An Energy-Aware Method for the Joint Recognition of Activities and Gestures Using Wearable Sensors

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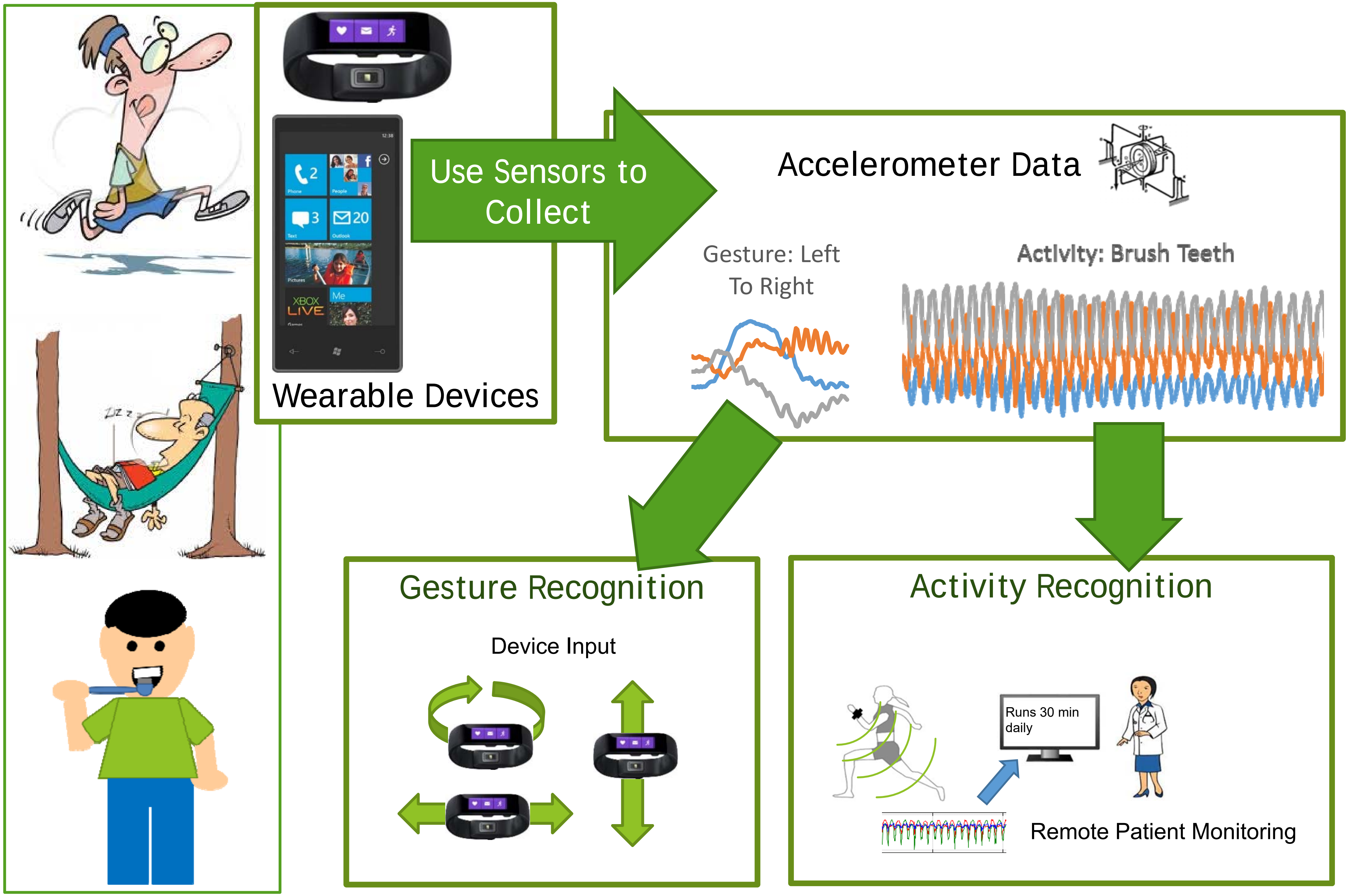
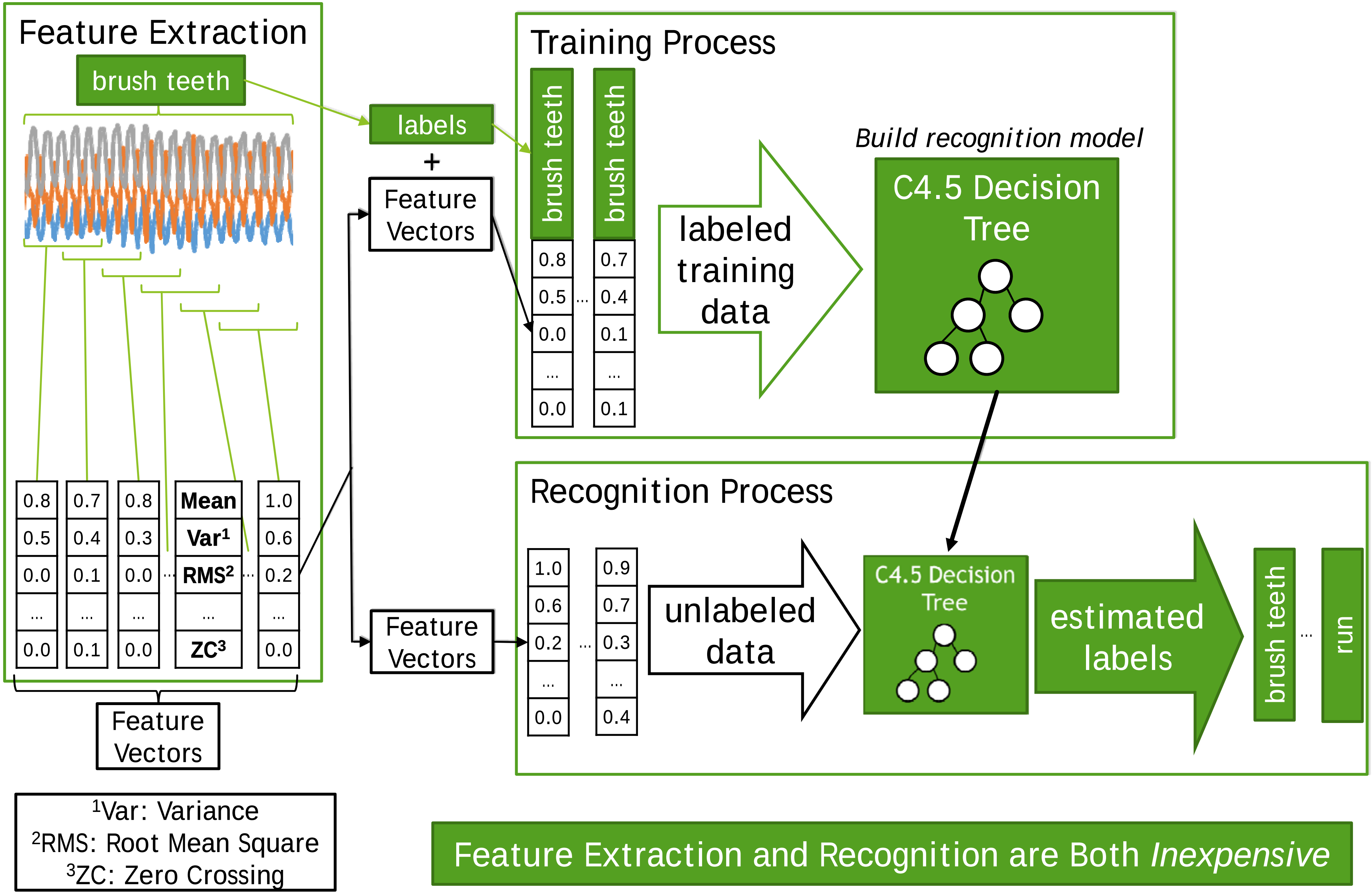
Activity/Gesture Recognition

