Automatic Recognition of Bodily Activities via Accelerometery with Emphasis on Proactive Healthcare

Adil Mehmood Khan

Advisor: Prof. Young-Koo Lee, Ph.D.
Co-advisor: Prof. Sungyoung Lee, Ph.D.

Department of Computer Engineering
Kyung Hee University
South Korea

Our Most Valuable Possession

- Health!

"When we have health, we have everything"

"Staying healthy requires maintaining a complete physical, mental and social well being, not just the absence of disease"

- Healthcare Infrastructure

Reactive Healthcare

- The healthcare we have today and the healthcare we could have lies a huge gap
- The biggest and the most important problem is the way it works

"99% of the healthcare is reactive*"

"Seeking care after illness"

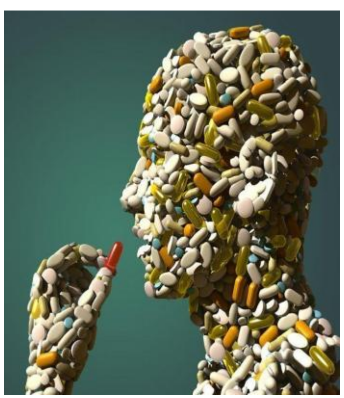
"emphasizes **Treatment**"

Journal of the American Medical Association, Protecting Health, Sept. 21, 2005

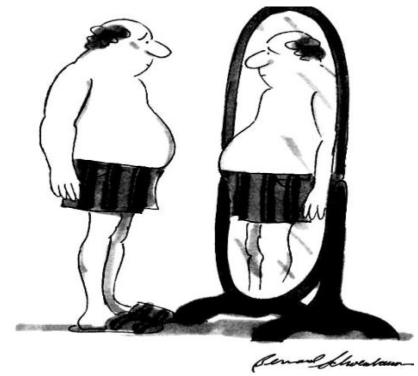
Reactive Healthcare: Problems

- High Cost

- Antibiotics



- Lifestyle diseases: Obesity



- Elderly

Proactive Healthcare

- Prevention

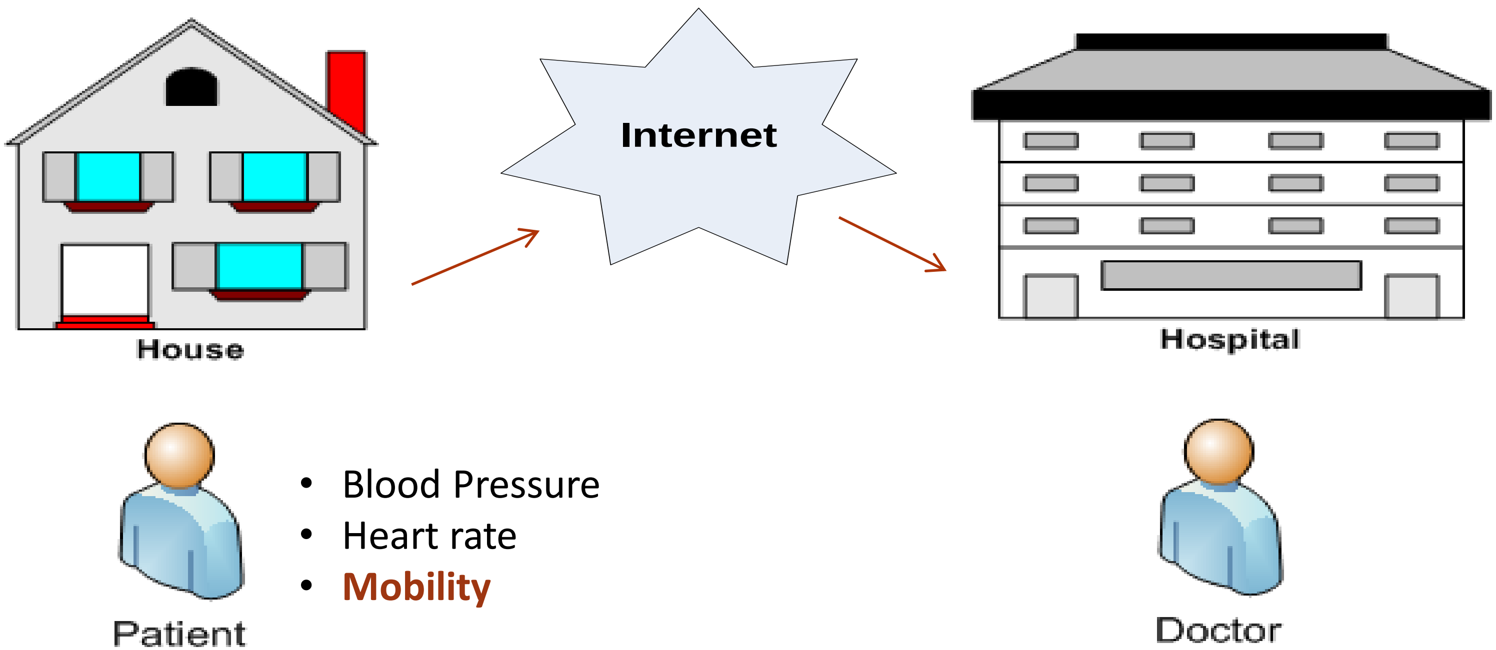
"Taking action early to prevent diseases or minimize complications"

- Emphasizes prevention more than cure

Components of healthcare model	Reactive	Proactive
Focus	Fighting sickness	Building health
Patient Role	Passive recipient of treatment	Active in treatment and health
Physician Role	Determines treatment and manages the healing process	Collaborates in treatment and healing process

Telemonitoring

- A Technology to realize Proactive Healthcare
- Independent living, Healthcare cost reduction, and Clinically useful trends



