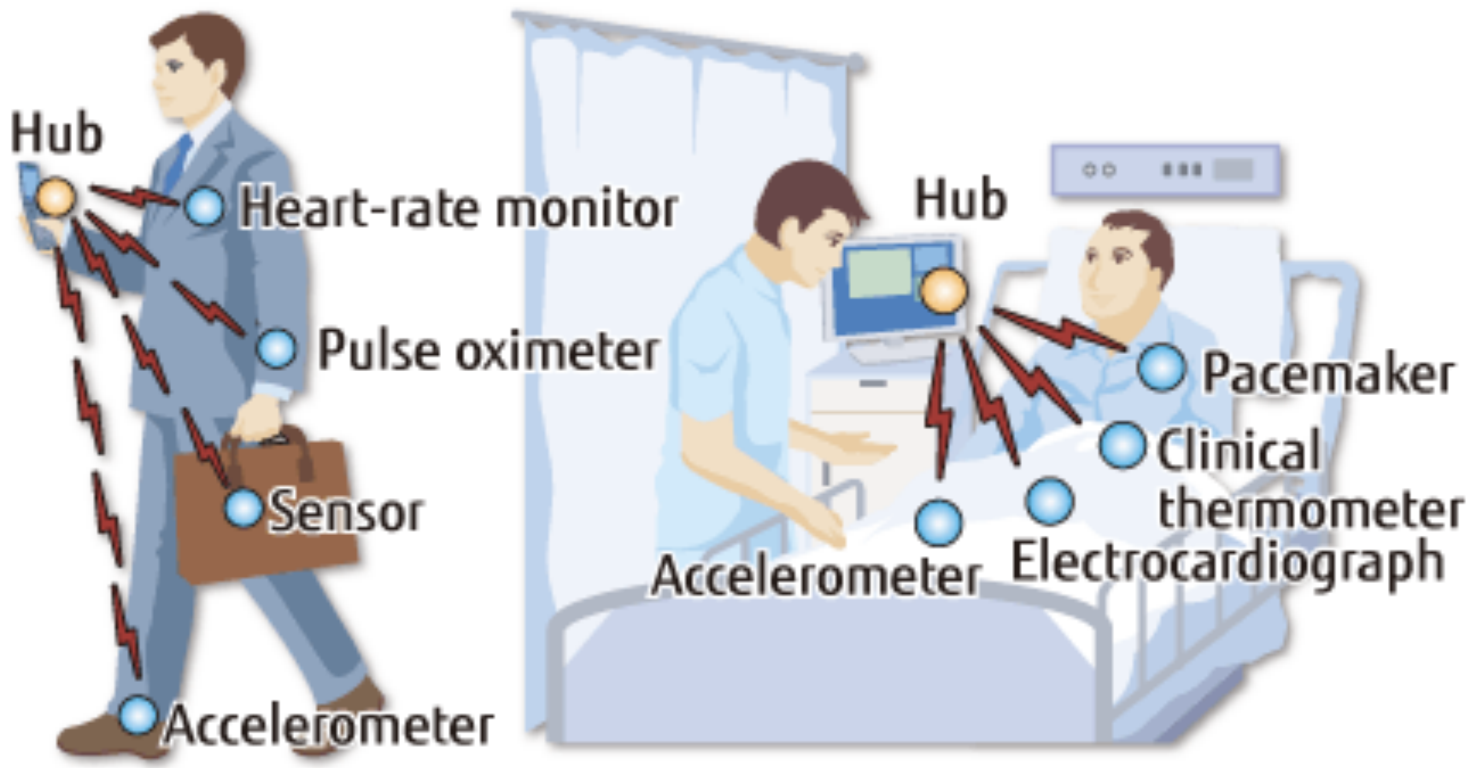
- **Extremely Noninvasive**
  – Social acceptance
- **Tiny in Size**
  – Smaller battery, Constraint resource, Tradeoffs between energy and fidelity
- **Packaging and placement**
  – Neither prominent nor uncomfortable
- **Amortize nonrecurring costs**
  – Either significant volume in a single app or aggregate volume across apps
- **Emphasis on “value to user”**
  – Useful apps that deliver valuable information to users

What could be potential applications of BASN?



