Analyzing Features for Activity Recognition

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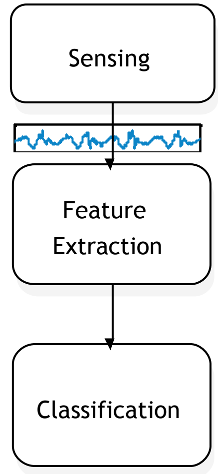
Activity Recognition using Wearable Sensors

- Basic Activities (Movements)
  - Walking, Standing, Sitting, Jogging, etc.
  - Clearly defined by motion of body parts
  - Well-suited for recognition with acceleration sensors



Steps in Recognition

- Sensing
  - Conversion from physical inputs to signal data
  - e.g. human motion to acceleration signal
- Feature Extraction
  - Measuring of signal properties useful for classification
  - e.g. mean, variance
- Classification
  - Assignment of the sensed data to a category
  - e.g. "Walking"



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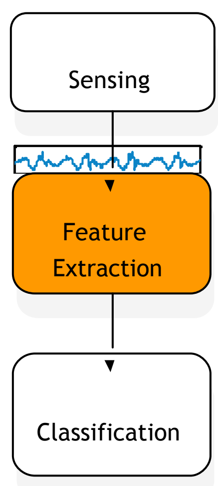
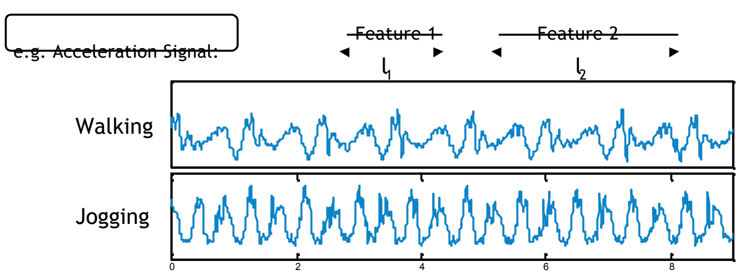


Outline

- Motivation
  - Choosing Features and Window Lenghts
- Experimental Setup
  - Hardware
  - Data Set
- Evaluation
  - Features
  - Windows
- Summary & Outlook

Motivation

- Features for Recognition – a common approach:
  - For all activities:
  - ... take a fixed set of features and
  - ... compute them on fixed window lengths



Motivation

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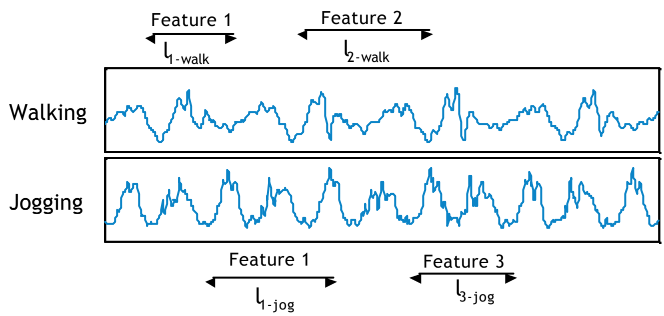
- Can we do better if we select features and window lengths separately for each activity?



Hardware & Data Set

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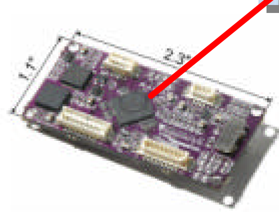
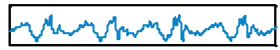
- Recordings by Intel Research, Seattle
  - Integrated sensor board attached to shoulder
    - Sensors for 3D-acceleration, audio, IR/visible light, temperature, compass, barometric pressure, humidity
  - 200 min of Basic Activities
    - Walking, standing, jogging, skipping, hopping, sitting (in a bus)



Features

- One-dimensional features computed over acceleration signal



  - Mean [e.g. Ravi05, Intille04, Kern03]
  - Variance [e.g. Ravi05, Heinz03, Kern03]
  - Energy [e.g. Ravi05, Intille04]
  - Spectral Entropy [e.g. Intille04]
  - Pairwise correlation b/w axes [e.g. Ravi05, Intille04]
  - FFT coefficients [e.g. Intille04]
- Each feature computed over five different window lengths
  - 0.25, 0.5, 1.0, 2.0 and 4.0 seconds