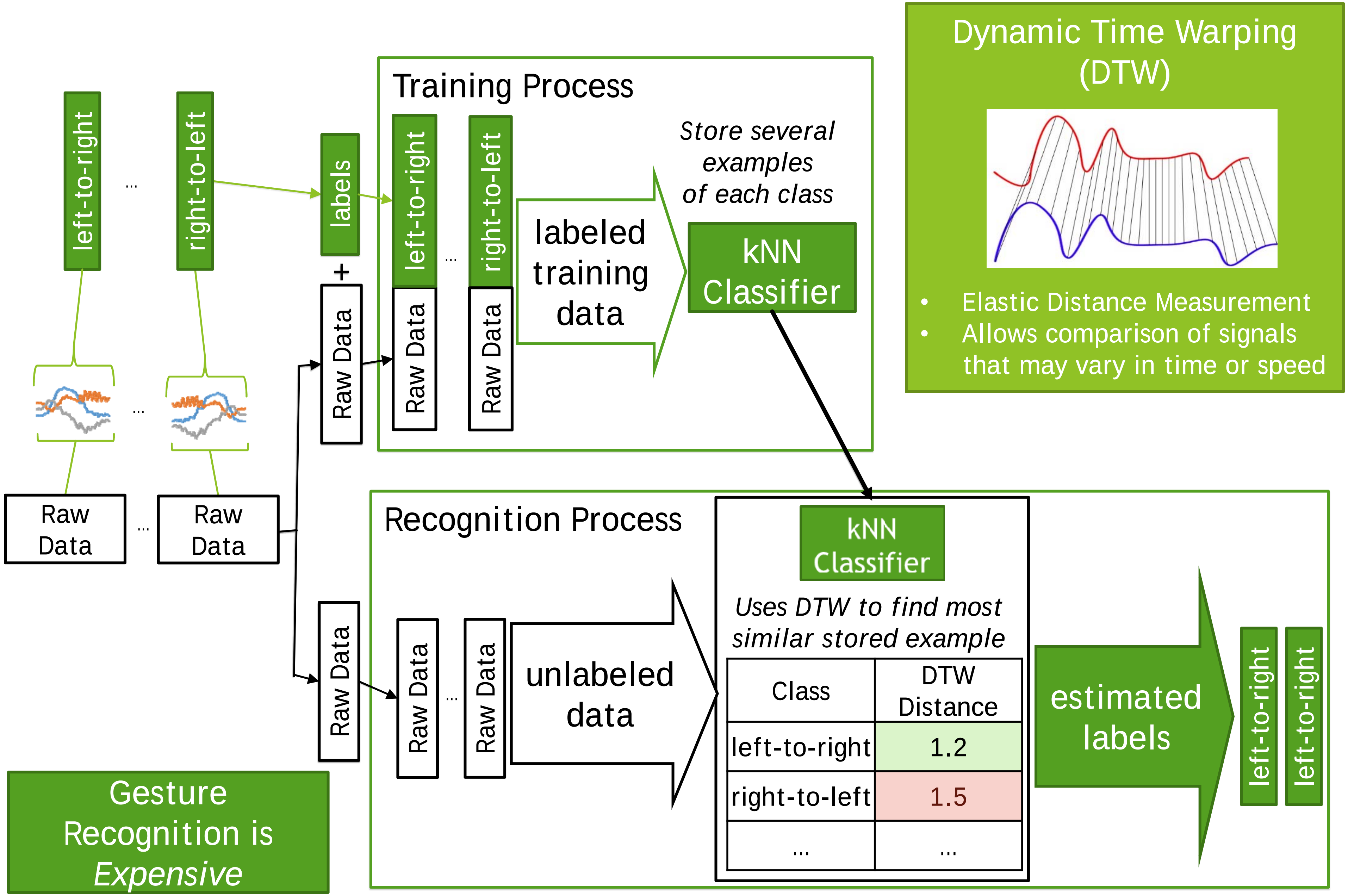


Activity Recognition



Feature Extraction and Recognition are Both *Inexpensive*

Gesture Recognition



Energy-Aware Recognition

- Energy-Aware Activity Recognition
  - Reducing sampling rates of sensors/shutting down sensors
  - Assumes many consecutive data segments of same activity