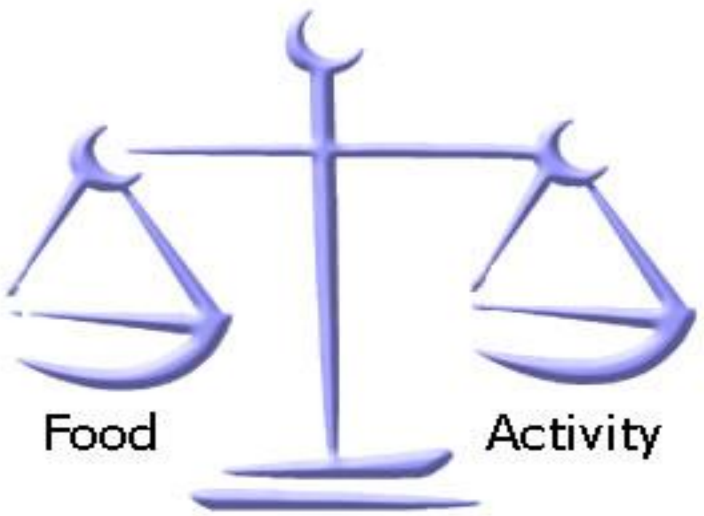
- Blood Pressure
- Heart rate
- **Mobility**

Mobility and its importance

- Time spend in performing daily physical activities
- Helps in determining

“Average Energy Expenditure (EE)”

- Good indicator of functional ability and a healthy life style



Components of Mobility

- Vigorous exercises: weight training, rowing

- Non-exercise daily activities: walking, walking-upstairs, sitting, standing, light running **(More Important)**

  "Non-Exercise-Activity-Thermogenesis (NEAT)*"

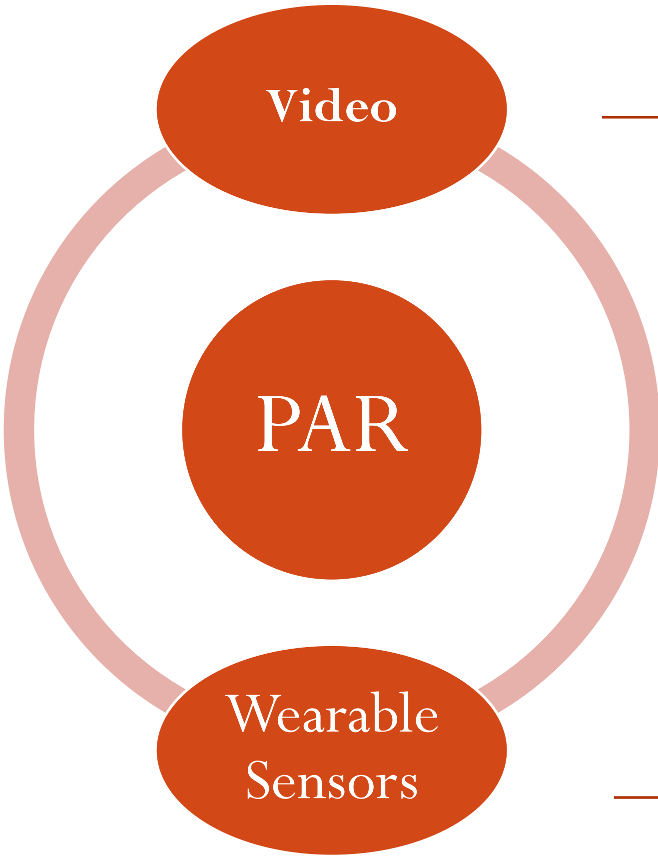
- Determines major part of average daily EE

- Can be used to promote healthy life-style

  " stairs vs. elevator, standing vs. sitting"

* Role of Non-Exercise Activity Thermogenesis in protecting health, Science, *1999.*

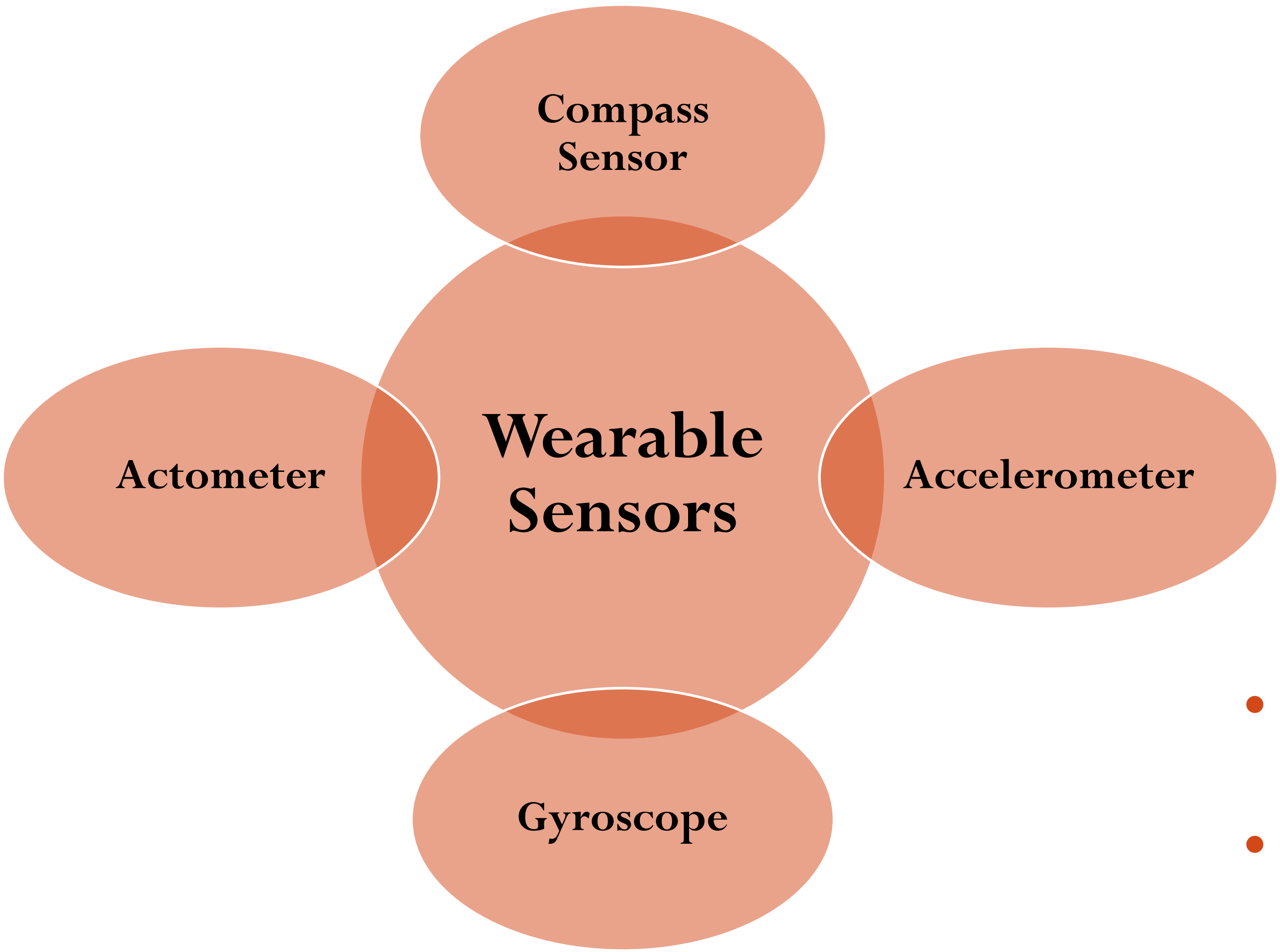
Bodily Activity Recognition (BAR)