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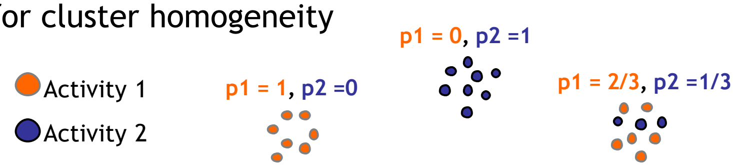
Data Analysis

- Goal
  - For each activity, analyze combinations of
    - Feature
    - Window length
  - Evaluate relative recognition performance
- Approach: Cluster Analysis
  - Cluster Precision as an indicator for relative recognition performance

Cluster Analysis

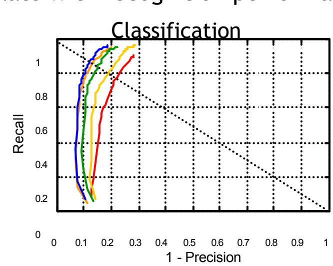
- Judge quality of a (feature, window length) combination by looking at how well it clusters activities
- K-means clustering in feature space
- For each cluster, compute precision *p* as indicator for cluster homogeneity



- Overall precision *p* for an activity = weighted average over precision for individual clusters
  - p(activity) <= 1; 1 is best

Cluster Precision vs. Recognition

- Is cluster precision an indicator for recognition performance?
  - Comparison of cluster precision to results of a simple classifier
    - Nearest cluster centroid
    - Variation of distance threshold to obtain ROC curves
  - Cluster precision seems to correlate with recognition performance:



- Activity: walking
- Feature: variance of acceleration
- Window sizes: 0.25, 0.5, 1.0, 2.0 and 4.0 seconds

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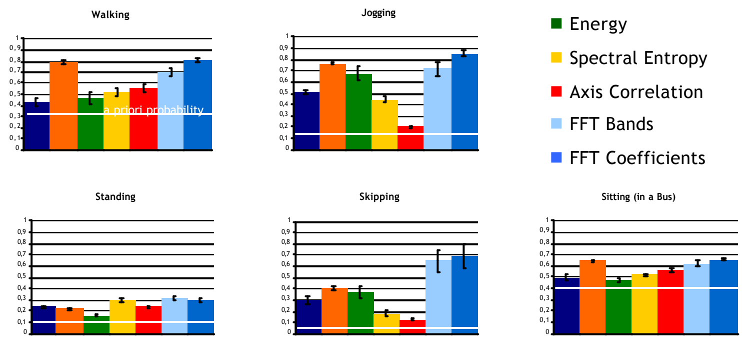
Results - Features

- Cluster Precisions of five activities:



- Mean
- Variance
- Energy
- Spectral Entropy
- Axis Correlation
- FFT Bands
- FFT Coefficients

- No single ‚best' feature for all activities
- FFT features and Variance do consistently well

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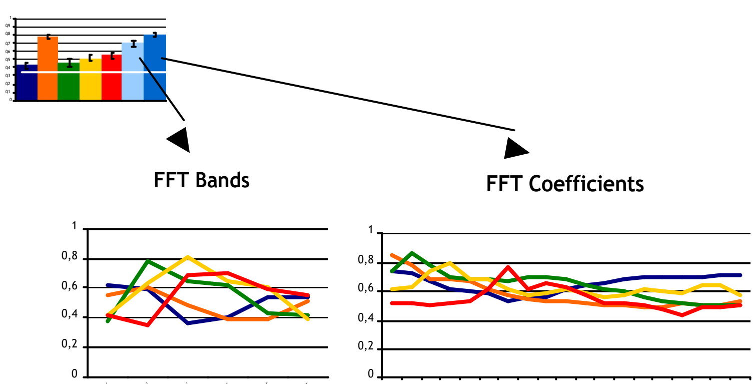
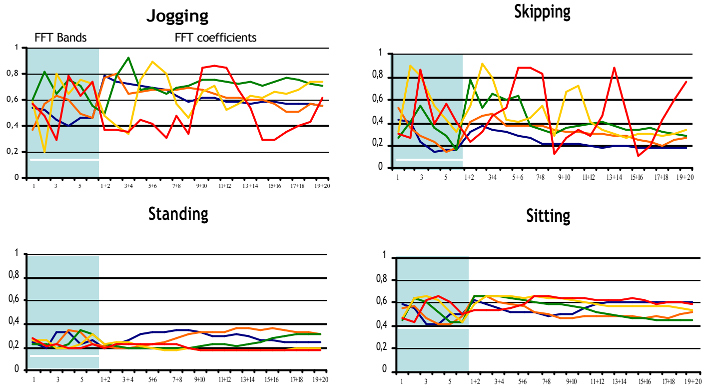
Results - FFT Features