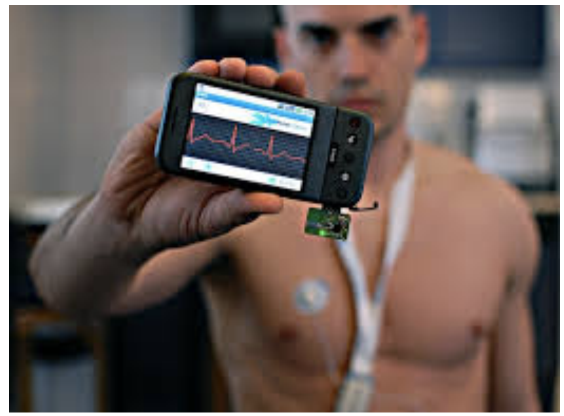
BASN Application Areas

- Healthcare Applications



BASN Application Areas

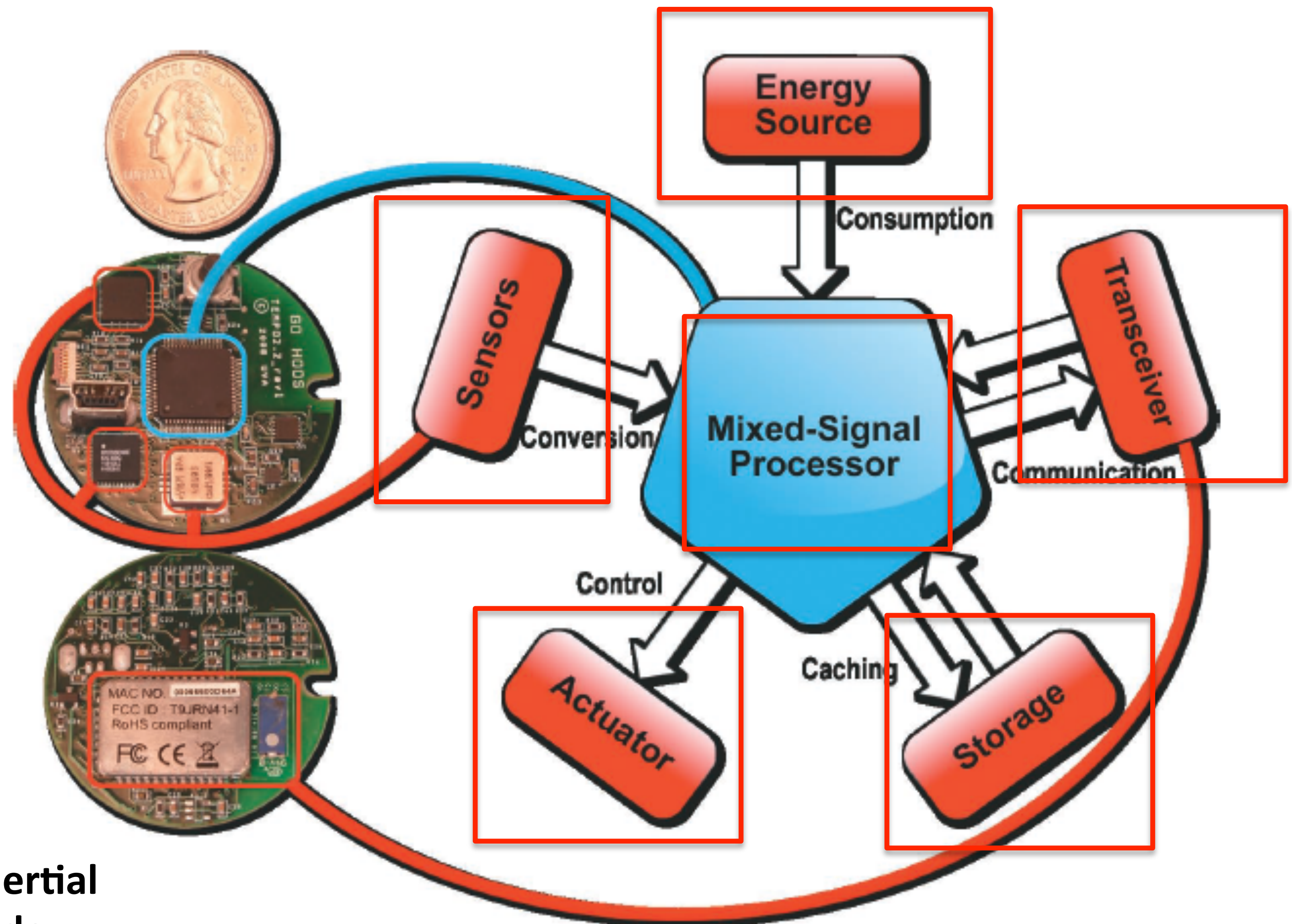
- Fitness Applications



BASN Application Areas

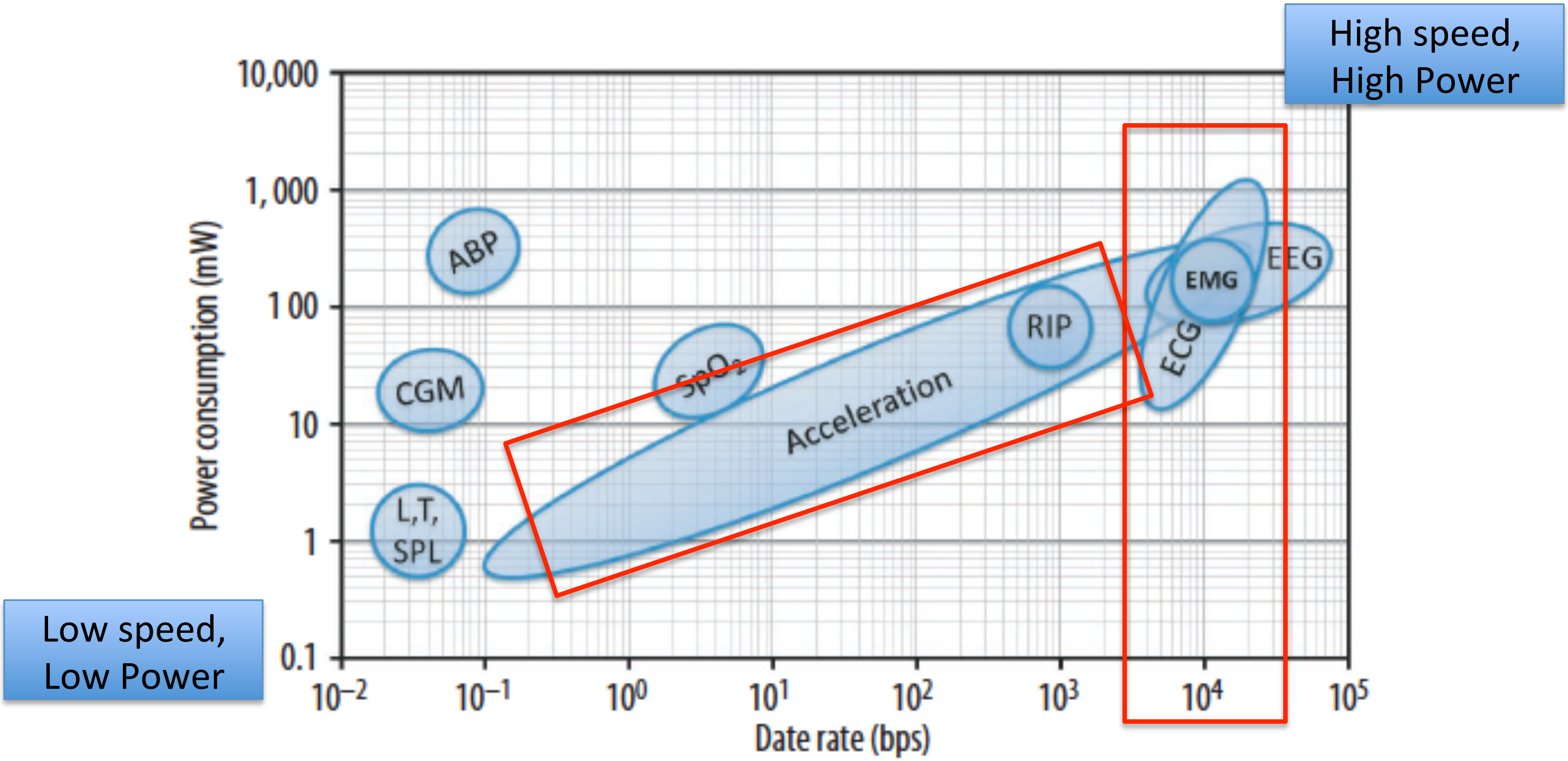
- Entertainment Applications

BASN Components: Sensors



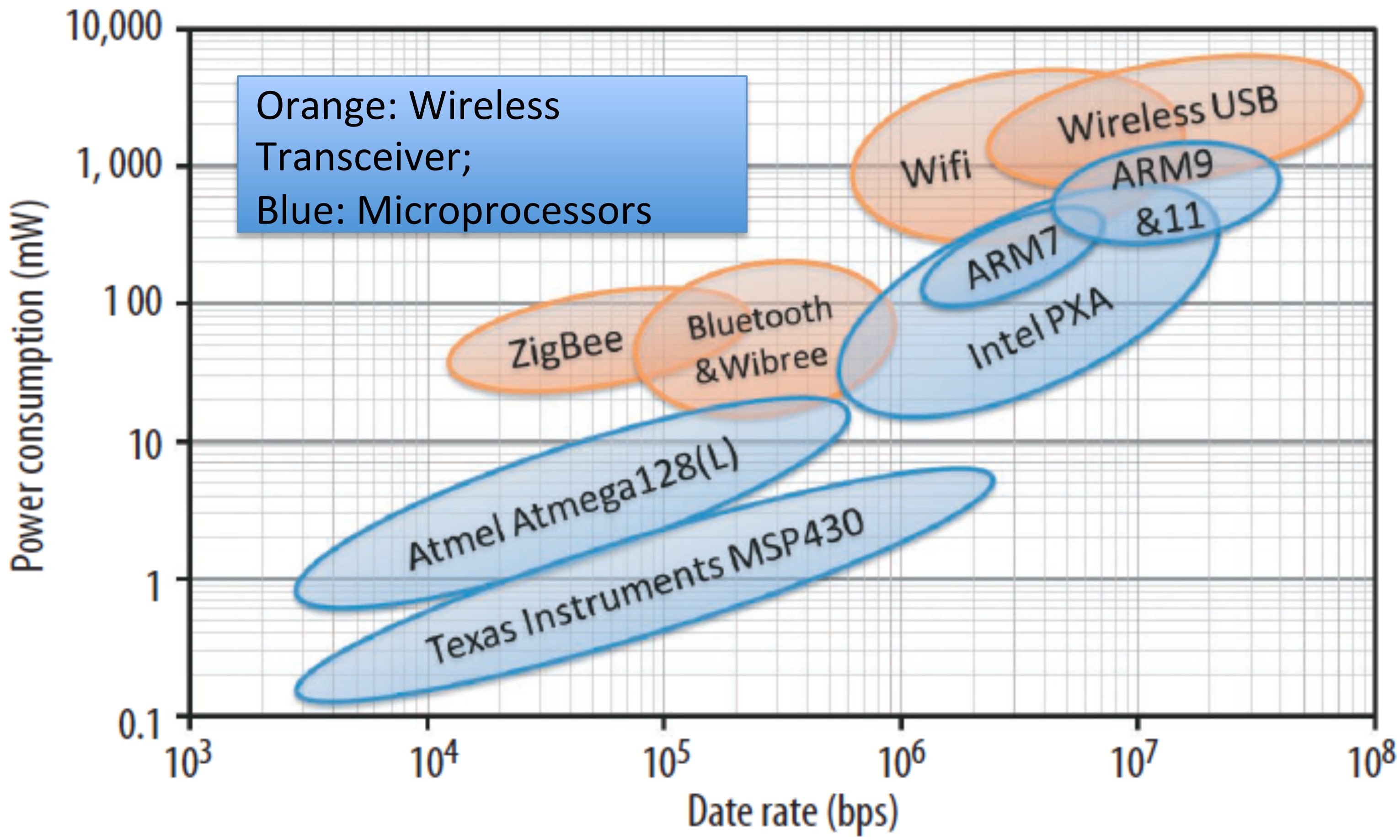
TEMPO inertial sensor node (UVA)

BASN Components: Sensors



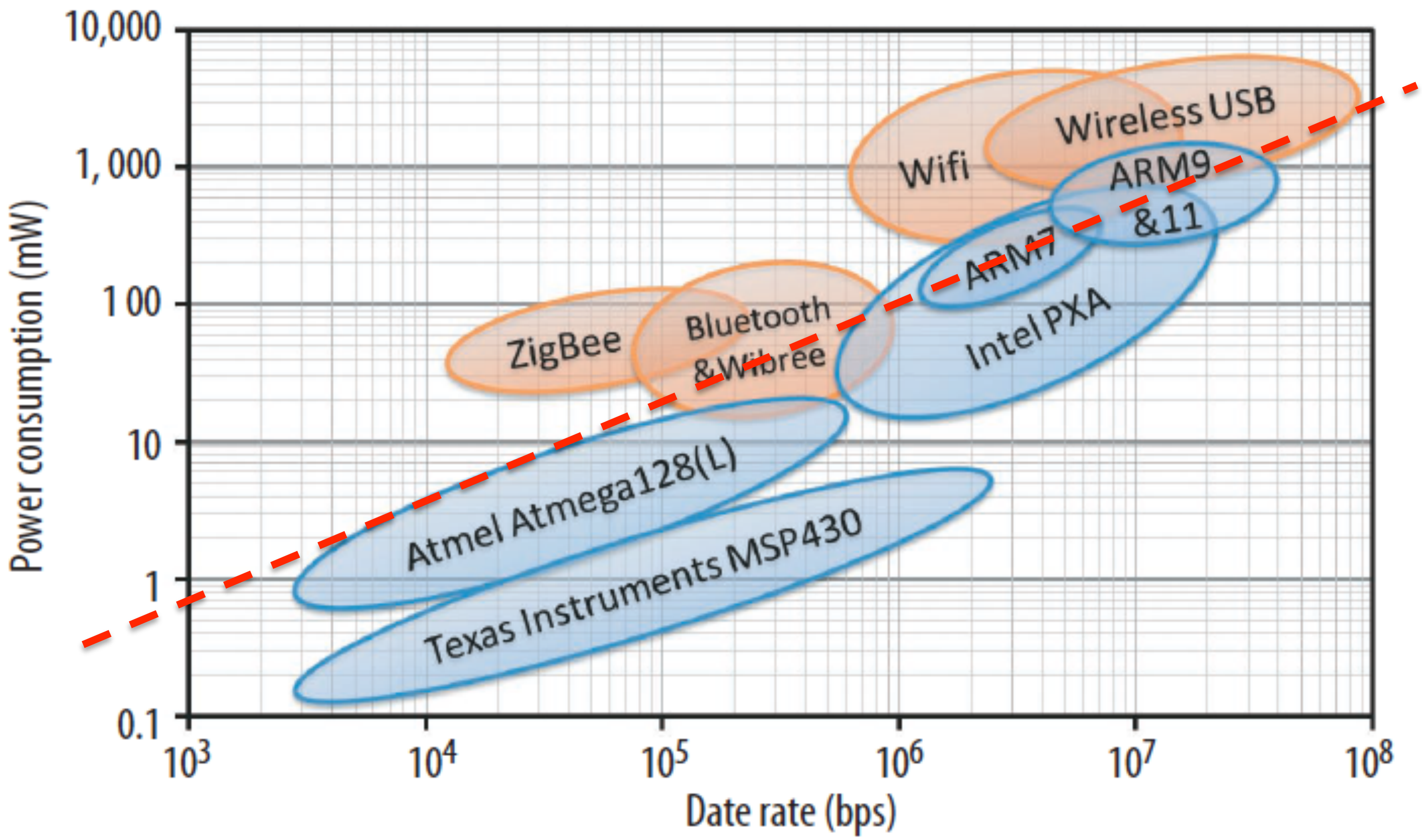
ABP: ambulatory blood pressure; **CGM:** continuous glucose monitoring;
L, T, SPL: light, temperature, sound pressure level;
SpO2: pulse oximetry; **RIP:** respiratory inductive plethysmography;
ECG: electrocardiography; **EMG:** electromyography;
EEG: electroencephalography.

BASN Components: Signal Processing



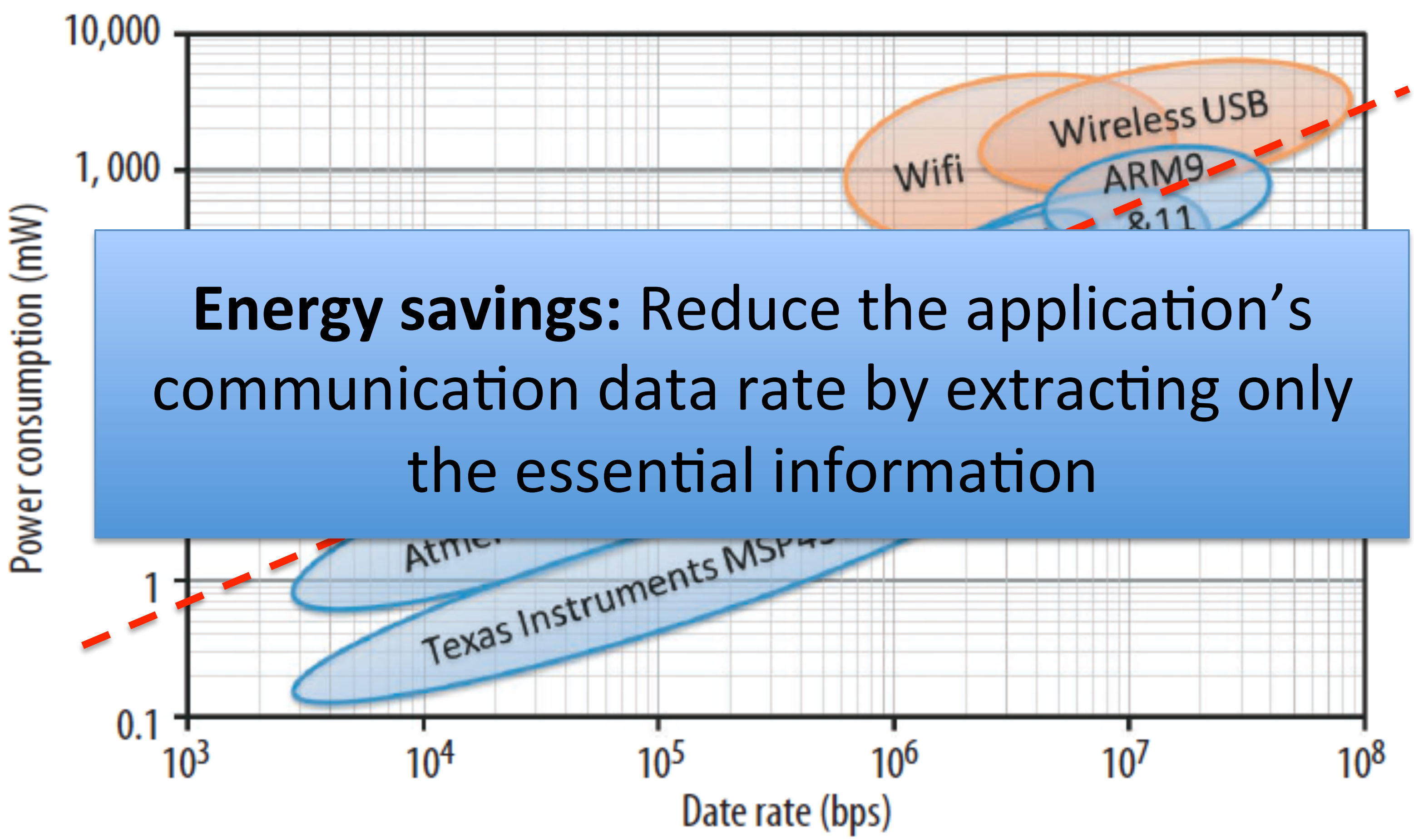
Q: What interesting observations can you get from this figure?

BASN Components: Signal Processing



Processing data at given rate consumes less power on average than transmitting the data

BASN Components: Signal Processing



Energy savings: Reduce the application's communication data rate by extracting only the essential information

Tradeoff: On-node Data Processing vs Wireless Communication

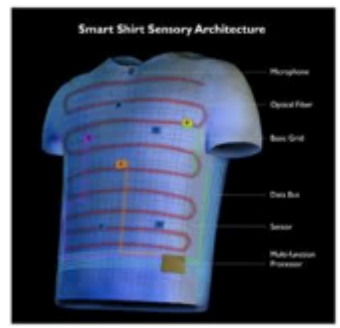
BASN Components: Communication

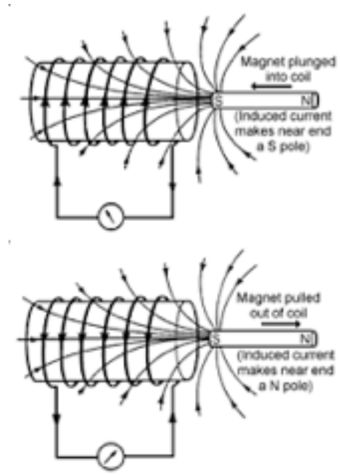
- Essential for Node Coordination
- Restrict the communication radius to the body's periphery (Why?)
- RF Channel: 850 MHz-2.4 GHz
- What is the key challenge of node communication in BASN?
- Big problem of **"Body Shadowing"**
  - Body's line of sight absorption of RF energy
  - Movements cause highly variable path

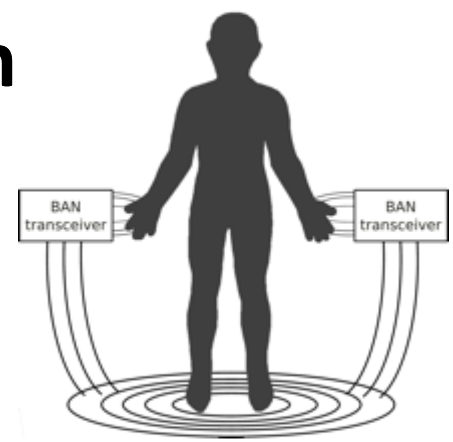
BASN Components: Communication

New/Future communication methods:

- **Smart textiles**
  - Embed wires in clothing
- **Magnetic Induction**
  - Use near field effect to communicate
- **Body-coupled communication**
  - Use human body as a channel
  - Highly stable, low energy
  - Safety is critical