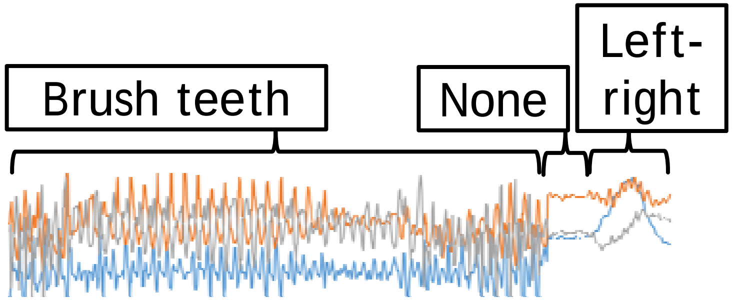
if recognition_result == “run”:
sleep(3)

- Energy-Aware Gesture Recognition
  - Assumes most data segments don’t have target actions

ax, ay, az = sample_accelerometer()
if $\sqrt{ax^2 + ay^2 + az^2} - G$ > 0.15G:
gx, gy, gz = sample_gyroscope()
if $\sqrt{gx^2 + gy^2 + gz^2}$ > 25:
transmit_data()[1]

Previous research has focused on activity recognition or gesture recognition, not both

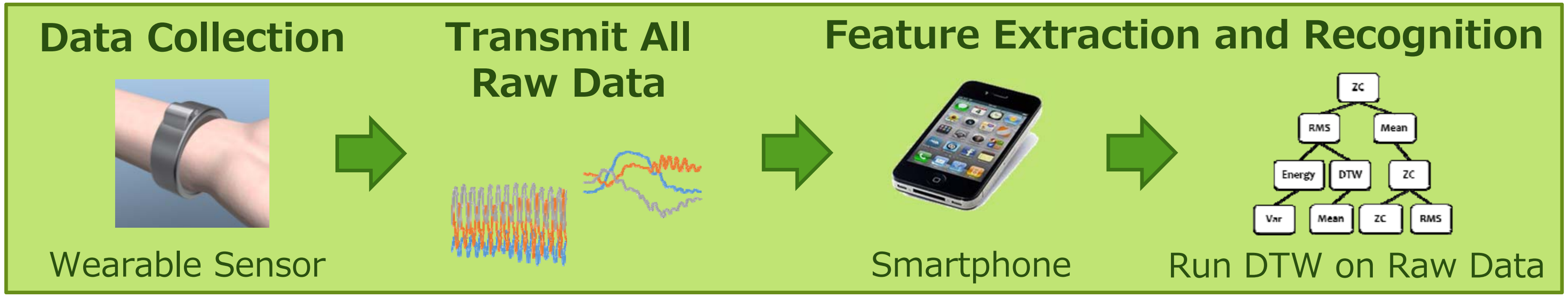
- Our research: joint recognition of activities and gestures
  - Must recognize all data segments



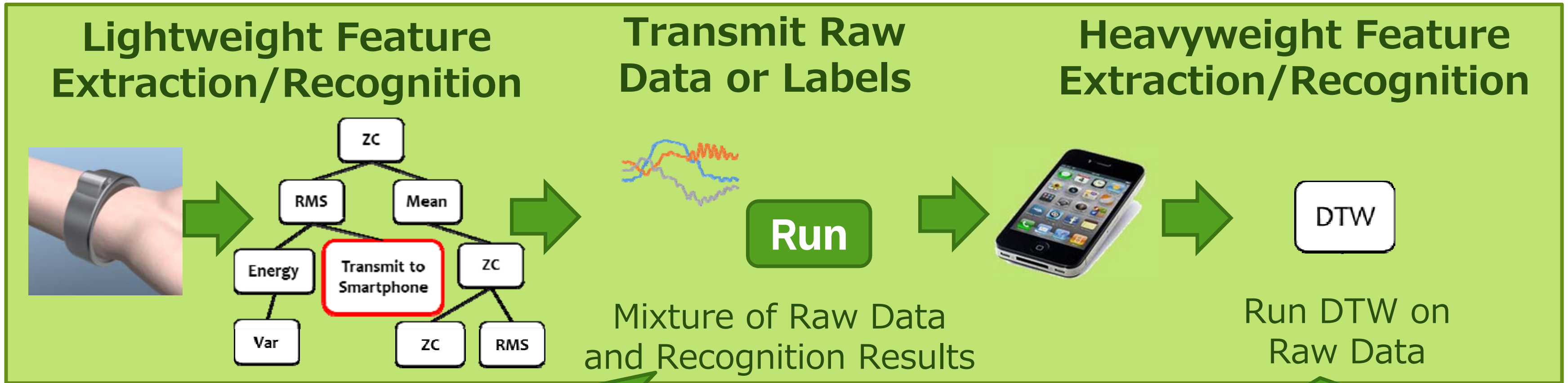
1. Park, T., Lee, J., Hwang, I., Yoo, C., Nachman, L., and Song, J. E-gesture: a collaborative architecture for energy-efficient gesture recognition with hand-worn sensor and mobile devices. In SenSys 2011 (2011), 260–273.