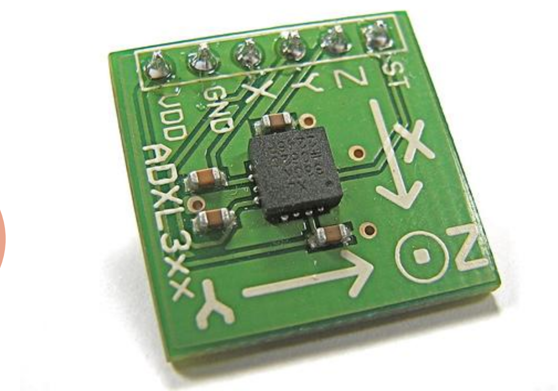


- Work in laboratory
- Fail in real home-settings
  - Clutter
  - Variable Lightening
- Expensive
- Invasive

- Capable of measuring mobility directly
- Low-cost
- Independent of Infrastructure
- Associated with the person

Wearable Sensor-based PAR



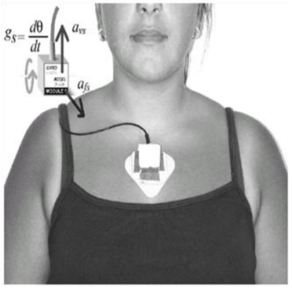


- **Most widely used wearable sensor**
- **Measure acceleration along 3-axes**
- **Several systems have been developed in the past**

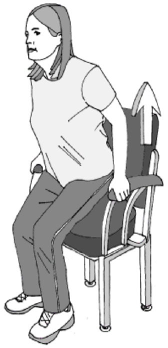
Limitations of the existing systems[1]-[10]

- Majority systems employ multiple accelerometers
  - High recognition rate but not feasible for long-term recognition

- Single accelerometer based systems are convenient but exhibit low accuracy

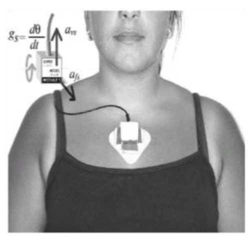


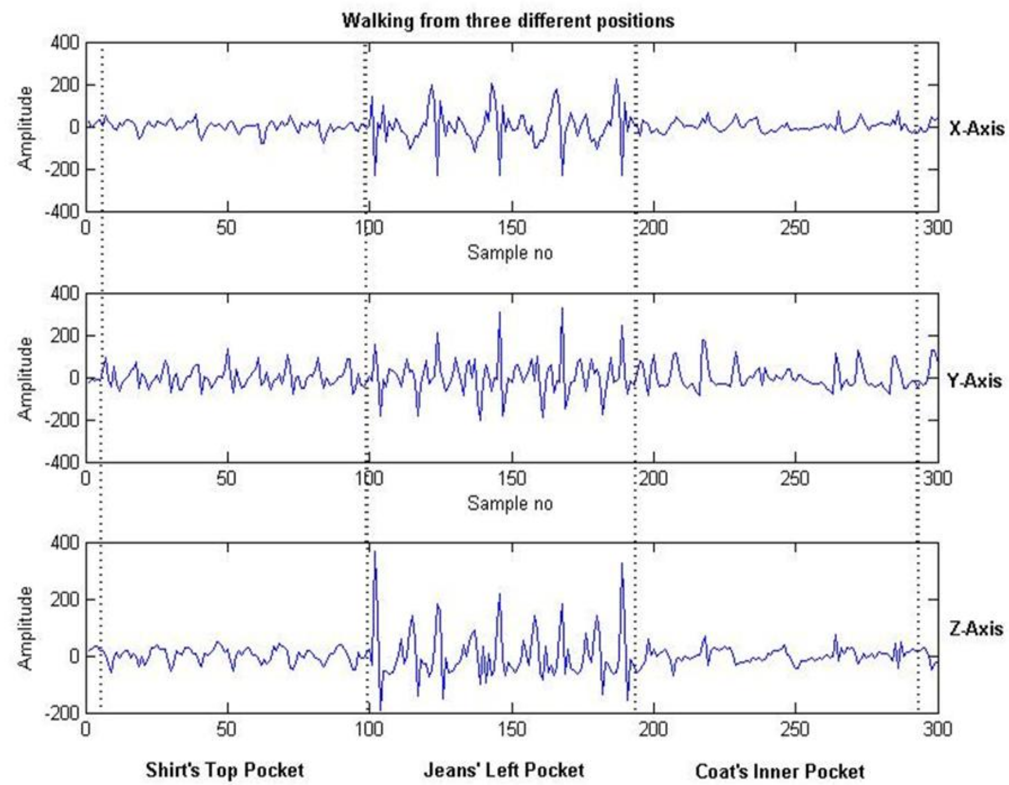
- Low accuracy in distinguishing
  - Short-duration movements, such as transitions
  - Postures, such as sitting and standing



Limitations of the existing systems[1]-[10]

- Output of a body-worn accelerometer depends on the position it is attached
- Therefore, existing systems required firm attachment





- Fixed life pattern
- Hinder daily activities
- Not feasible for long-term monitoring

- Changes in magnitude, orientation, and frequency result in high within-class variance

Challenges

1. How to recognize a large number of physical activities with a high accuracy using only a single tr-iaxial accelerometer?

2. How to achieve the same accuracy when the sensor is placed freely in any pocket without a firm-attachment to user's body?

Why BAR is Challenging?