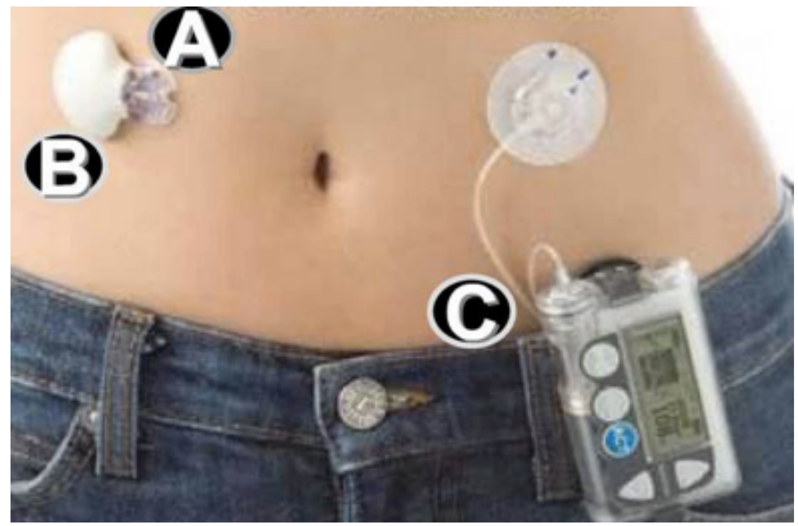


BASN Components: Storage

- **On-node Storage:**
  - Low power nonvolatile storage (e.g., MRAM, RRAM)
- **Cache data and wait for good channel conditions:**
  - Prolong battery life, decrease transmitting error
- **Archive data for signal classification:**
  - Detect longitudinal trends (e.g. recover from surgery)
  - Detect instantaneous events (e.g., falls)

BASN Components: Feedback Control

Prosthetics Devices



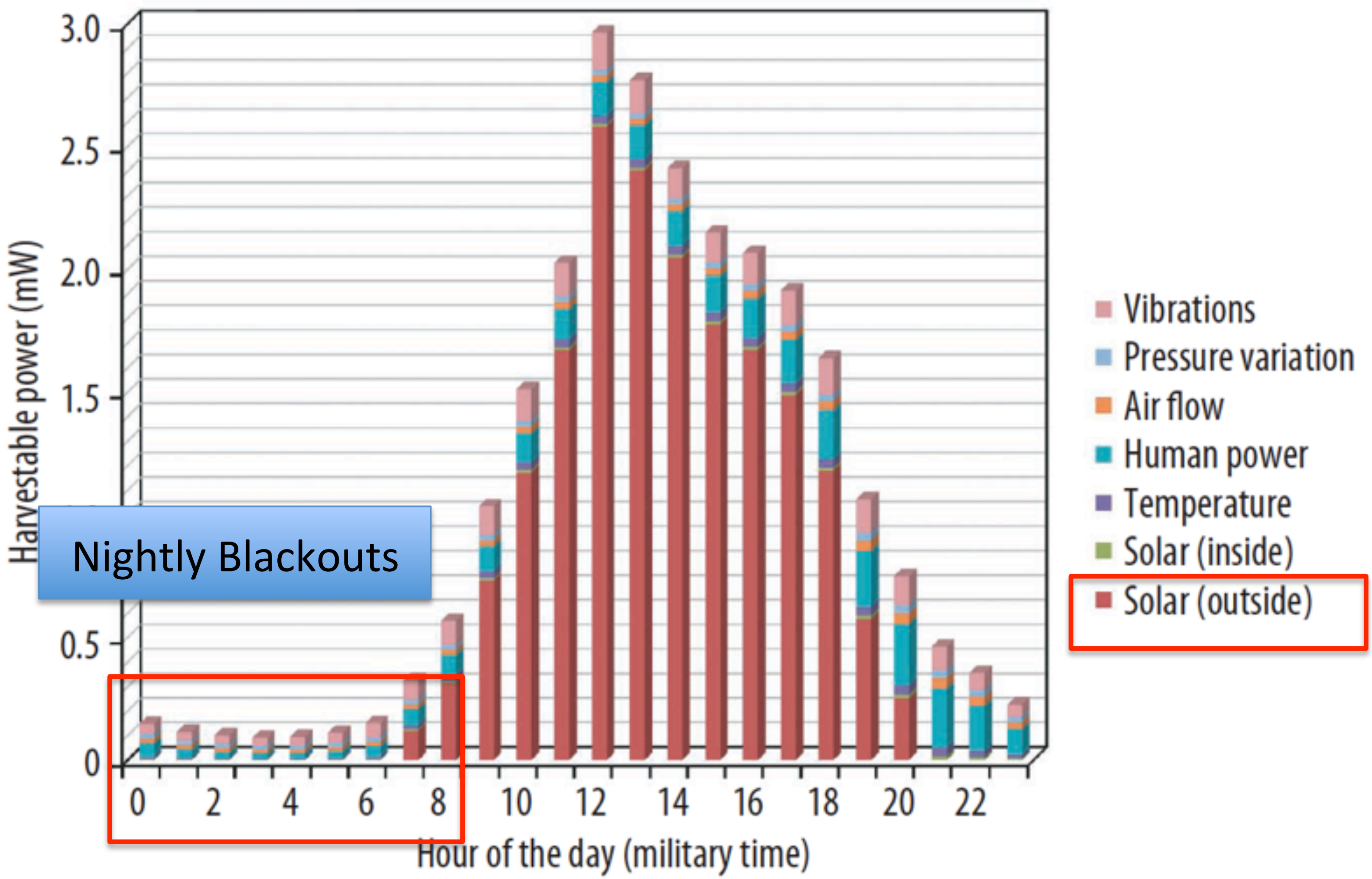
Diabetes Monitoring

EMG signals from the eyelid or jaw might be used to control prosthetics devices

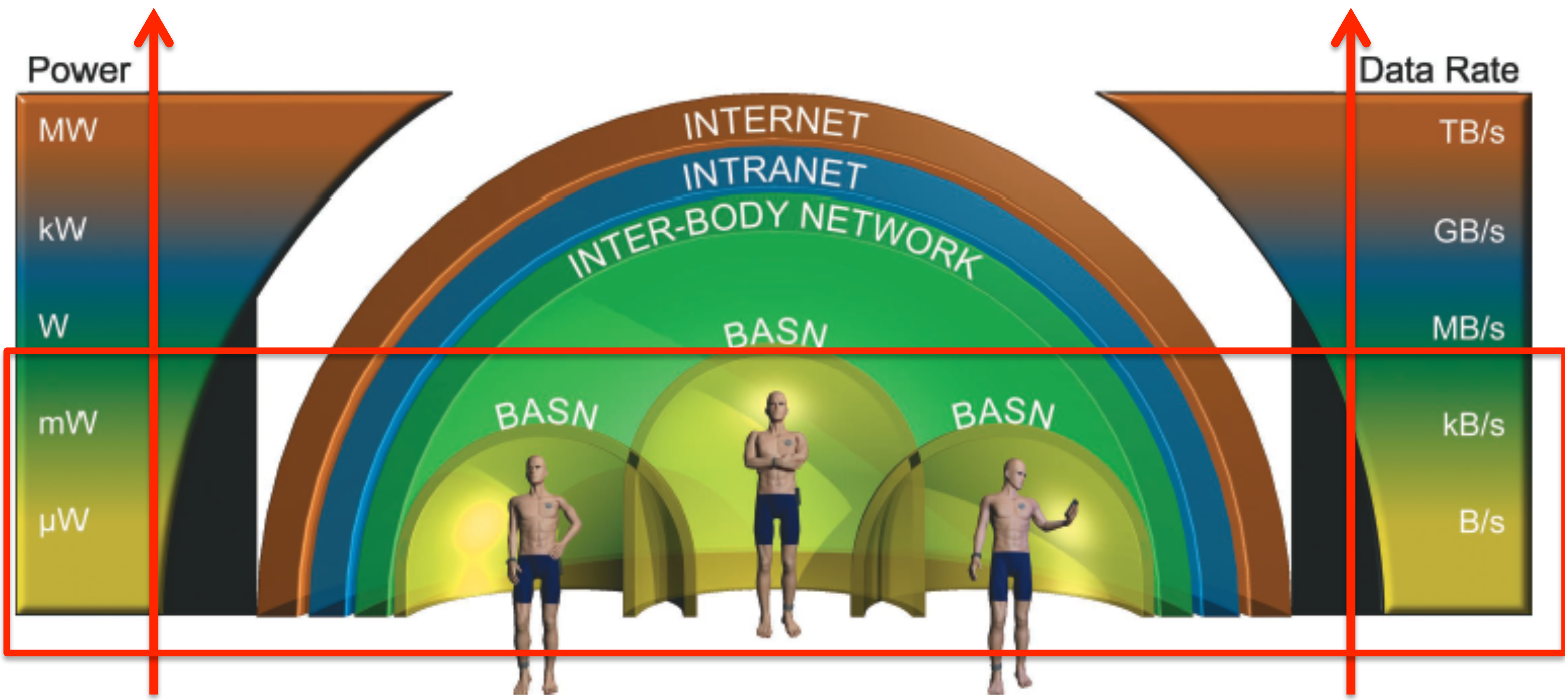
Use blood glucose measurements from biosensors to control insulin delivery

Energy Harvesting

Q: What can you observe from this figure?



Body Area Networking

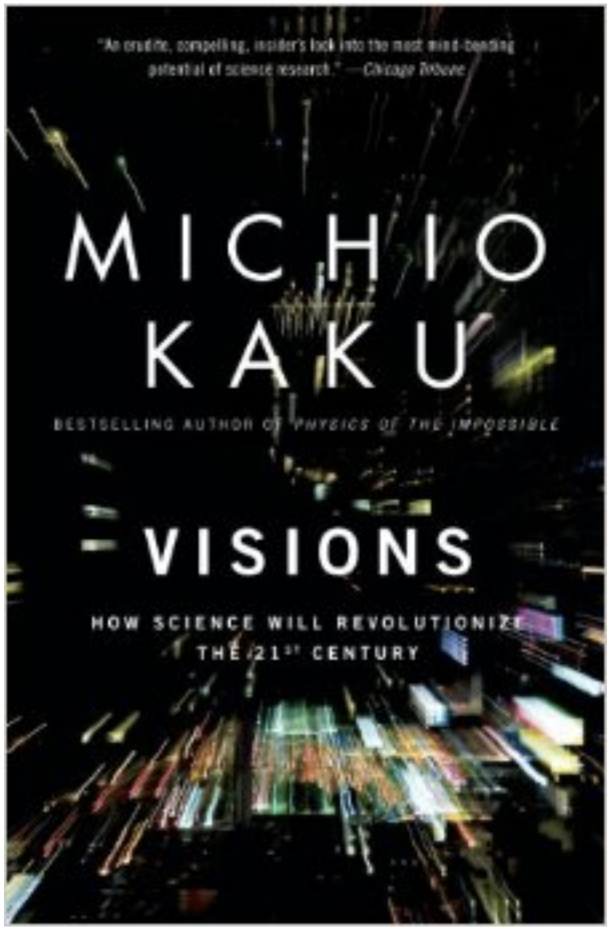


BASN is operating at low power and low data rate domain

Open Questions

- What are the factors that will affect the widespread BASN adoption and diffusion (e.g., value, safety, privacy, compatibility, ease of use)?
- Who will be the stakeholders of BASN (e.g., users, emergency services, caregivers, researchers, etc.)?
- Who will pay for the BASN? Who will own the BASN data? How will access to data and information be granted? Who is liable for damages involving BASN?

From Science Fiction to Reality



The book described **a vision** where **wearable technologies** that will "silently monitor" heart rhythm, detect irregularities, and alert emergency personnel in the event of a heart attack ..

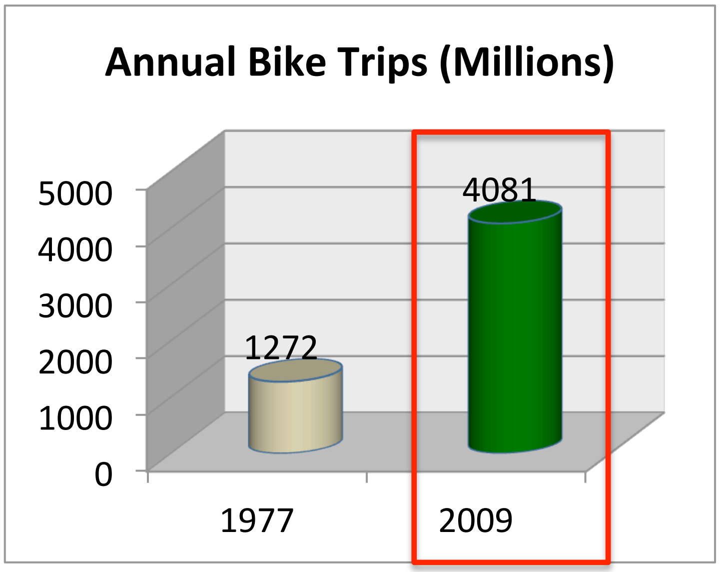
How Science Will Revolutionize the 21st Century and Beyond-Futurist Michio Kaku (Oxford University Press, **1999**)

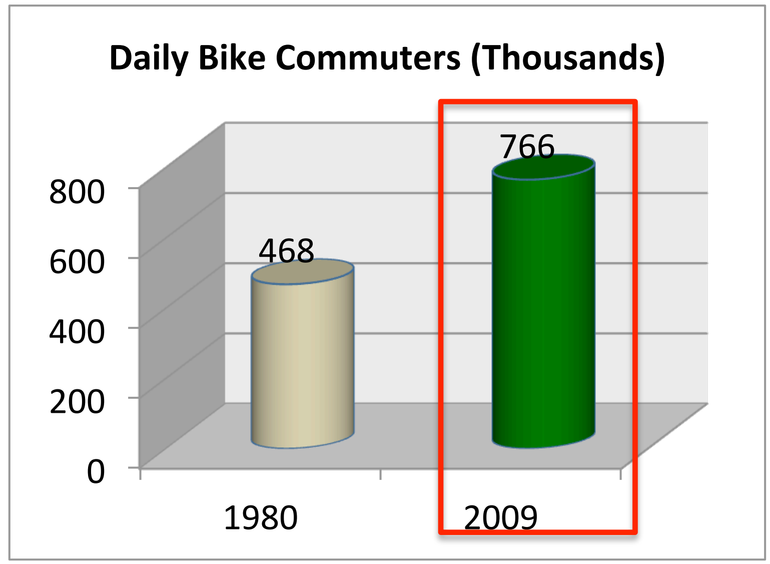
Paper Discussion

- Paper 1: "Accurate caloric expenditure of bicyclists using cellphones.” Zhan, Andong, et al. Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems. ACM, 2012.