- Walking: Cluster Precisions for different window lengths of FFT features



■ 0.25 ■ 0.5 ■ 1.0 ■ 2.0 ■ 4.0 seconds

Results - FFT Features



Window lenghts:
- 0.25,
- 0.5,
- 1.0,
- 2.0,
- 4.0 seconds

- Clear differences b/w high- and low-intensity activities
- Crucial which coefficient/ window length is chosen

Results - Window Lengths

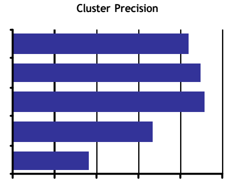
- No single best window length when looking at average

Window length: 0.25 0.5 1.0 2.0 4.0 seconds

- Significant gains in precision when choosing features and window length individually for each activity

Cluster Precision

Walking: (Variance/ 1 sec)
Jogging: (FFT coeff. 5+6/ 2 sec)
Skipping: (FFT coeff. 2+3/ 2 sec)
Sitting: (FFT band 3/ 2 sec)
Standing: (FFT coeff. 13+14/ 0.5 sec)



Summary

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- Analysis of single features/window lengths for basic activities
  - Cluster precision as indicator for recognition performance
- Results
  - Features
    - No single ‚best' feature for any activity
    - FFT features often perform well
      - But different coefficients for different activities
    - FFT bands might be compromise to individual coefficients
    - Variance does consistently well
    - Mean is less discriminant than variance
  - Window Lengths
    - No single ‚best' length for all activities
  - For best results, choose an individual (feature, window length) combination for each activity

Outlook

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- Current and future work
  - Extend approach to more activities
  - Use more sensors and a larger set of features
  - Apply more elaborate classifier scheme (SVM, AdaBoost, ..)

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Thanks

... Questions?

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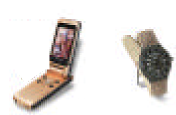
Activity Recognition using Wearable Sensors

- Context Awareness plays a central role in ubiquitous computing
- Activity is an integral part of a user's context
- Wearable Sensors are well-suited for recognizing basic activities
  - E.g. Walking, Standing, Sitting, etc.
  - Acceleration sensors are small enough to be integrated into phones, watches, clothes, etc.



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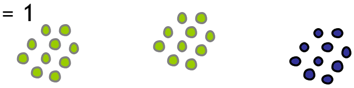
Cluster Analysis

- Judge quality of a (feature, window length) combination by looking at how well it clusters activities
- Calculate precision *p* as an indicator for how homogeneous the clusters are
  - Best case: p = 1



  - Worst case: *p* = a priori probability of activity

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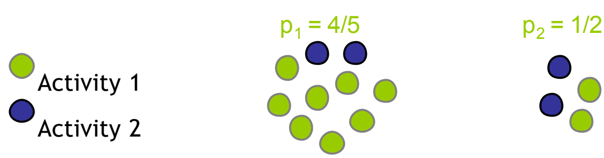
Cluster Precision

- Example: Cluster Precision of Activity 1



$$p = \frac{8 \cdot p_1 + 2 \cdot p_2}{8+2} \sim 3/4$$

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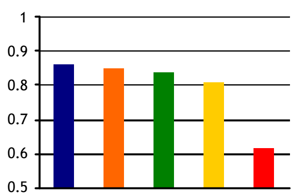
Cluster Precision vs. Recognition

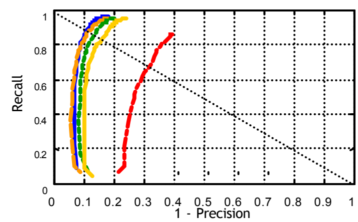
- Is cluster precision an indicator for recognition performance?
  - Example: Walking

(feature, window size):
- (acceleration FFT coeff. 2+3, 1.0 sec)
- (acceleration FFT coeff. 1+2, 0.5 sec)
- (acceleration variance, 1.0 sec)
- (acceleration FFT bands, 2.0 sec)
- (acceleration FFT coeff. 7+8, 2.0 sec)

Cluster Precision



Classification



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Results - Window Lengths