Complexity of activities*:

- Number of activities
  - Recognizing a larger set of activities is harder
  - In case of activities 10 is a large number
- Types of activities
  - Similar activities are very hard to discriminate
  - Similar posture patterns (Sitting and Standing)
  - Similar movement patterns, Walking (corridor, upstairs, downstairs)

* Using machine learning for physical activity recognition, MIT, *2003*

Why BAR is Challenging?

Complexity of sensors*:

- Number of Sensors
  - Recognition using multiple sensors is easier
    - “High complexity as much more data to analyze and also hinders activities”
  - Recognition using single sensor is difficult
    - “Especially when postures and movements are considered together”
- Position of Sensor
  - Output depends on the position of attachment

* Using machine learning for physical activity recognition, MIT, *2003*

Chosen Bodily Activities

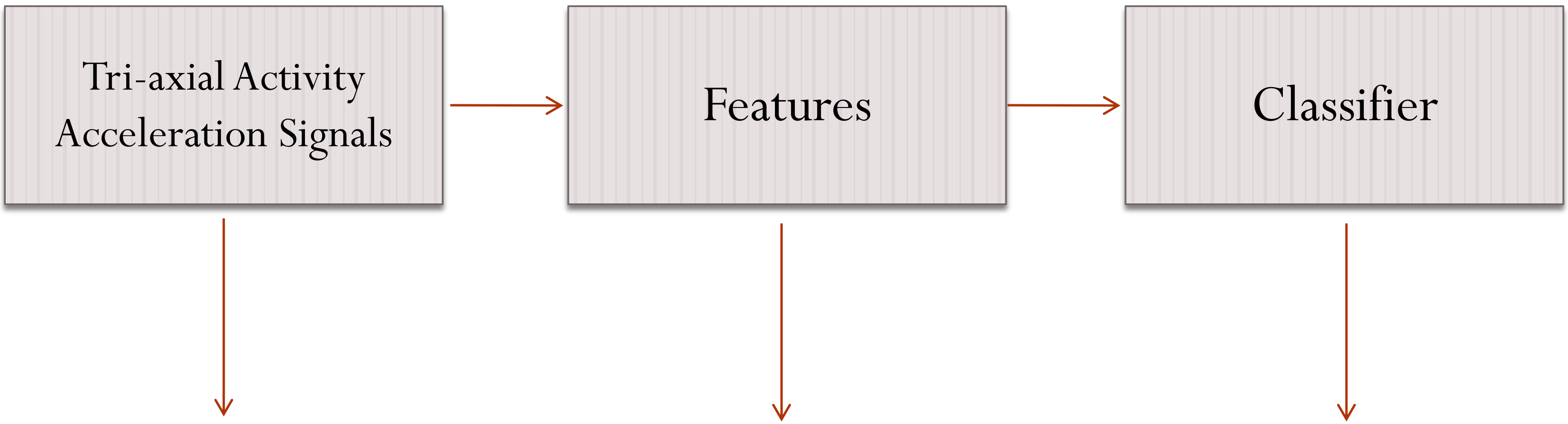
- All factors are present
  - Large number of activities (13)
  - Highly similar activities.
  - Postures, short and long-duration movements
  - Single sensor
- Furthermore this similarity lies in local clusters
  - Subset of activities share similarity
  - Subsets are very different

Activities
Lying
Sitting
Standing
Sit-Stand
Stand-Sit
Lie-Stand
Stand-Lie
Walking
Walking-Upstairs
Walking-Downstairs
Running

State-Activity based Classification Framework for Activity Recognition via a Single Tri-axial Accelerometer

IEEE Trans. on Information Technology in Biomedicine, Sep, 2010

Problem Statement



- Single Sensor
- Large number of activities
- High Similarity

Augmented Feature Model

- Features employed in previous studies
  - Frequency domain features (FFT Coefficients)
  - Wavelets
  - Time domain features (standard deviation, energy and so on)
- FFT and Wavelets: require much higher components and increase computation
- Time domain: can be extracted in real-time however assume that the activity-acceleration signals are deterministic, however such signals are random in nature*
- Thus, a better mathematical model using stochastic time series analysis should be established to describe these data

*Activity Recognition using Acceleration Data and SVM, Machine learning and cybernetics, July. 2008

Augmented Feature Model

- Autoregressive Modeling of the activity acceleration signals

$$y(t) = \sum_{i=1}^{p} a(i).y(t-i) + \varepsilon(t)$$

where

- p is the order of the model
- ε is the output uncorrelated error
- $a_1, a_2, \ldots, a_p$ are the coefficients of the AR Model

Augmented Feature Model

- Moreover, an acceleration signal is a linear combination of two components
  - Component due to gravity (GA) (Explains Body-tilt)
  - Component due to bodily motion (BA) (Explains Movement)
- Can be separated by means of
  - Band-pass filter [0.1 – 20Hz] (BA)
  - Low-pass filter [cutoff freq: 1 Hz] (GA)