Biking Renaissance

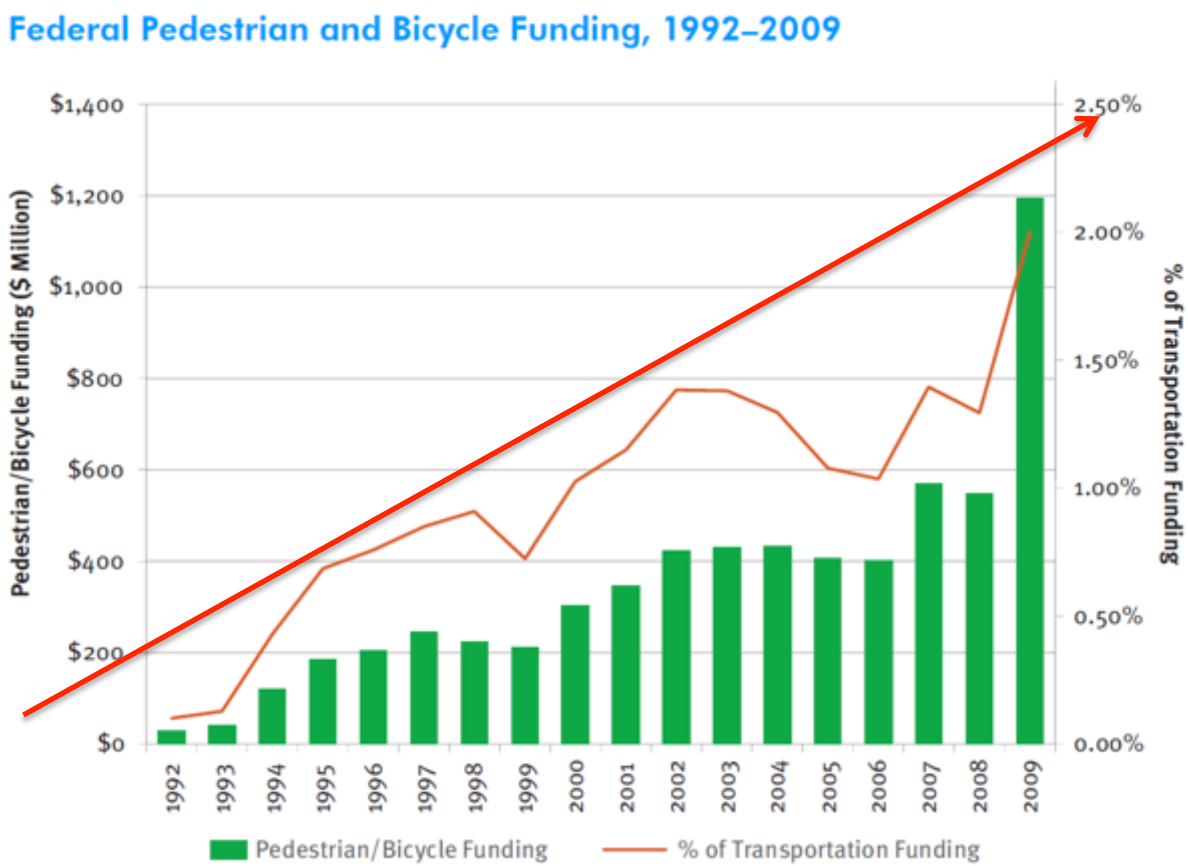
- A biking renaissance has been underway over the past two decades in North America





Pucher et al., *Bicycling renaissance in North America? An update and re-appraisal of cycling trends and policies*, Transportation Research Part A 45 (2011) 451-475

Biking Renaissance (Cont'd)



The National Bicycling and Walking Study: 15-Year Status Report, May 2010
Pedestrain and Bicycle Information Center, U.S. Department of Transportation

Go with Mobile

- Bikers' cellphones become smarter
- Bikers start to use mobile apps to track their trips
  - E.g., iMapMyRIDE, endomondo
  - Trace route, mange workouts, share experience with friends
- A important feature is to estimate caloric expenditure

Quantify their exercises and keep fit.

Estimate Caloric Expenditure

- Q 1: Is there some simple approach we can use to quickly estimate caloric expenditure of a bike trip without using smartphones and special sensors?
- Q 2: What are the inputs you might need to estimate the caloric expenditure?

Estimate Caloric Expenditure

- Current approach – search table

Speed	130 lbs	155 lbs	190 lbs
$<$10mph, leisure	236	281	345
10-11.9mph, light effort	354	422	518
12-13.9mph, mod. effort	472	563	690
14-15.9mph, vig. effort	590	704	863
16-19mph, very fast	708	844	1035
$>$20mph, racing	944	1126	1380

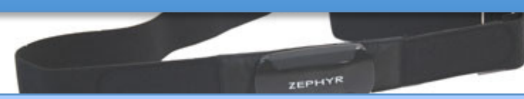
State of Wisconsin Department of Health and Family Services: Calories Burned Per Hour

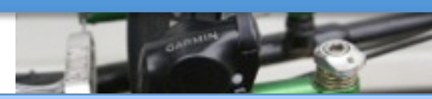
What could be the problems of using the search table?

Estimate Caloric Expenditure (Cont'd)

- How to track caloric expenditure accurately?
  - Integrate more sensors!

It seems the only way to get accurate caloric expenditure is to buy more hardware sensors.





Is it really the only way to do it?

Used by professionals, cost more than 1,000 each

Bikers need to wear strap on their chest

It senses revolution per minute, but it ignores elevation change

Est

- How to
  - Integrate

Can we use just one smartphone without any accessories to accurately track caloric expenditure?

Cadence sensor

The answer is YES!!!

Share your thoughts

- How would you design a smartphone based system to accurately estimate the calorie expenditure of bikers?

- What are the technical challenges that need to be addressed to design such system?

Related Work

- **BikeNet**
  - Use T-mote Sensors + Nokia Smartphones
  - Collect samples from a broad range of sensors
  - Primarily used for data collection and route tracking
- **Jigsaw Sensing Engine**
  - Continuously monitor and classify user activity (walking, cycling, running, etc.)
  - Do not quantify the physical aspects of these activities
- **Biketastic**
  - Use accelerometers and microphones to gauge the "roughness" of a road and comfort of a ride
  - Do not compute calorie consumptions of bikers

Contribution

- Design and implement a modular mobile sensing system to enable four major calorie estimators
- Introduce a "software method" on smartphone to replace external "hardware sensors"
  - **Cadence:**
    - Cadence sensor → software method 1
  - **Elevation:**
    - Pressure sensor → software method 2
- Accurately estimate caloric expenditure with just one smartphone: achieve the goal ☺

Caloric Estimators

1. Search Table
   – Cal = f(speed, time, weight)
2. Heart Rate Monitor
   – Cal = f(bpm, weight, age, time)
3. Cadence Sensing [Al-Haboubi et. al.]
   – Cal = f(rpm, speed, weight)

bpm: beat per minute; rpm: revolution per minute;

Al-Haboubi et al., Modeling energy expenditure during cycling, *Ergonomics,* 42:3:416-427, 1999

Caloric Estimators (Cont'd)

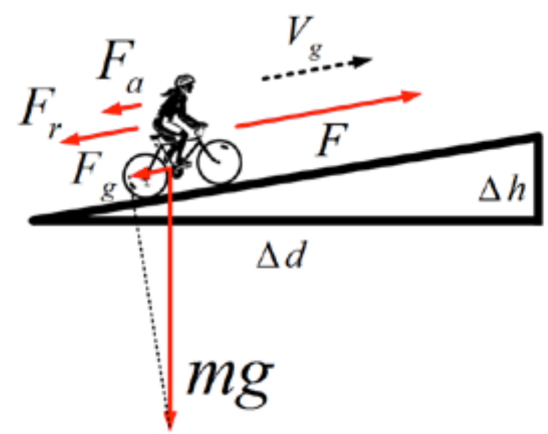
4. Power measurement [Martin et al.]
   – Calorie is linear with the total amount of work to move the combined mass of the bike and the biker

Fr: rolling resistance;
Fg: gravity component on the moving direction;
Fa: Aerodynamic drag

$$P = FV_g$$

$$\boxed{F = F_r + F_g + F_a}$$

$$\begin{aligned} F_r &= mgC_r \\ F_g &= mgs \\ F_a &= \rho(T)C_aV_a^2 \end{aligned}$$



Martin et al., Validation of a Mathematical Model for Road Cycling Power. *Journal of Applied Physiology,* 82:345, 2000.

Caloric Estimators (Cont'd)

4. Power measurement [Martin et al.]
   - Calorie is linear with the total amount of work to move the combined mass of the bike and the biker

Cr: rolling test;
Slope: obtained from elevation difference
Ca: recommended value from UK's cyclists organization
Va, T: web service and local weather station