Research Goal

- Naïve approach



- Proposed approach

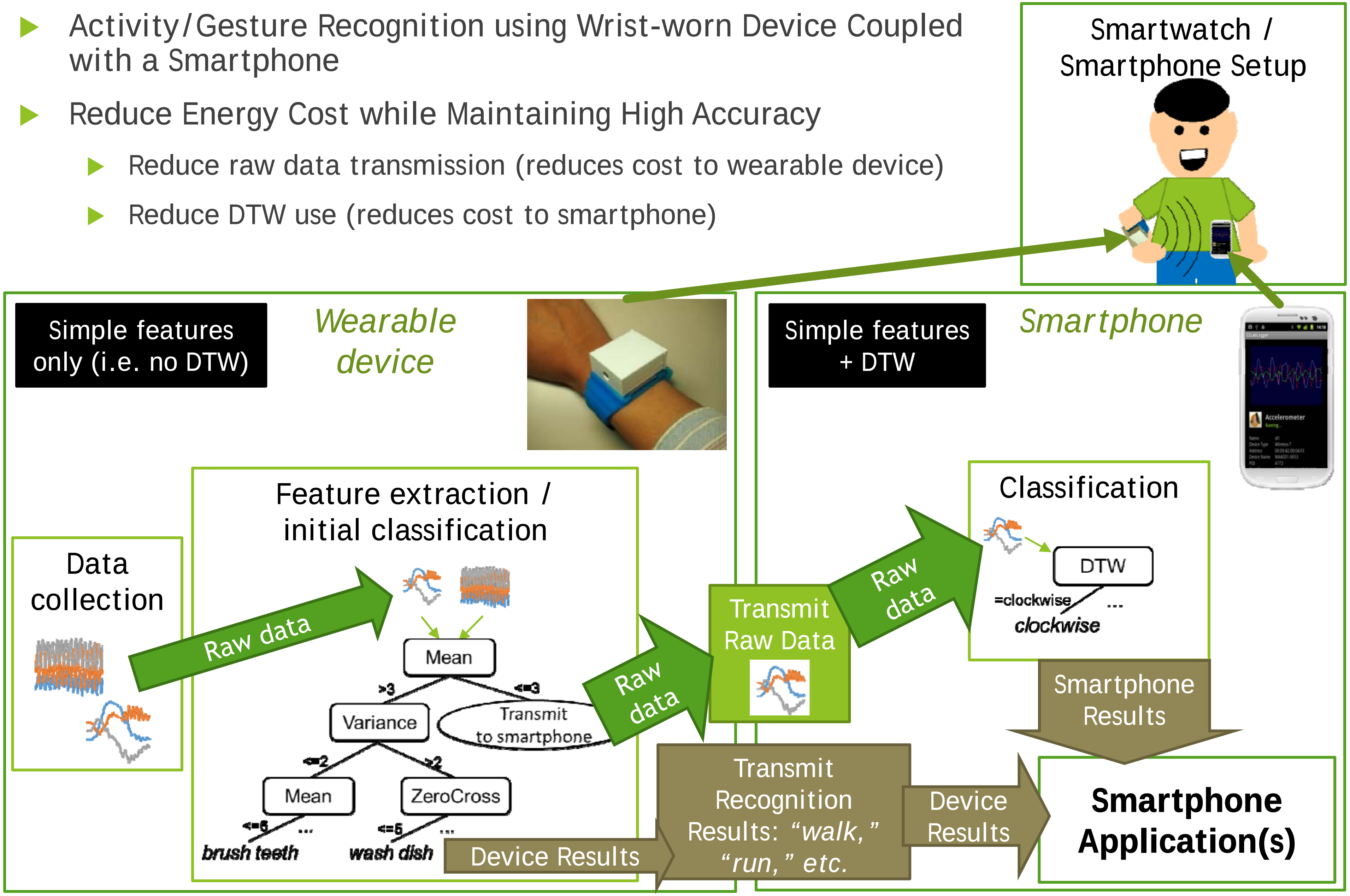


Using an adaptive pipeline:

1) Feature extraction/raw data transmission based on input data segment
2) Pipeline constructed automatically using the training data

Method Overview

- Activity/Gesture Recognition using Wrist-worn Device Coupled with a Smartphone
- Reduce Energy Cost while Maintaining High Accuracy
  - Reduce raw data transmission (reduces cost to wearable device)
  - Reduce DTW use (reduces cost to smartphone)



Energy Costs

[1]Calculated using wearable device built for this study
[2]Calculated using Google Nexus 5 smartphone

Feature Extraction		
	Cost (mJ)	
	Device[1]	Smartphone[2]
Mean	0.000329	0.000359
Var	0.000575	0.001034
ZC	0.000530	0.000291
RMS	0.000497	0.000312
Energy	0.001951	0.006345
DTW-12.5*		0.101000
DTW-25*		0.276000
DTW-50*		0.823000
DTW-100*		2.940000

mJ: milliJoules
Var: variance
ZC: Zero crossing
RMS: Root mean square
Energy: FFT-based energy
DTW: Dynamic time warping

Data Transmission		
	Cost (mJ)	
	Device[1]	Smartphone[2]
Label	0.109	8.485
Data-12.5*	0.148	8.564
Data-25*	0.186	8.642
Data-50*	0.264	8.8
Data-100*	0.418	9.115

Label: Transmit recognition results only
Data: Transmit raw data

*Refers to % of raw data used, with reduced data sizes
attained by averaging adjacent data points in the data stream

Tree Structured Classifier

- Two types of nodes
  - **Simple features** (activity recognition)
  - **DTW** (gesture recognition)
- Generating trees with C4.5 algorithm
  - Constructed to maximize accuracy
  - More useful features at shallower nodes
  - Fig. 1: In our case: More useful = DTW
- Only extract features on the path used in the tree
  - Fig. 2: Not very useful if all paths have DTW
  - Fig. 3: ZC-X → Mean-Y → RMS-Z/Var-X no longer require DTW