Augmented Feature Model

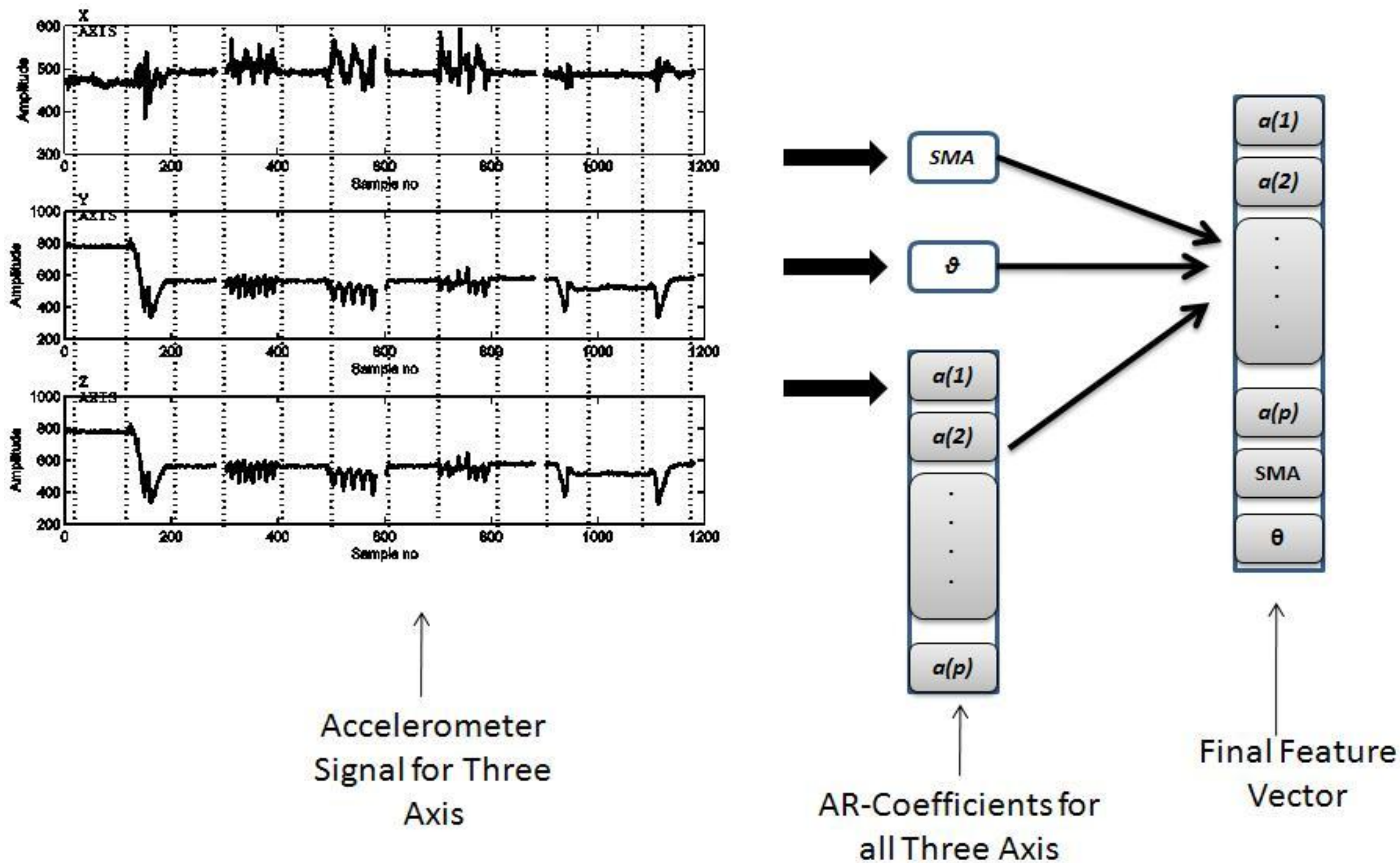
- Signal Magnitude Area (SMA) using BA to explain the intensity of a movement

$$SMA = \sum_{n=1}^{N} (|x[n]|) + (|y[n]|) + (|z[n]|)$$

- Tilt-angle (TA) using GA to describe the body tilt.

$$\theta = \arccos(z)$$

Augmented Feature Model



Discriminating Feature Extraction

- As mentioned earlier
  - High similarity/low between class variance exists among activities (such as Sitting and Standing)
  - Activities overlap in the augmented feature space
- Thus a method is needed to
  - Extract the discriminating features
  - Increase the between class variance
- One well-known method is Linear Discriminant Analysis.

Discriminating Feature Extraction

- Linear Discriminant Analysis: maximizes the following

$$J(w) = \frac{w^T S_B w}{w^T S_W w}$$

$$S_B = \sum_{i=1}^{c} N_i (m_i - m)(m_i - m)^T$$

$$S_W = \sum_{i=1}^{c} \sum_{x_k \in C_i} (x_k - m_1)(x_k - m_1)^T$$

- Maximizes total scatter of the data, while minimizing within scatter of the classes

Global Mean Problem

$$S_B = \sum_{i=1}^{c} N_i (m_i - m)(m_i - m)^T$$

- Total scatter is calculated using the global mean
- However, the similarity among activities lies in local clusters
  - Sitting and Standing are very similar but are very different from walking, upstairs and downstairs
- To achieve effective activity-separation, LDA should be applied to the local clusters

Concept of States

Activities
Lying
Sitting
Standing
Sit-Stand
Stand-Sit
Lie-Stand
Stand-Lie
Walking
Walking-Upstairs
Walking-Downstairs
Running