$$P = FV_g$$

$$F = F_r + F_g + F_a$$

coefficient of rolling resistance

$$F_r = mgC_r$$

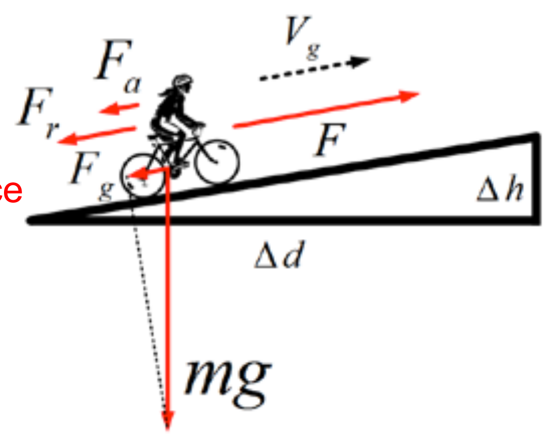
$$F_g = mgs$$

slope

$$F_a = \rho(T)C_a V_a^2$$

Wind velocity

coefficient of aerodynamic drag



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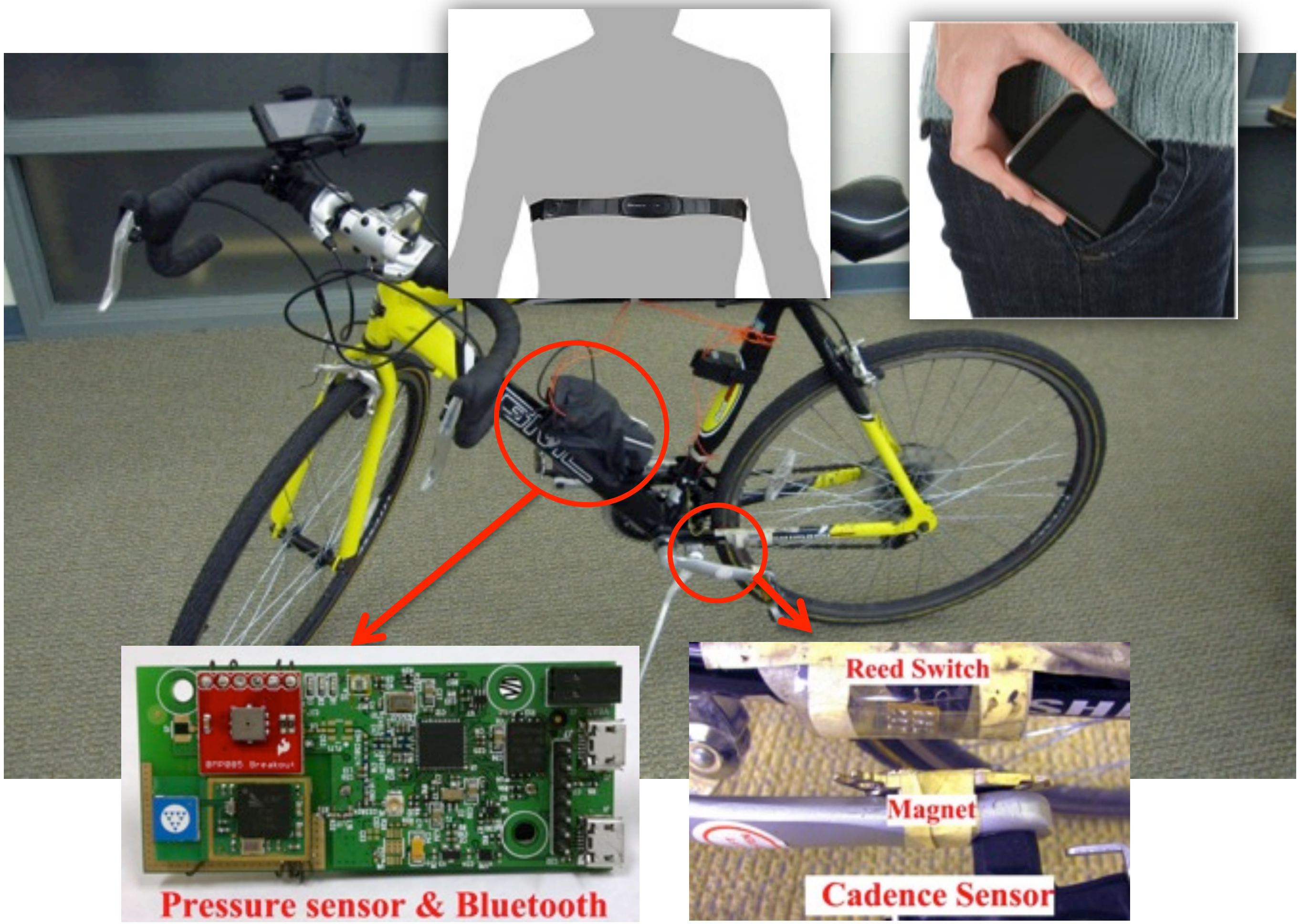
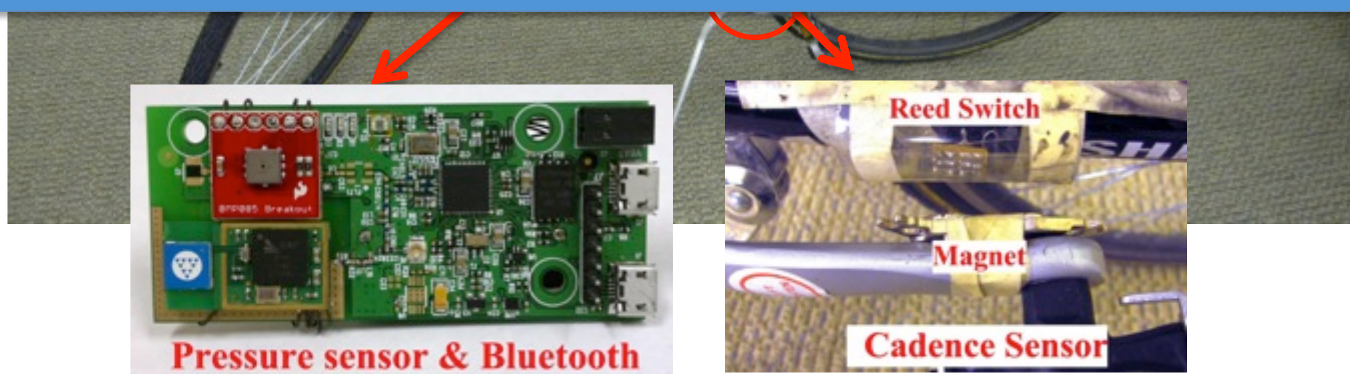
System overview



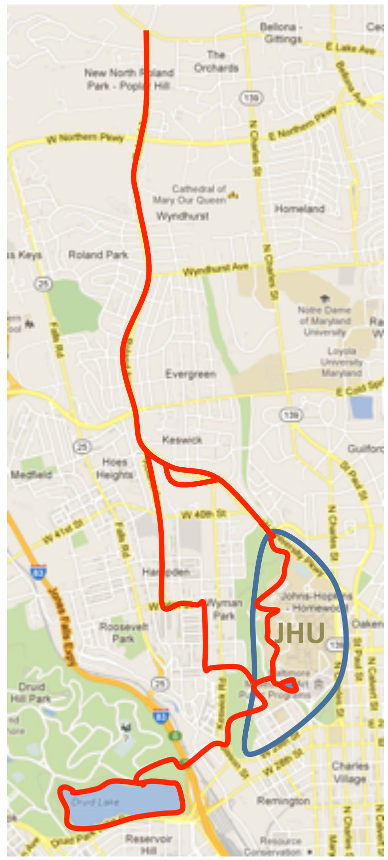
System overview

Key Q: How to replace cadence sensor and pressure sensor by using a smartphone and some additional services?



Data collection

- 15 bike routes around JHU campus
- Each can be completed within 20 min
- Stable weather condition
- sample GPS, heart rate, and pressure sensor once per second
- Accelerometer sample rate at 50 Hz



Route	Dist. (km)	Road Conditions
R1	1.5	Neighborhood, uphill
R2	2.1	Neighborhood, uphill
R3	0.8	Neighborhood, downhill
R4	0.8	Neighborhood, uphill
R5	2.1	Neighborhood, downhill
R6	1.1	Neighborhood, downhill
SMDN&S MDS	1.5	Woods, river valley, ups and downs, winding path
SMDC	2.4	Woods, river valley, ups and downs, winding path
DL	2.5	Lakeside, flat, open field
WW	1.7	Bridges, ups and downs
WE	1.7	Bridges, ups and downs
HJ	2.9	Neighborhood, bridge, downhill
JH	2.9	Neighborhood, bridge, uphill
C	3.9	Flat, circle, open field

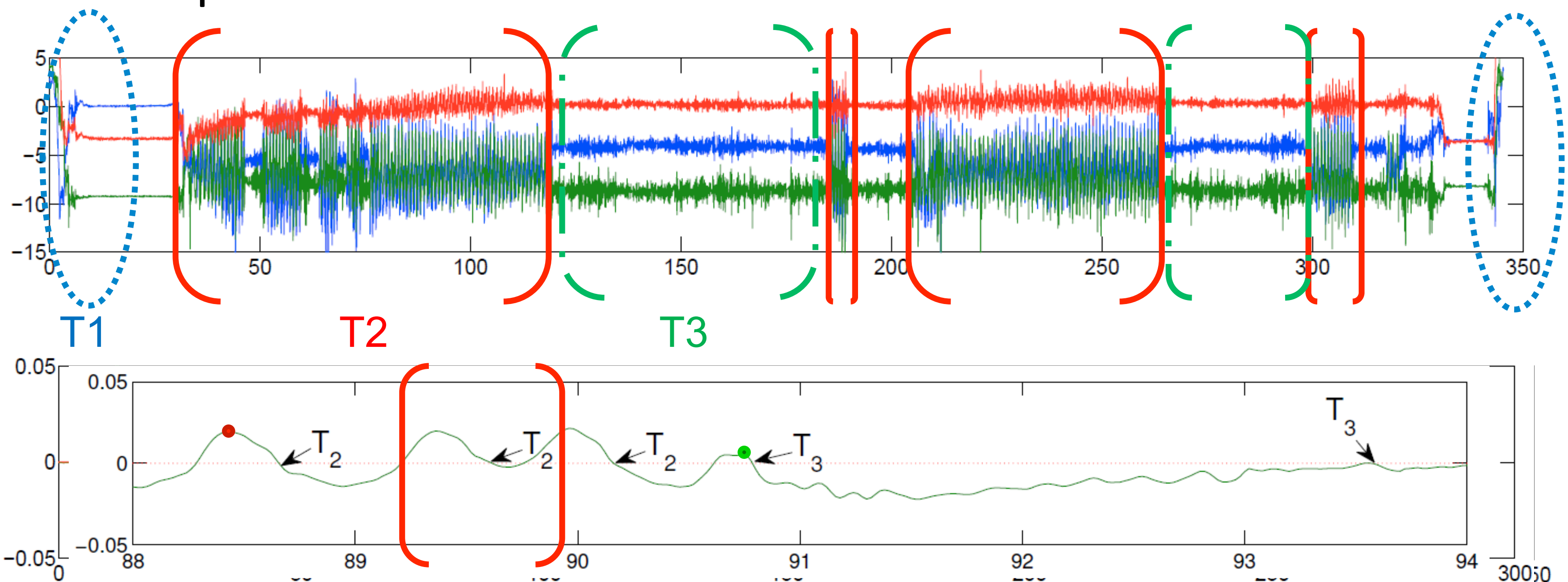
Routes: Uphill, Downhill, Up and Downs

Software Method 1

- Q: How to use smartphone sensor data to figure out the rpm (revolution per minute) of the bikers? (We do not want to use a cadence sensor)

Cadence Sensing in the Pocket

- Get rpm from raw accelerometer data



Step 2: apply a low-pass filter and get the derivative of the data

Step 3: utilize k-means to cluster two types based on the amplitude of the immediately previous peak

T1: Move phone in/out of pocket; **T2:** Pedaling; **T3:** Non-pedaling vibration, e.g., turn, cross a bump, etc.

Software Method 2

- Q: How to use smartphone sensor data and some external database knowledge to figure out the elevation of the bikers? (We do not want to use a pressure sensor)

Elevation measurement

- Where to get elevation?
  - Pressure sensor (< 2m): most accurate method

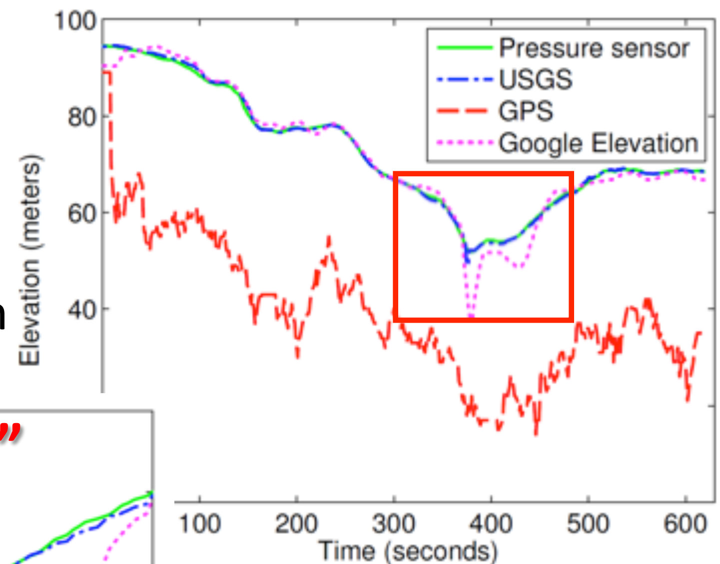
$$\text{altitude} = 44330 \cdot \left(1 - \left(\frac{p}{p_0}\right)^{\frac{1}{5.255}}\right)$$

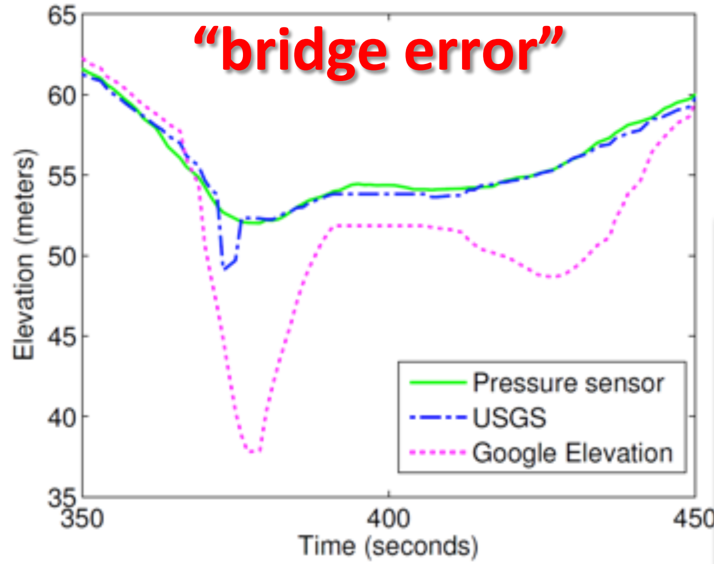
1 hPa ~= 8.43 m;
Pressure sensor accuracy:
0.2 hPa -> 2 m error

  - GPS (unknown accuracy)
  - U.S. Geological Survey (USGS) (3-10 m)
    - Provides an HTTP interface to National Elevation Dataset (NED)
    - 10-meter resolution in general, 3-meter resolution in dense areas
  - Google Maps (~ 20 m)

Elevation measurement

- Where to get elevation?
  - Pressure sensor (< 2m)
  - GPS (unknown accuracy)
  - U.S. Geological Survey (USGS) (3-10 m
  - Google (~ 20 m)





Q: Why USGS and Google estimations deviate on bridge ?