Need to find a tree that gives a good balance of cost to accuracy

Fig. 1: C4.5 Tree

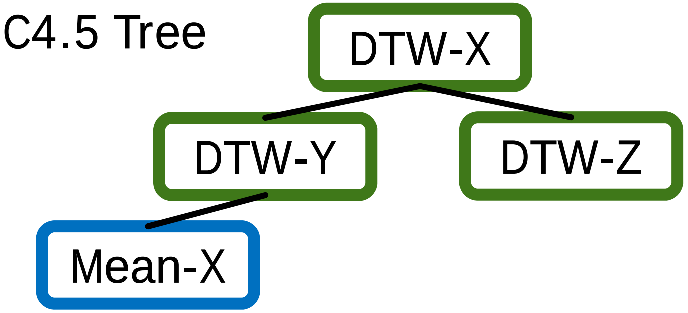


Fig. 2: High Cost / High Accuracy

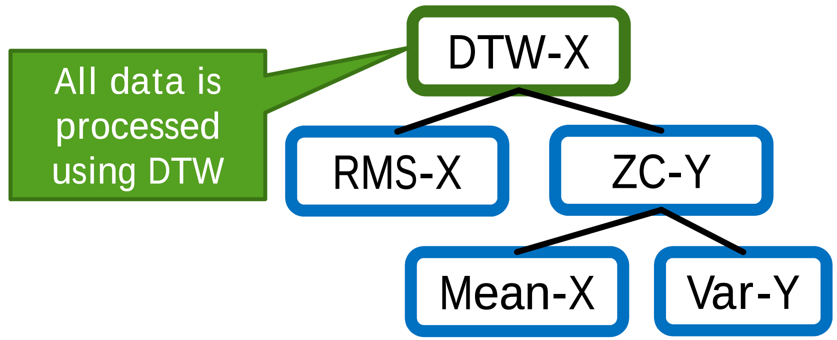
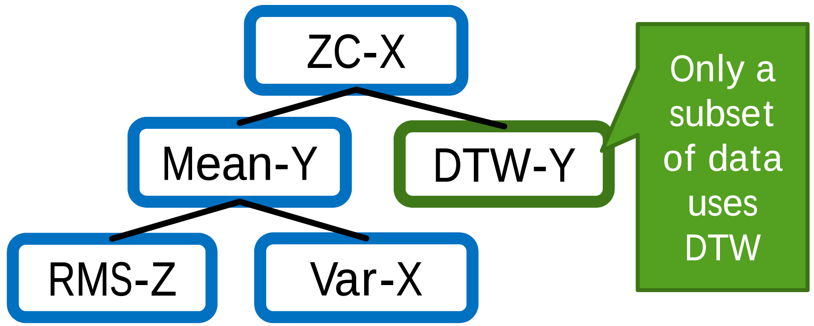
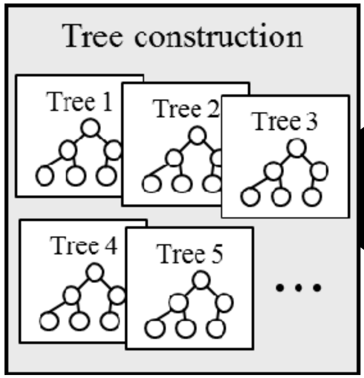


Fig. 3: Reduced cost

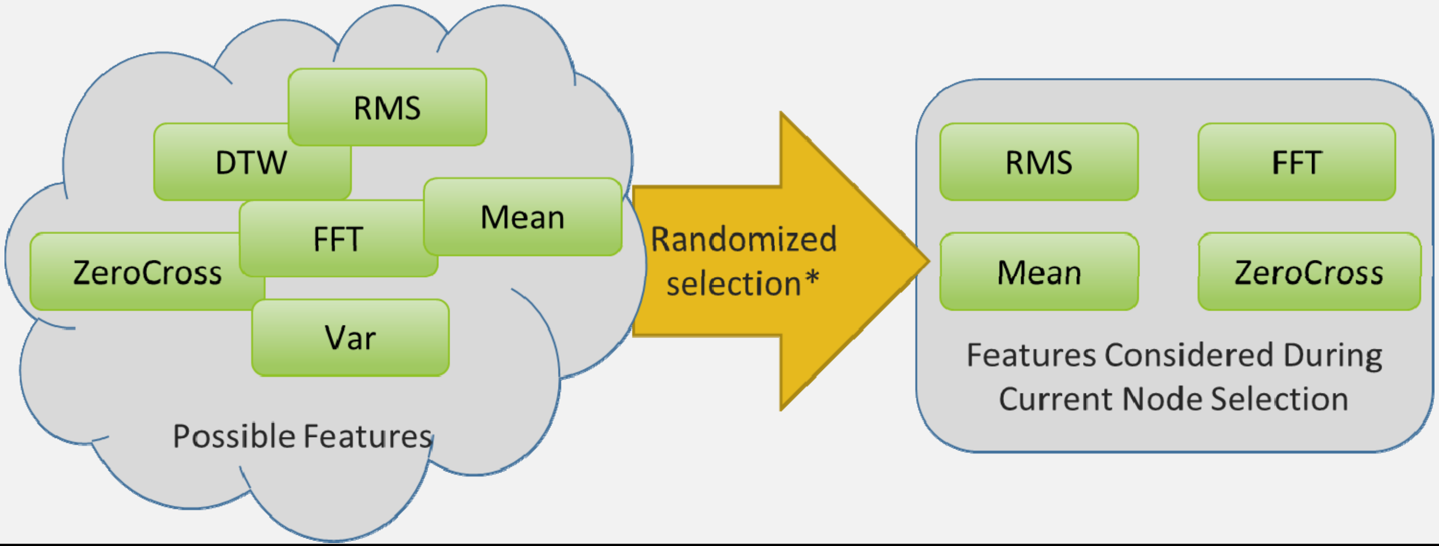


Generating Energy Aware Trees

- Use an approach based on random forests algorithm
- Step 1. Generate several trees
  - Varying balances of cost to accuracy

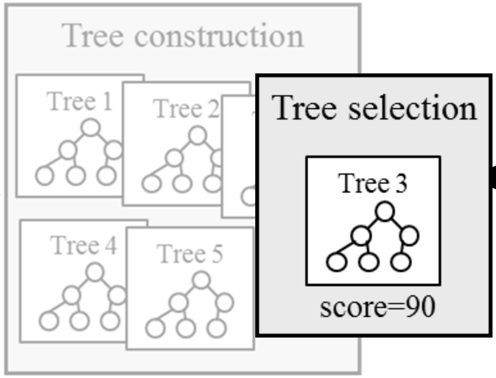


- Random forests algorithm
  - Builds a forest of decision tree classifiers
  - Induces variation in trees by creating each node in a tree using only a subset of the possible features
- Our version
  - Modify the randomized selection*
    - Bias the probability of selection for each feature based on its energy cost