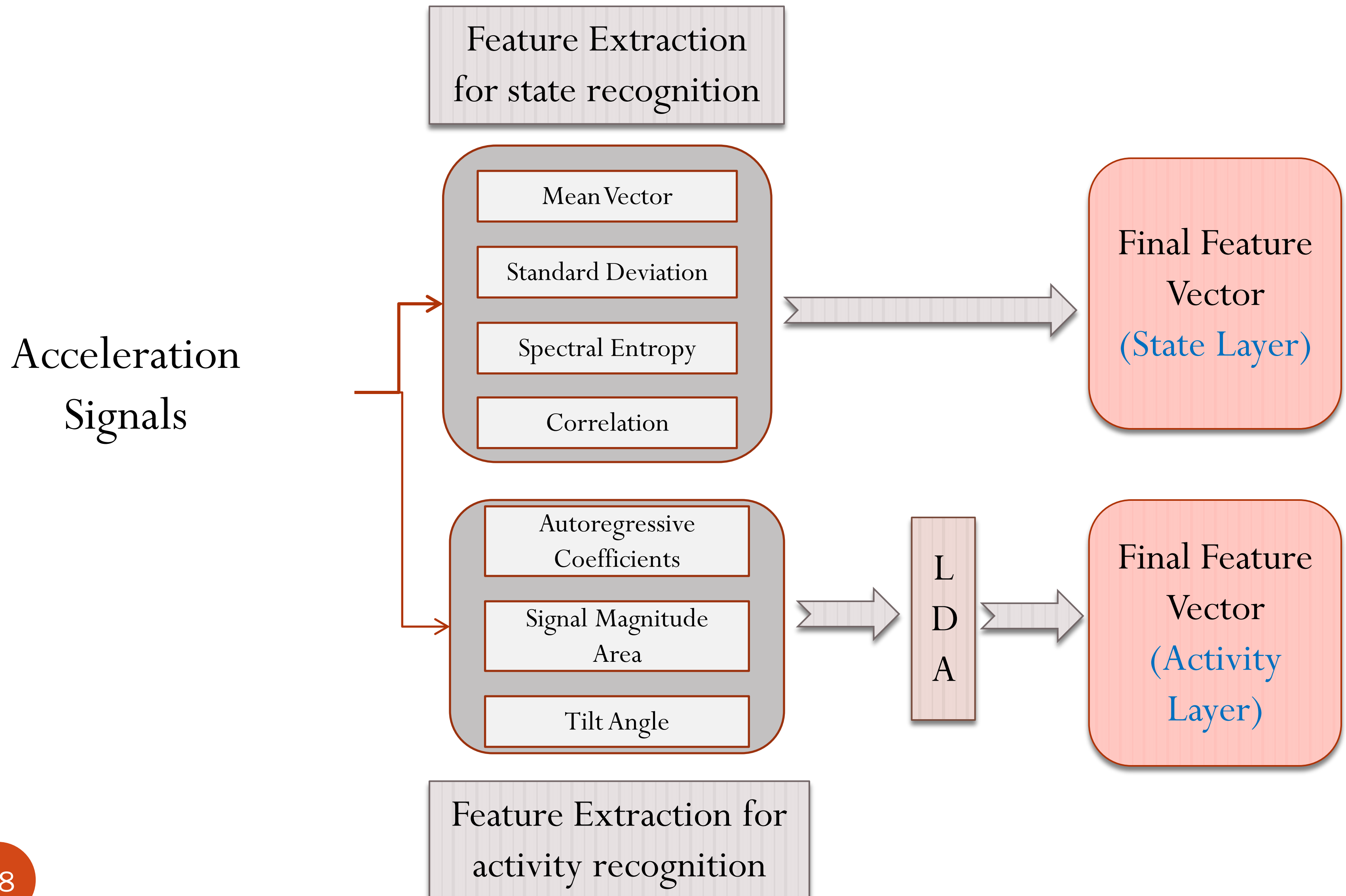
Static

Transitions

Dynamic

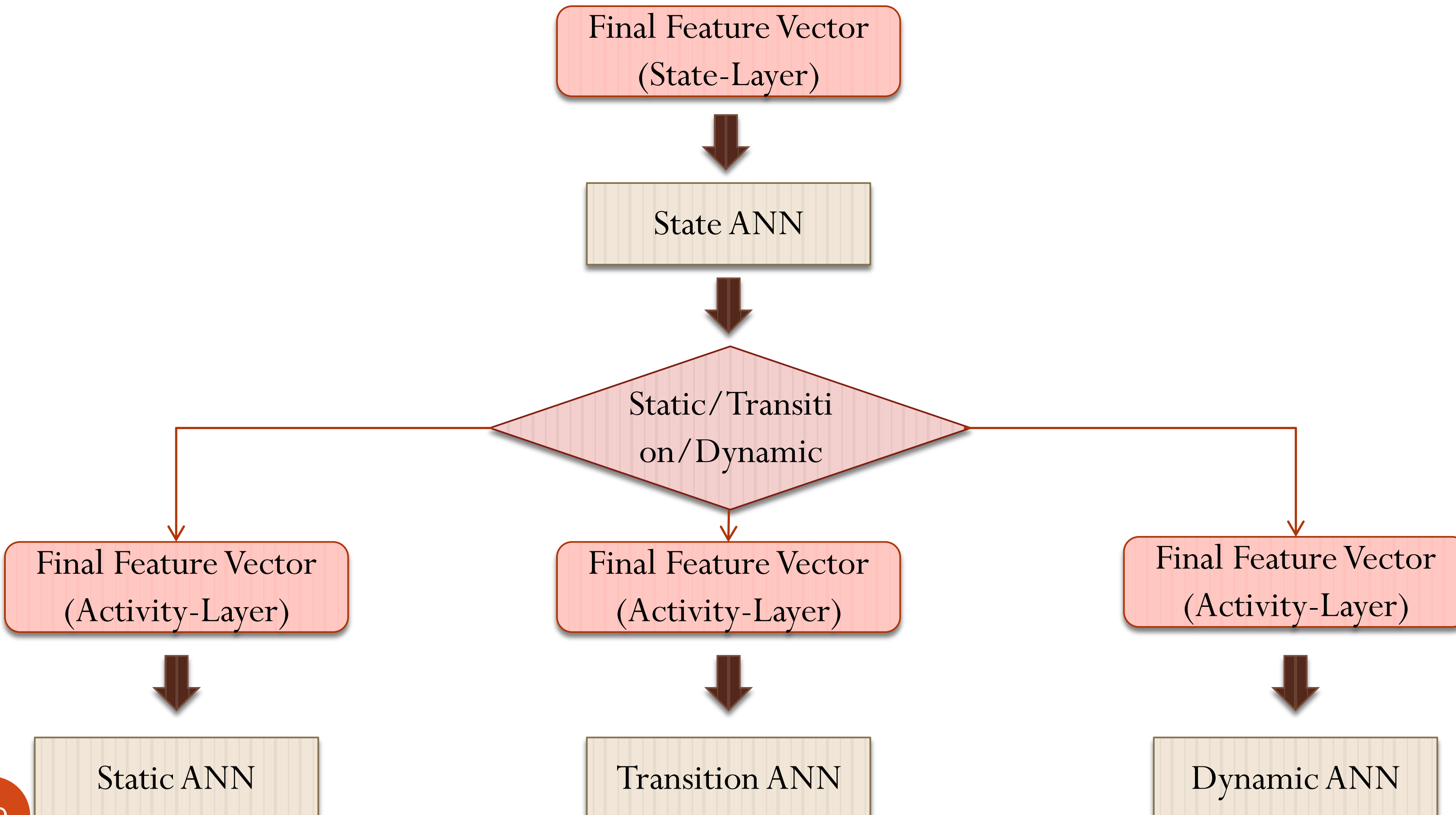
States (Can be easily separated using simple statistical features