A: Their data provides the elevation of the terrain (i.e., river bed under the bridge)

Elevation measurement

- Where to get elevation?
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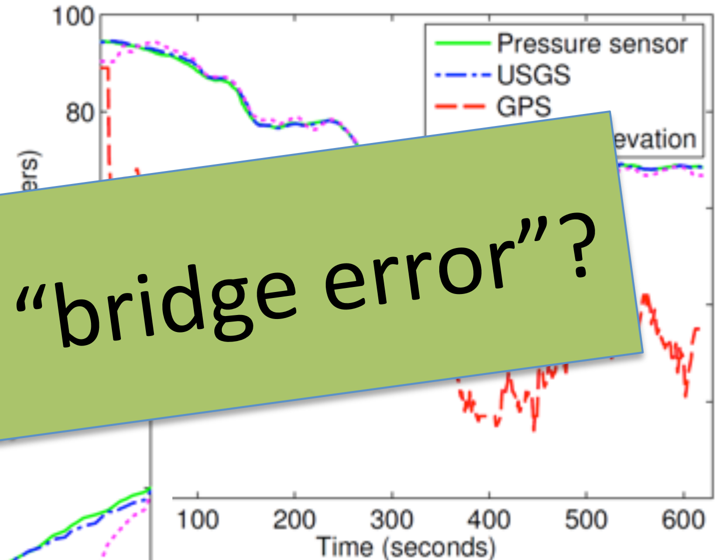
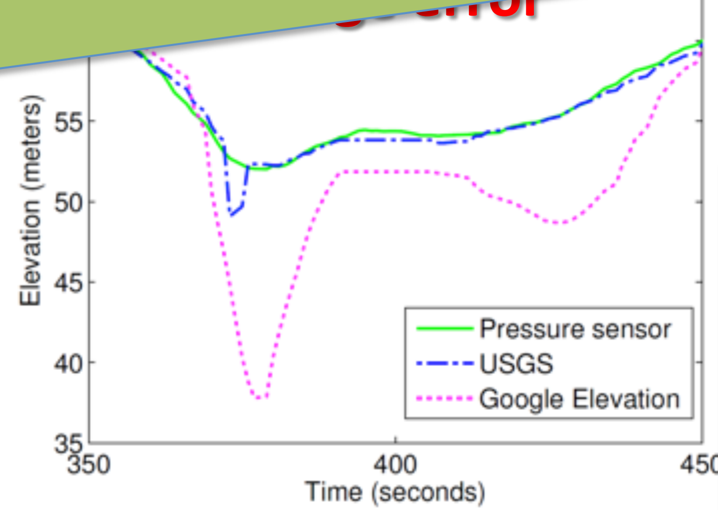
  - GPS (unknown accuracy)



Q: How to address the "bridge error"?



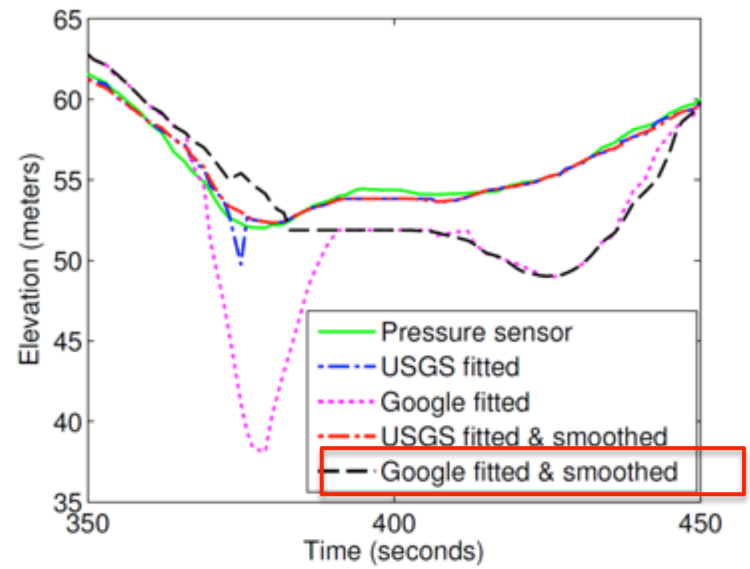
Q: Why USGS and Google estimations deviate on bridge ?

A: Their data provides the elevation of the terrain (i.e., river bed under the bridge)

Elevation measurement (Cont'd)

- Fitting
  - Assume all bike trips take place on either marked paths or roads
  - Fit (x, y) to the most likely road in OpenStreetMap
- Smoothing
  - Treat data from USGS and Google over the bridge section as "outliers"
  - Use a robust local regression method: fit to a quadratic polynomial model with robust weights:

$$w_i = \begin{cases} (1-(r_i/6MAD)^2)^2, & |r_i| < 6MAD, \\ \boxed{0, \quad |r_i| \geq 6MAD,} \end{cases}$$



Bridge error is corrected by smoothing

Set weights of outliers to be 0

Calibration: Estimation of Coefficients of Rolling Resistance

- A simple experiment:
  - Find a flat path that is at least 50 meters long
  - Activate GPS Tracking
  - Bikers Follow the following 3 steps:
    - Accelerate the bike before the start of the 50-m path
    - Stop pedaling and keep the bike straight on the path without breaking
    - Stop the bike at the end of the path
  - Calculate the rolling resistance coefficient Cr:

Measured coefficient: 0.07-1.15

$$C_r = \frac{a}{g} = \frac{\Delta v}{\Delta t g}$$

Computed from GPS Tracking Trace;

Evaluation

- Hardware sensors vs. software approaches
  - Cadence sensor vs. Accelerometer sensing in the pocket
  - Pressure sensor vs. Elevation services
- Caloric expenditure estimation for multiple bikers

Cadence sensing

- Use hardware cadence sensor as ground truth
- 29 traces collected by two volunteers
  - Public roads with real traffic situations, the trip includes uphill, downhill and sharp turns
  - Total length is 30.3 km, total 5,377 revolutions

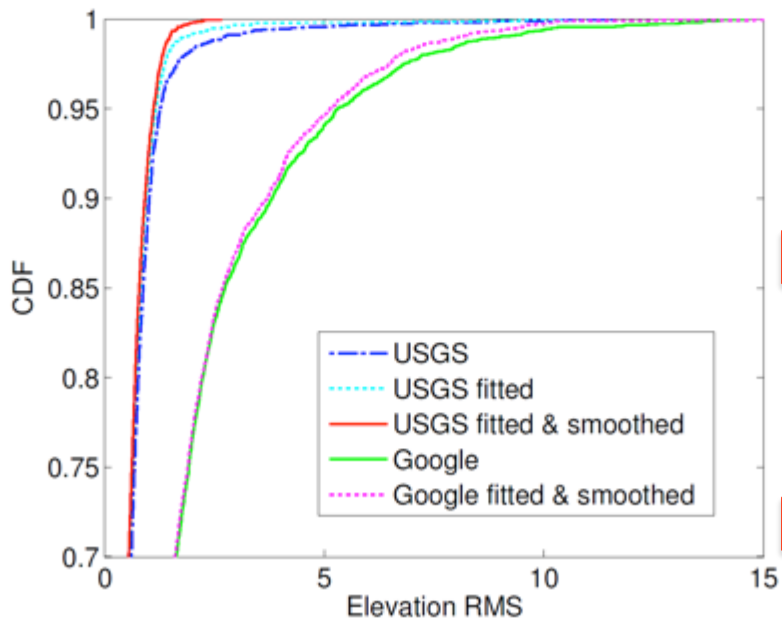
Relative error per trip (%)	0.19 ± 1.59
Error per kilometer	-0.09 ± 3.40

- The relative error is less than 2%
- The error per km is less than 4 revolutions

The error introduced by replacing hardware sensors with software sensors (smartphones) is negligible

Elevation services

- 15 traces on 12 routes from Mar. to Apr. 2012
- Total of 4,780 GPS and pressure sample pairs



Elevation Service	R	RMS (m)
USGS	0.9993	0.9
USGS fitted	0.9995	0.7
USGS fitted & smoothed	0.9997	0.6
Google	0.9957	2.4
Google fitted	0.9958	2.4
Google fitted & smoothed	0.9960	2.3
GPS	0.9540	39

- 95% of USGS's RMS are less than 1.2 m
- 95% of Google's RMS are less than 5.4 m

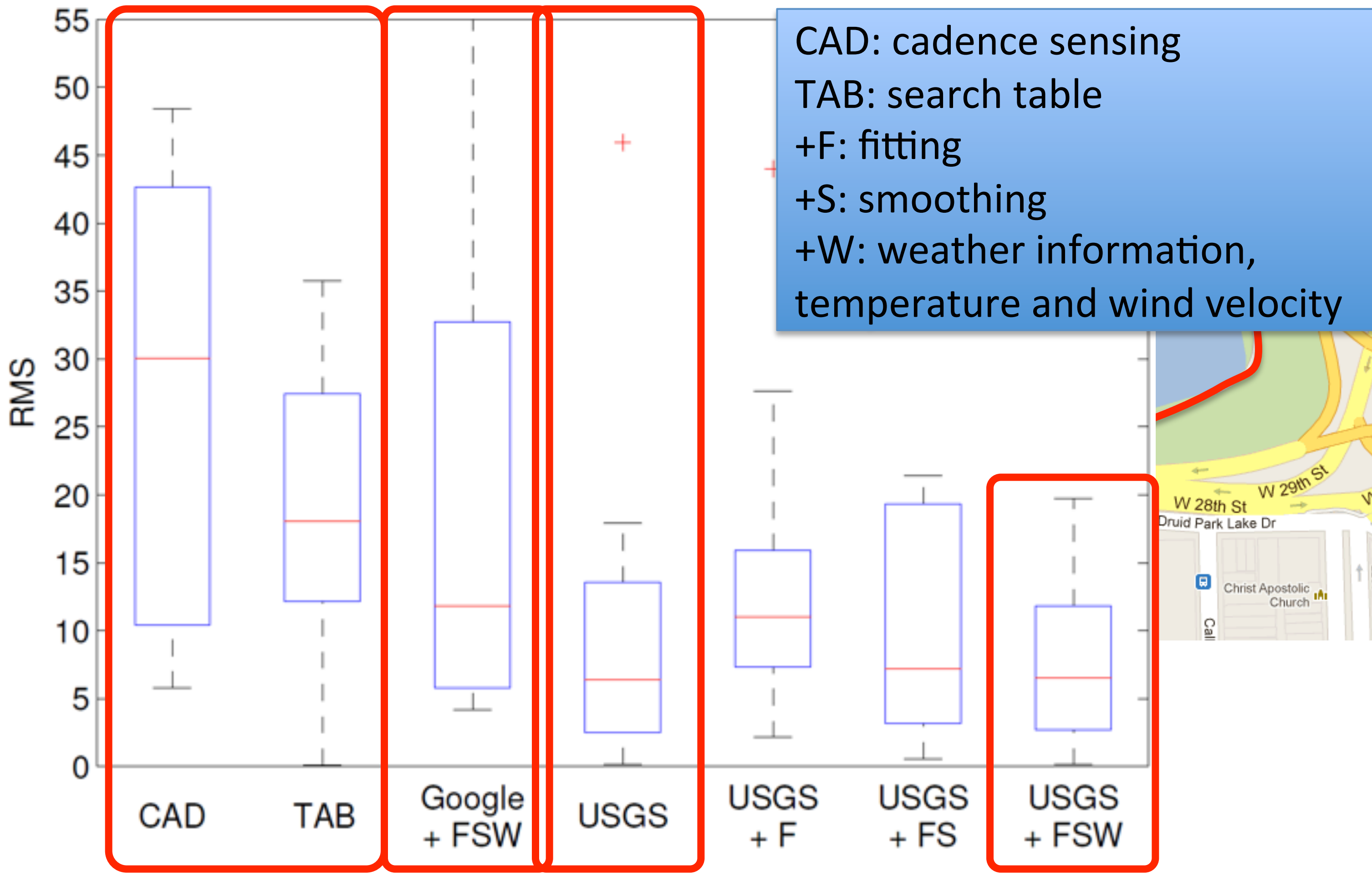
Evaluation

Caloric Expenditure Estimation for Multiple Bikers

- Use Heart Rate Monitor as ground truth
- Compare calories estimated from Search table (TAB), Cadence sensing (CAD), and power measurement (USGS+FSW)
- Recruited 20 volunteers from JHU
  - Wear a heart rate strap + a smartphone in the pocket
  - 17 male and 3 female
  - Age from 24 to 32, weight from 110 to 175 lbs.
- Calibrated 8 bikes
  - 3 road, 4 cruiser, and 1 mountain bikes
  - Cr = 0.07 ~ 0.21, Ca = 0.26
- Collect 70 trips during one week
  - At least 3 trips for each volunteer

Evaluation

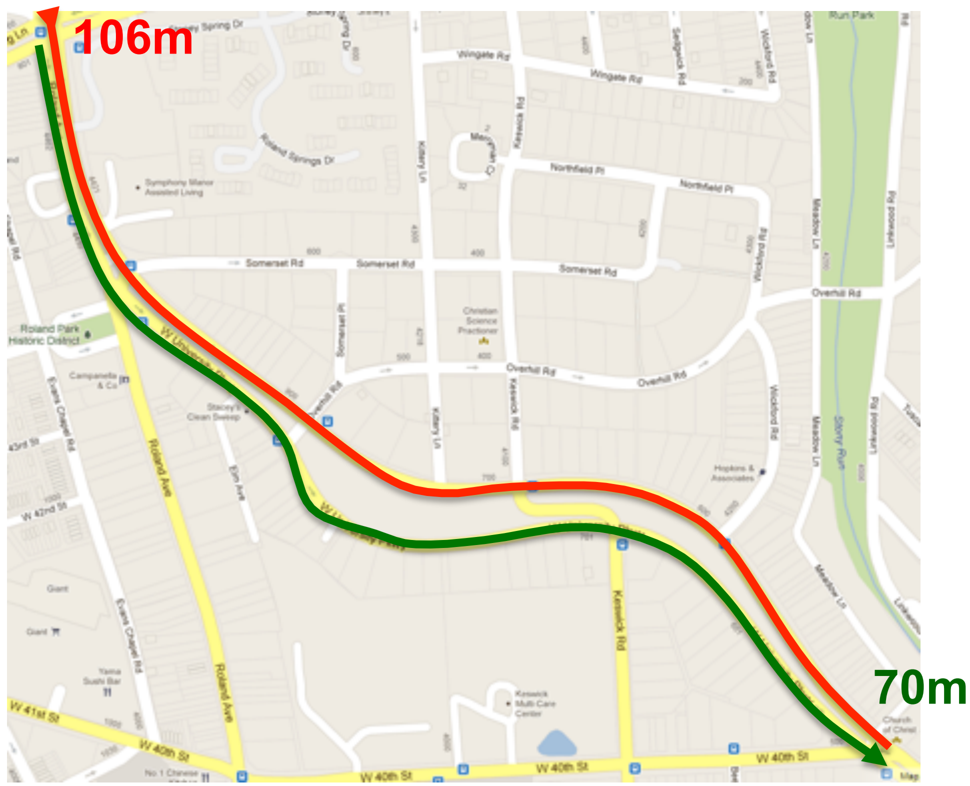
Flat route: Druid Lake



CAD: cadence sensing
TAB: search table
+F: fitting
+S: smoothing
+W: weather information, temperature and wind velocity