Choosing an Optimal Tree

- Step 2. Pick a single tree with a good balance of cost to accuracy



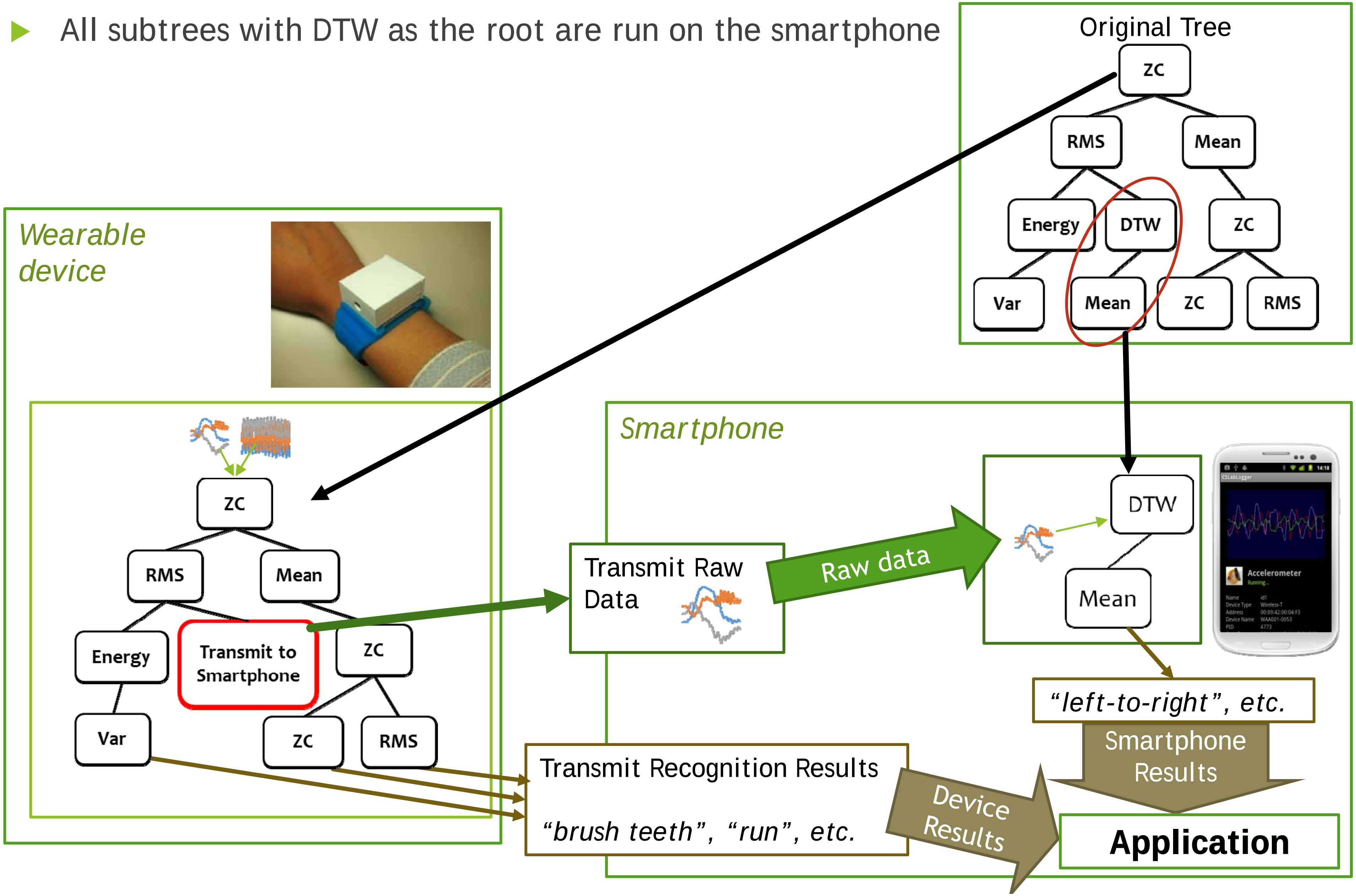
- Cost criteria
  - Estimate the cost of each tree based on training data
  - Set a cost threshold
- Accuracy criteria
  - Can't directly measure accuracy using training data
  - Choose smallest tree (below cost threshold)
    - Found a strong negative correlation between size and accuracy in tests done early in our study
    - Other research has suggested smaller trees are less likely to overfit the training data (Quinlan 1996[1])

Optimal Tree = Smallest tree with cost below our threshold

[1]Quinlan, J. Improved use of continuous attributes in c4.5. J. Artif. Intell. Res. 4 (1996), 77–90.

Partitioning the Tree Across Devices

- All subtrees with DTW as the root are run on the smartphone



Evaluation Methodology

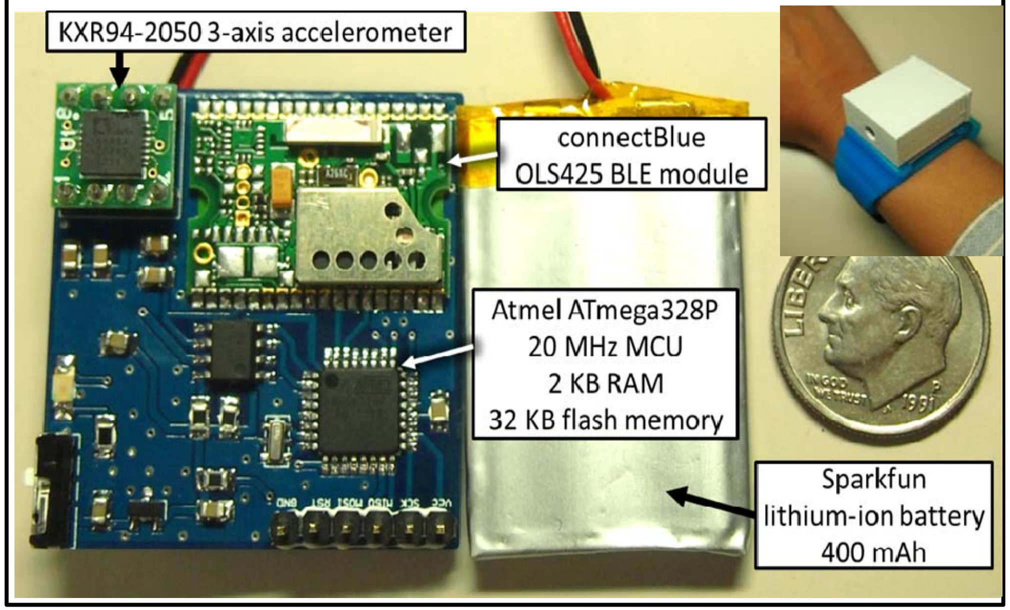
- 50 sessions of data
  - 5 Participants each performing 10 sessions
  - Each session contains each of the activities/gestures in Table 1
  - Leave-one-session-out cross-validation
- Accuracy calculated using:
  - Macro-averaged F-measure
- Costs calculated using:
  - Google Nexus 5 smartphone (Fig. 1)
  - Wearable device (Fig. 2)