State-Activity based Classification Framework

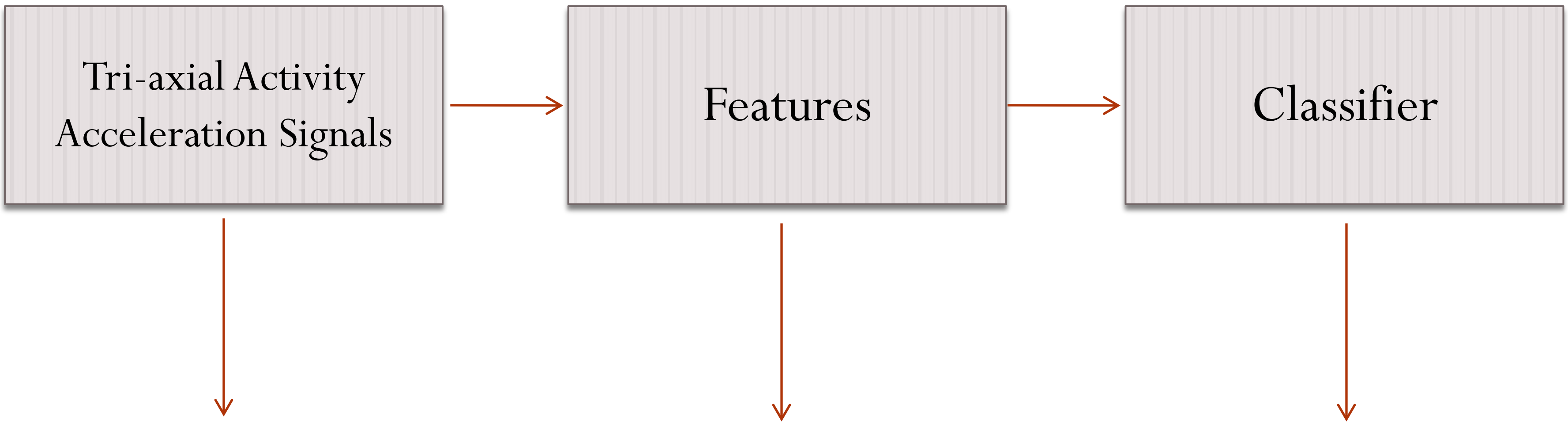


State-Activity based Classification Framework

State Recognition → Activity Recognition



Proposed Solution



- Single Sensor
- Large number of activities
- High Similarity

- Statistical features
- Augmented features

- State-activity based hierarchical classifier

Experimental Validation

- Two Experimental studies
- Controlled (C)
  - Activities are performed using a strict protocol
  - Same sequence, Same speed, Same distance, Same posture (Across all subjects)
- Uncontrolled, Naturalistic (N)
  - No protocol
  - Sequence, speed, distance and posture may vary across subjects

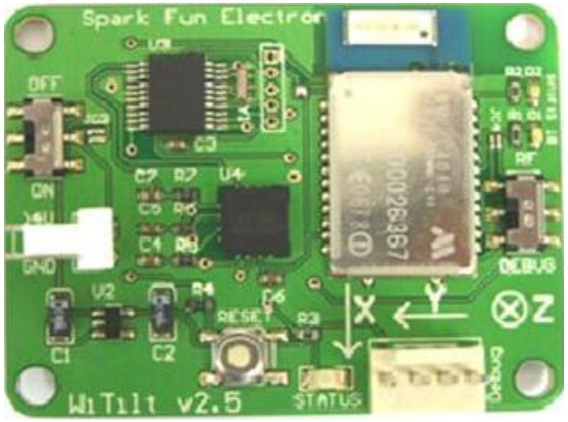
Experimental Validation

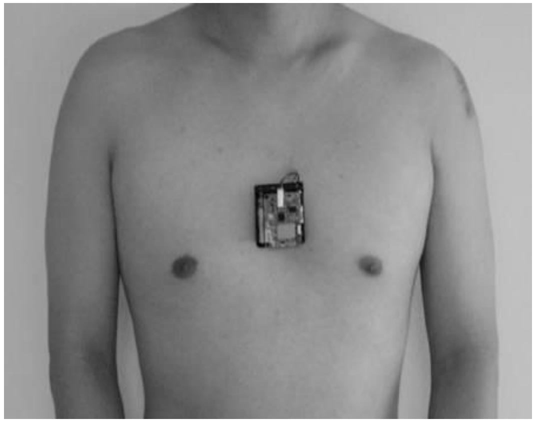
- First, evaluate via controlled laboratory data (easy-case)
- Second, evaluate on naturalistic data (hard-case)

Ref	Accuracy (C)	Accuracy (N)	Activities	No. Subj	No. Sensors
[1]	95%	--	Ambulation,	8	1
[2]	90%	83%	Ambulation, Posture	6	6
[3]	96.7%	68%	Ambulation, Posture, Cycling	24	4
[4]	93%	86%	Ambulation, Posture	1	3
[5]	95%	65%	Ambulation, Posture	4	Up to 36
[6]	90%	80%	Ambulation, Posture	10	2

Experimental Validation

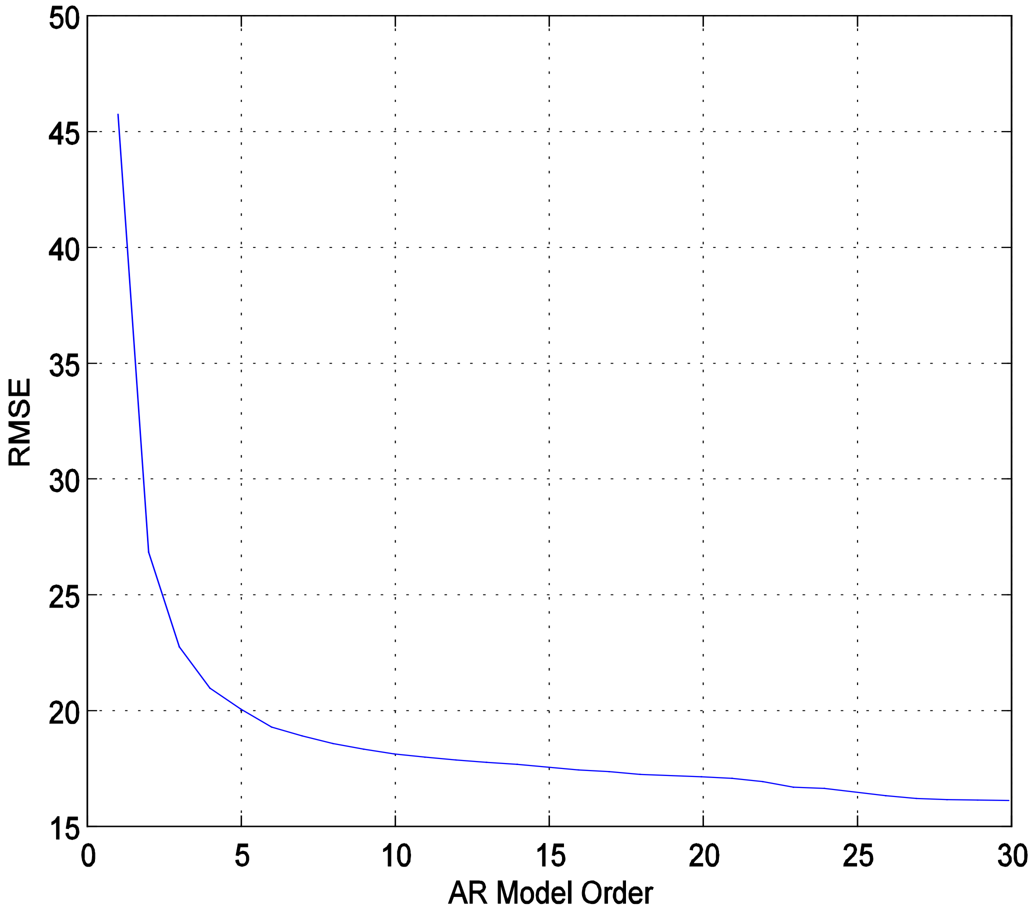
- In both cases
  - A tri-axial accelerometer (WiTilt)
  - Placed at subjects' chests
  - 10 subjects
  - 30 hours (L)
  - 24 hours (N)