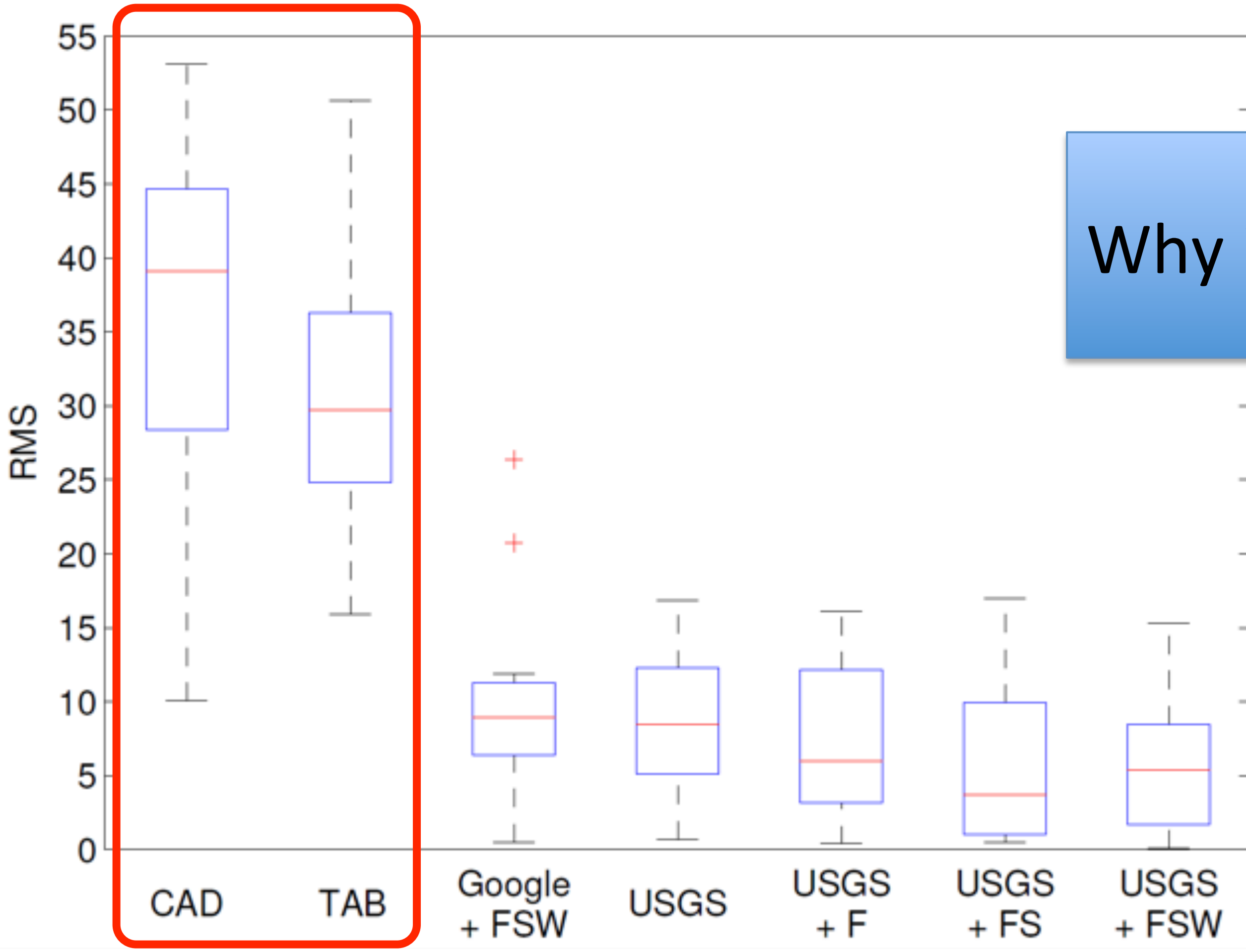
- 2.5
- Col

Route: Roland 1 & 6



- 1.8 km, cross neighborhood
- Uphill and downhill path

Route: Roland 1, uphill

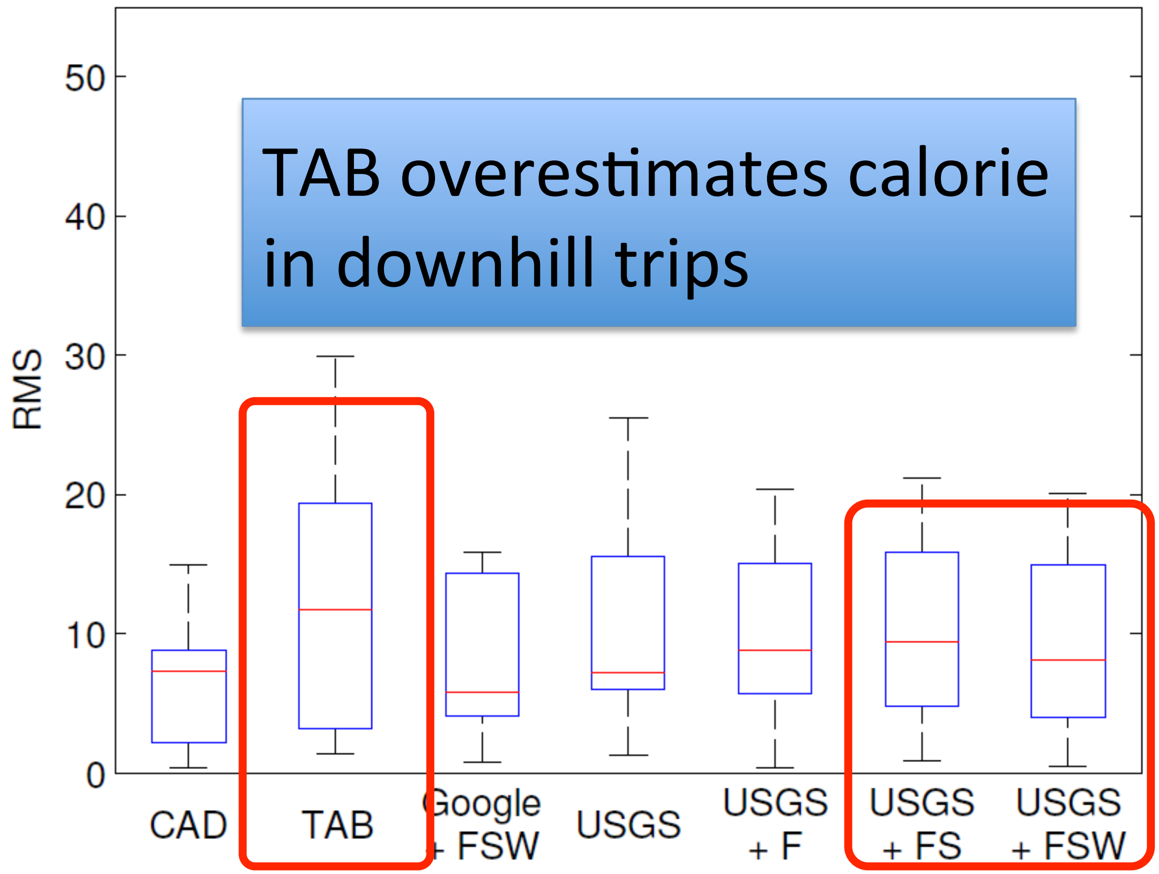


Why is that?

Both CAD and TAB fail to provide an accurate caloric expenditure estimation for uphill trips

Evaluation

Route: Roland 6, downhill



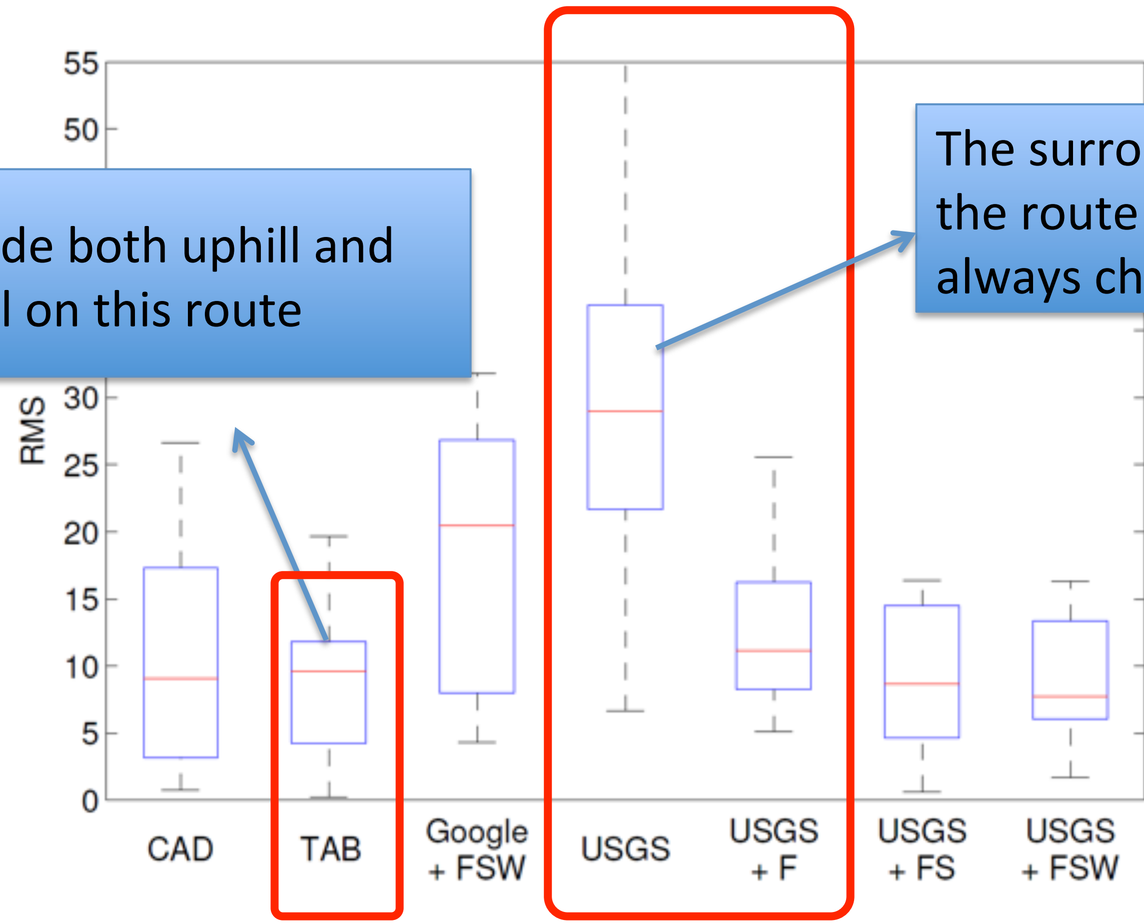
USGS+FSW adapt to both uphill and downhill trips

Route: St. Martin Dr.

- A winding road along with a river valley
- The elevation difference between two sides of the road can be 10 meters
- 11 trips across 8 bikers

Evaluation

Route: St. Martin Dr.