Table 1: Activities/gestures used in this study

Activity	Gesture
Run	Left to Right
Draw on Whiteboard	Right to Left
Wash Dishes	Clockwise
Write in Notebook	Counter-Clockwise
Brush Teeth	Down to Up
None	

Fig. 1: Google Nexus 5

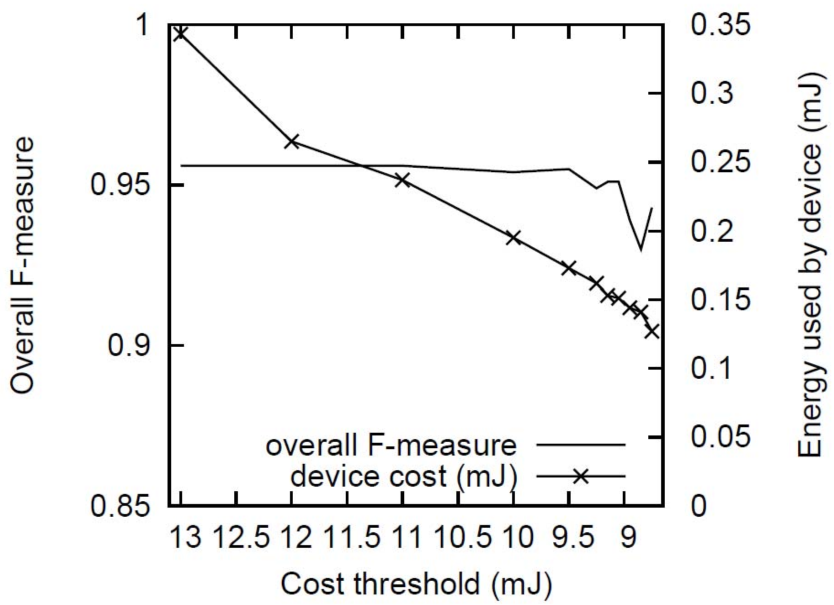
Fig. 2: Wearable device used in this study



Methods

- Baseline Methods:
  - ACT – C4.5 Decision Tree using activity recognition features (no DTW)
    - Represents a classifier specialized to activity recognition
  - DTW – DTW-based kNN classifier (no C4.5 tree/no activity recognition features)
    - Represents a classifier specialized to gesture recognition
  - Tree – C4.5 decision tree that combines activity recognition features with DTW-based kNN classifiers
    - Represents a classifier specialized to high accuracy joint recognition (not energy aware)
- Proposed Method:
  - Decision tree created using our random forests algorithm approach that combines activity recognition features with DTW-based kNN classifiers
  - Proposed (threshold): Refers to the proposed method using the given threshold

Overall Results



Transition in the accuracy and cost for the wearable device when the cost threshold is varied for the proposed method.

Cost and accuracy for each method

	cost (mJ)		avg. F-Measure		
Method (Threshold)	device	smartphone	overall	activities	gestures
ACT	0.119	8.485	0.914	0.949	0.845
DTW	0.418	17.935	0.935	0.935	0.934
Tree	0.345	11.168	0.956	0.974	0.936
Proposed (11 mJ)	0.237	9.741	0.956	0.969	0.941
Proposed (9.05 mJ)	0.151	8.768	0.951	0.969	0.929
Proposed (8.75 mJ)	0.127	8.575	0.943	0.964	0.918

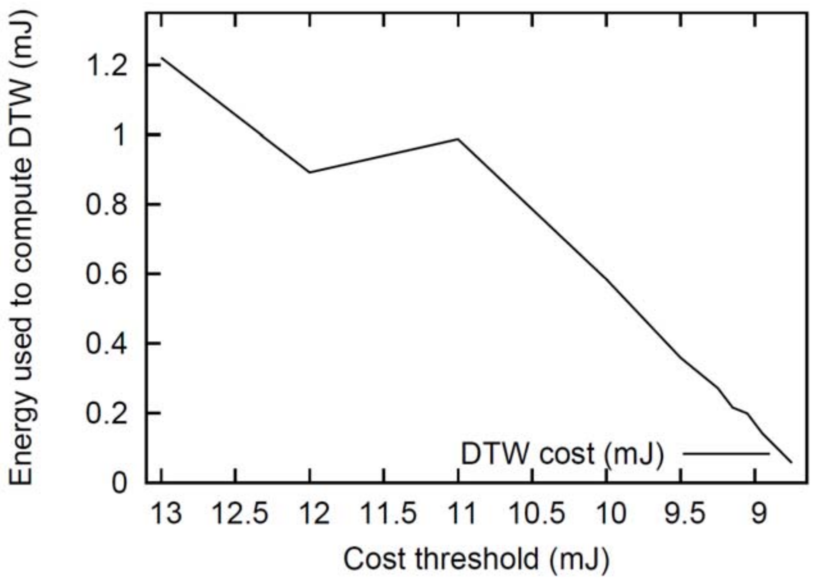
ACT: Activity recognition features / No DTW