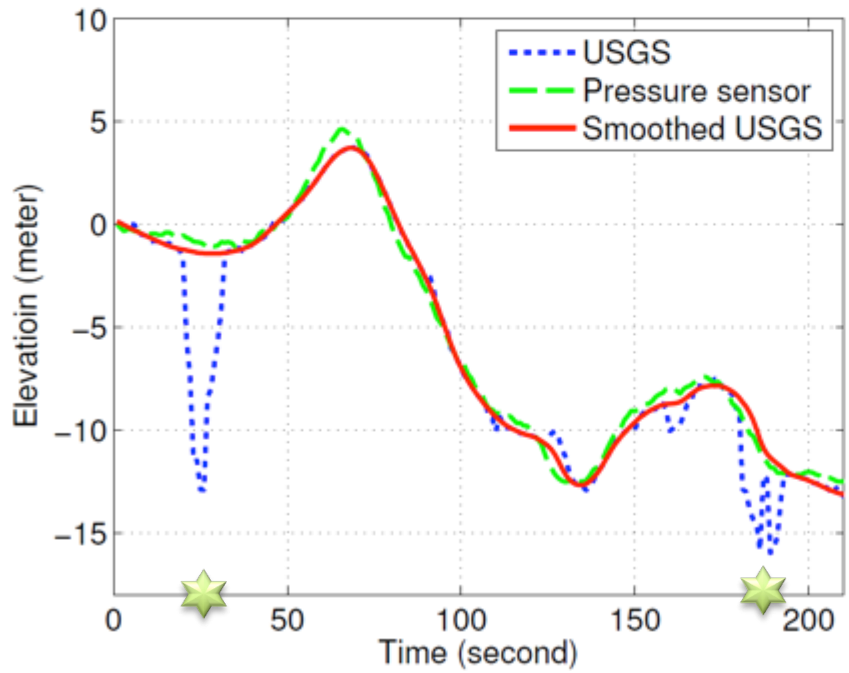
Bikers ride both uphill and downhill on this route

The surrounding terrain of the route is complicated and always changing

Fitting method eliminates most of the errors in this situation

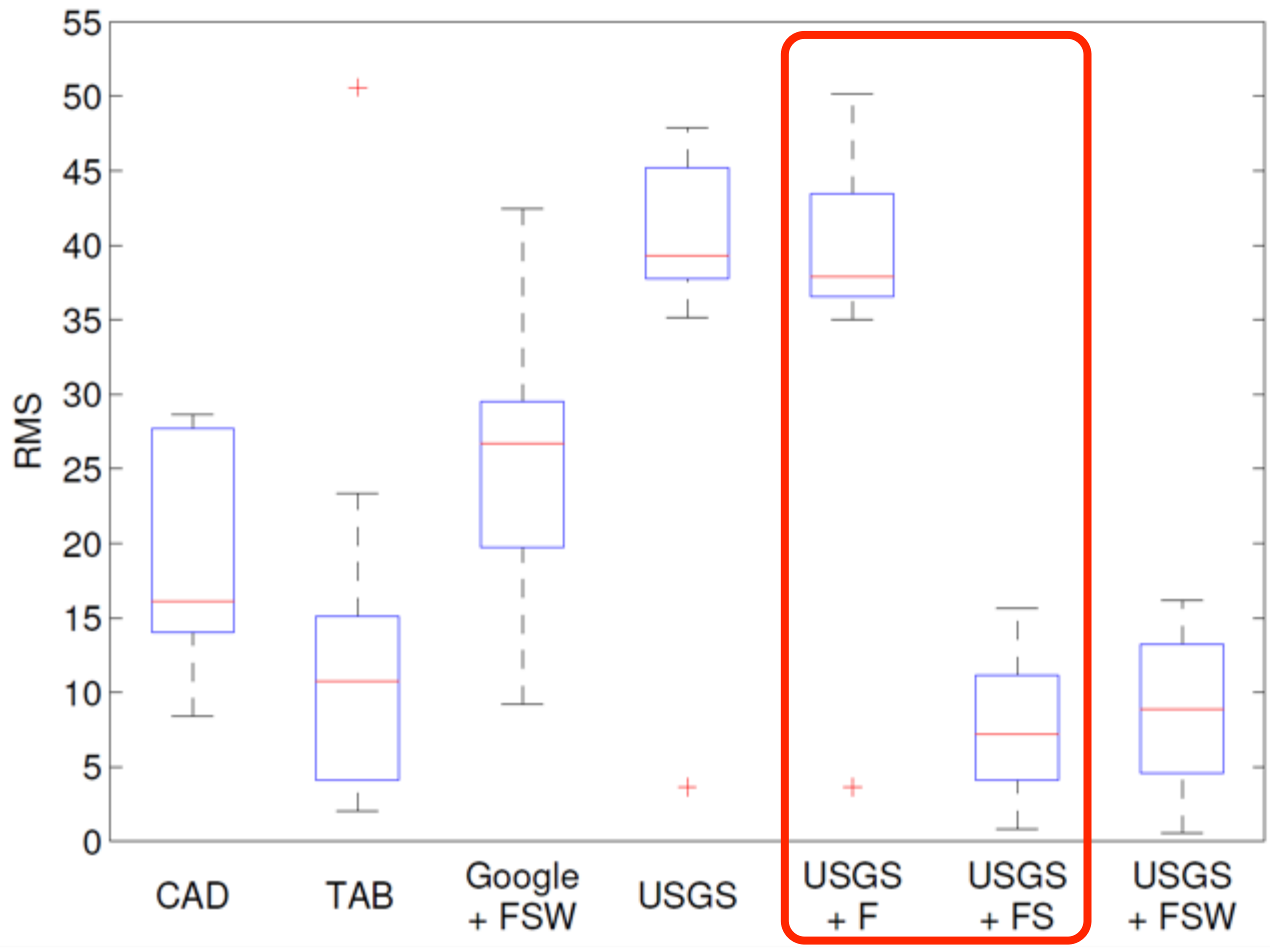
Evaluation

Route: Wyman Park



- Cross two bridges: 140, and 67 meters long

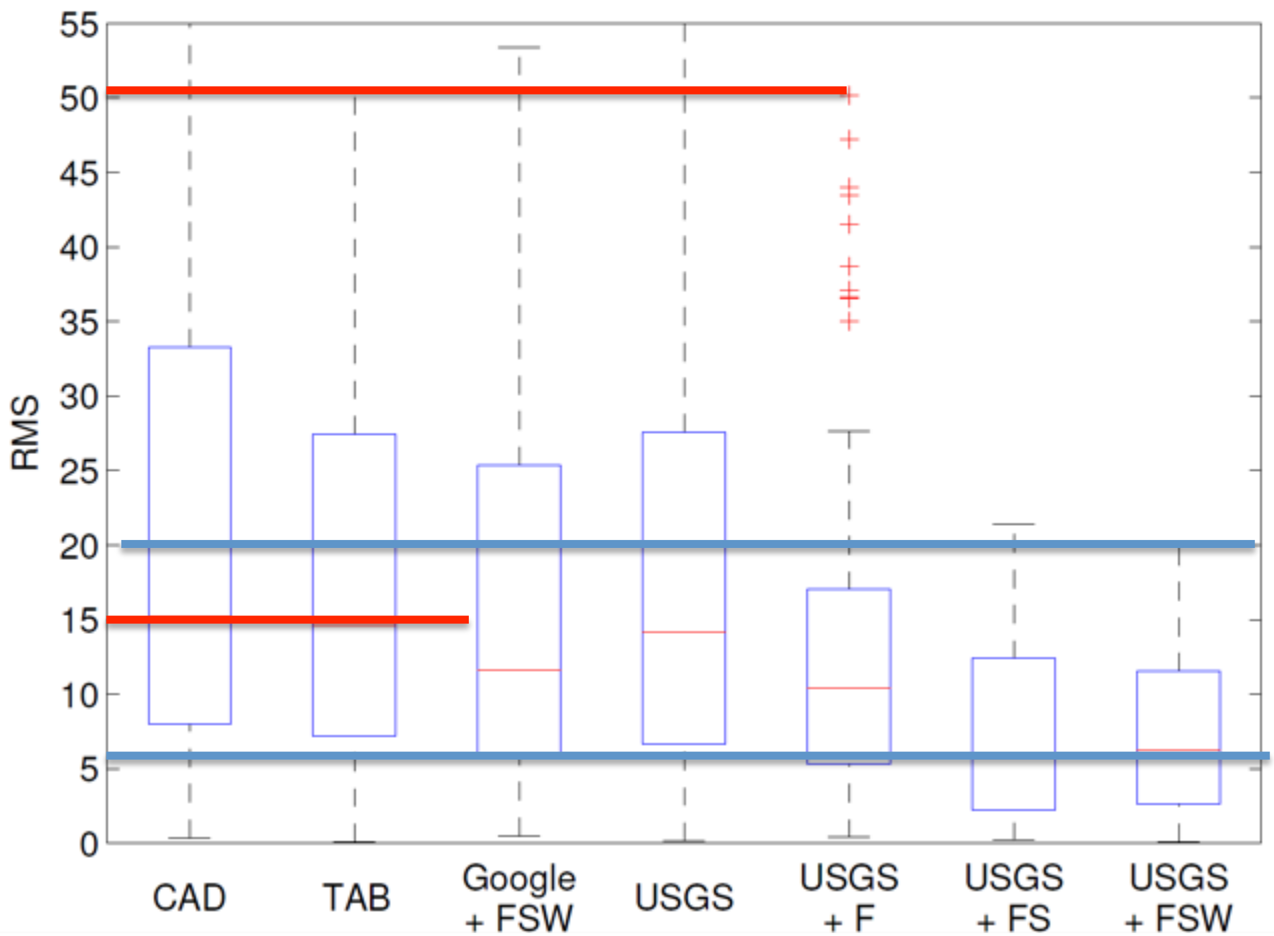
Route: Wyman Park



Smoothing corrects “bridge errors” without adding new errors

Evaluation

Overall – 70 Trips



USGS+FSW achieves the lowest error with lowest variance

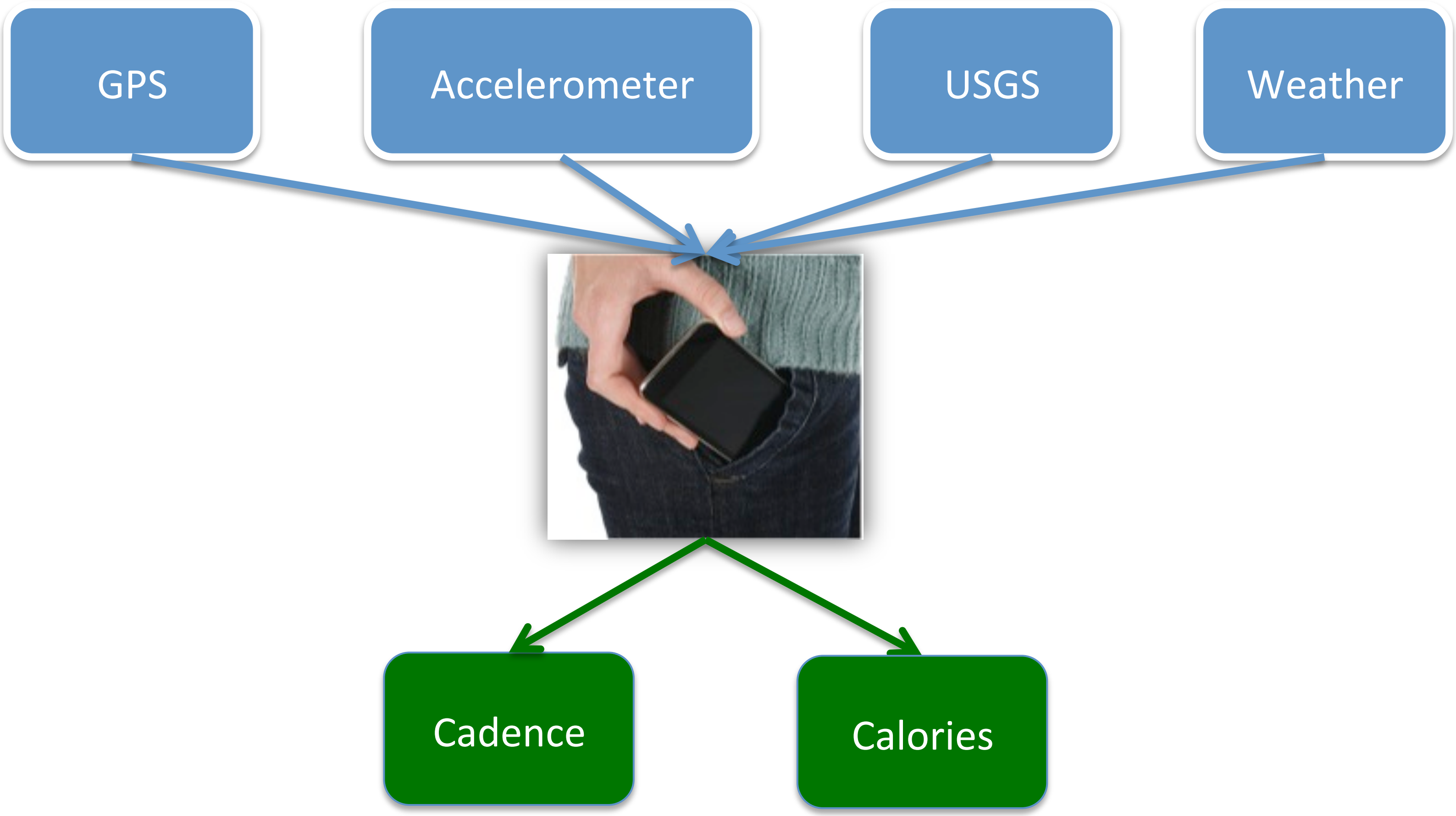
Reducing GPS Power Consumption

- Duty-cycling the GPS receiver (do not sample GPS signal that often)

Sampling Interval (s)	Interpolation (RMS)	EnAcq* (RMS)	Power (%)
0	28.6	28.6	100
5	31.6	28.5	100
10	34.7	27.8	100
15	36.7	30.5	83
20	42.6	29.8	65
25	55.0	31.1	54
30	72.1	34.4	43

*Fang et. al., EnAcq: *energy-efficient GPS trajectory data acquisition based on improved map matching*. In *Proc. of GIS '11, 2011*

Pocket Sensing Approach



Limitations and Future Work

- **Current system is designed for offline data analysis**
  - Implement a real-time bicycling calorie calculation application
- **A calibration phase is needed to learn those coefficients used in the model**
  - Develop an auto-calibration module to estimate model coefficients based on user's height, weight, bike model, etc.
- **Limited discussions on energy and privacy issues**
  - Design a more energy-efficient and privacy-aware system, which enables longer battery life and more privacy protection

Conclusion

- Just using a smartphone provides comparable accuracy to the best methods that uses external sensors
- This work immediately gives millions of bikers a zero-cost solution towards significantly improved biking experiences
- The shift from physical to *virtual* or *software* sensors will find other applications in quantifying daily lives and activities

Q&A