DTW: DTW / No activity recognition features

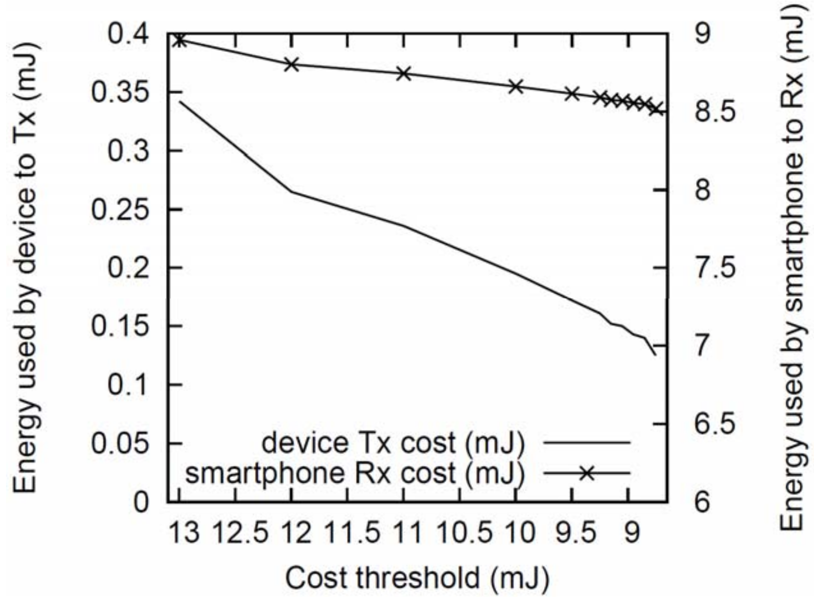
Tree: Activity recognition features and DTW / Not energy aware

Proposed (threshold): Proposed method (with cost threshold used)

Reductions in Energy Use



Transition in the energy consumed to compute DTW when the cost threshold is varied for the proposed method.

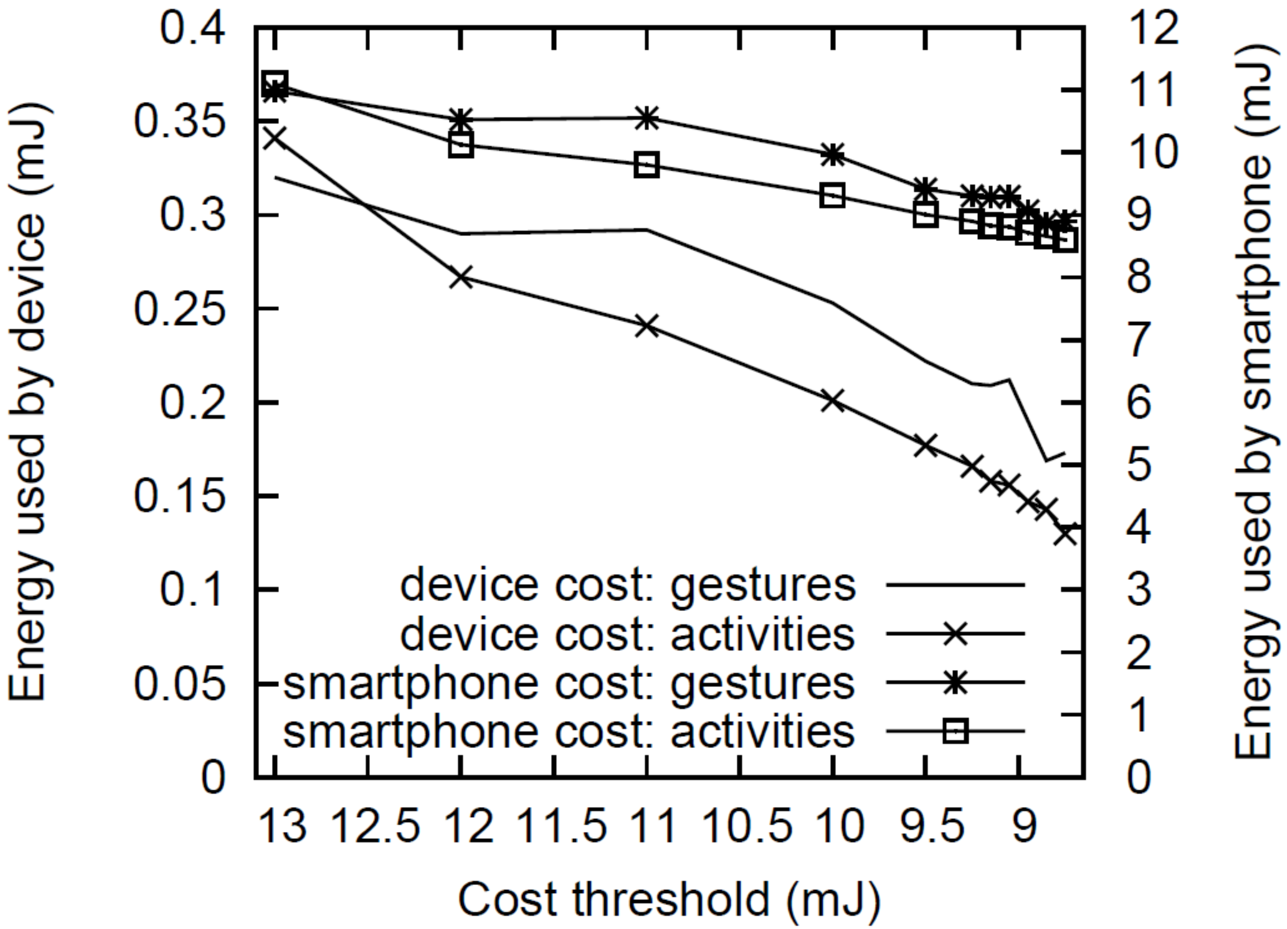


Transition in the energy consumed to transmit and receive data when the cost threshold is varied for the proposed method.

Battery life estimates are based on continuous recognition with no other processes run on either device

	Estimated Battery Life (days)	
	Device	Nexus 5
ACT	17.0	9.1
Tree	15.1	8.0
DTW	14.6	6.2
Proposed (8.75 mJ)	16.9	9.0

Energy Use for Activities vs. Gestures



Average energy used by wearable device and smartphone for recognizing activities and gestures when the cost threshold is varied for the proposed method.

Conclusions

Energy Aware Framework for Recognizing Activities and Gestures

- Combines features commonly used in activity recognition with DTW-based kNN classifiers
- Performs lightweight feature extraction and recognition on wearable device
- Reduces energy used for raw data transmission
- Reduces energy used to run DTW