Experimental Validation

AR Model Order Selection:



RMSE versus AR model order for the whole activity set

- RMSE values were calculated for each activity against different model orders.
- A decreasing trend
- Curve tends to even out near the model order 10.

Experimental Validation

Subject Dependent:

- First Study (C) Results: All subjects participated in training and testing (Total: 97.9%)
- Each subject:
  - Training data: 40%
  - Test data: 60%

State	Accuracy (%)
Static	99
Transition	99
Dynamic	99

Activities	Accuracy (%)
Lying	99
Sitting	95
Standing	96
Sit-Stand	99
Stand-Sit	99
Lie-Stand	94
Stand-Lie	96
Walking	99
Walking-Upstairs	99
Walking-Downstairs	99
Running	99

Experimental Validation

Subject Independent:

- Second Study (N) Results: 8 subjects (Training) 2 subjects (Testing) (Total: 84.93%)

State	Accuracy (%)
Static	99
Transition	95
Dynamic	97

Activities	Accuracy (%)
Lying	99
Sitting	74.7
Standing	78.6
Sit-Stand	80.1
Stand-Sit	79.2
Lie-Stand	82.3
Stand-Lie	78
Walking	92.2
Walking-Upstairs	87.7
Walking-Downstairs	86.3
Running	96.2

Experimental Validation

- Comparison

Ref	Accuracy (C)	Accuracy (N)	Activities	No. Subj	No. Sensors
[1]	95%	--	Ambulation,	8	1
[2]	90%	83%	Ambulation, Posture	6	6
[3]	96.7%	68%	Ambulation, Posture, Cycling	24	4
[4]	93%	86%	Ambulation, Posture	1	3
[5]	95%	65%	Ambulation, Posture	4	Up to 36
[6]	90%	80%	Ambulation, Posture	10	2
State-Activity based classification	97.9%	84.93%	Ambulation, Posture, Transitions	10	1

Accelerometer's Position and Attachment Free Recognition

A step towards further convenience

Medical & Biological Engineering & Computing, Springer Oct, 2010

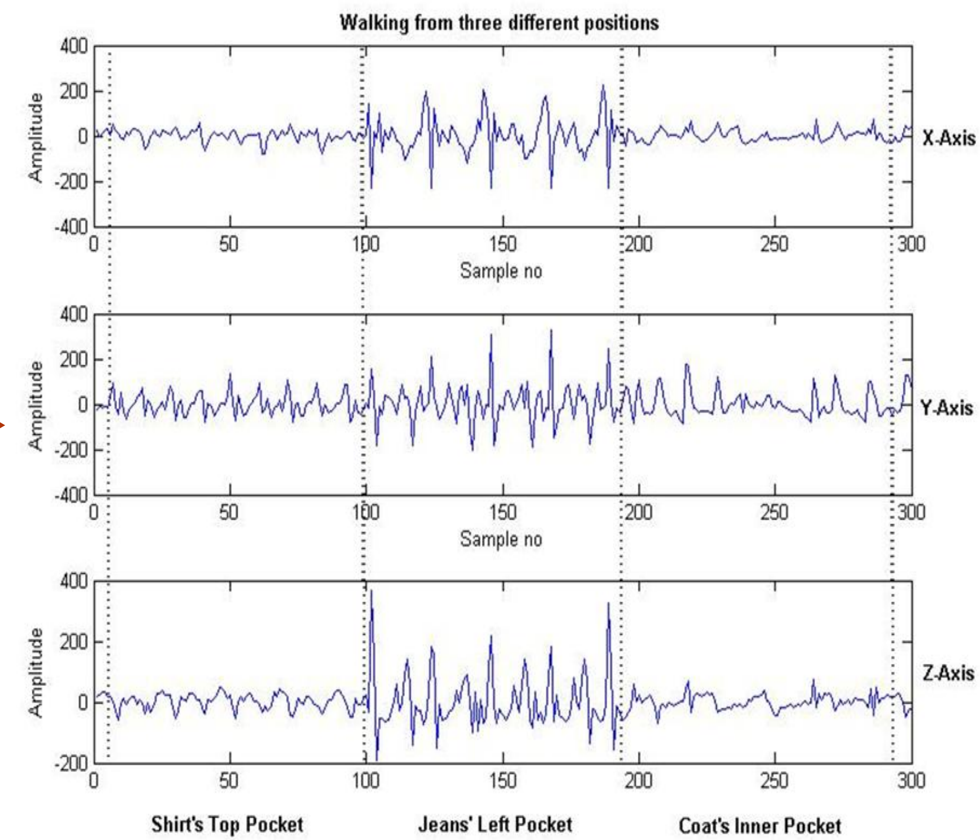
Sensor's Position and Attachment Free Recognition

- 24 hours of data, 10 subjects
- High within-class variance

Accelerometer

Positions

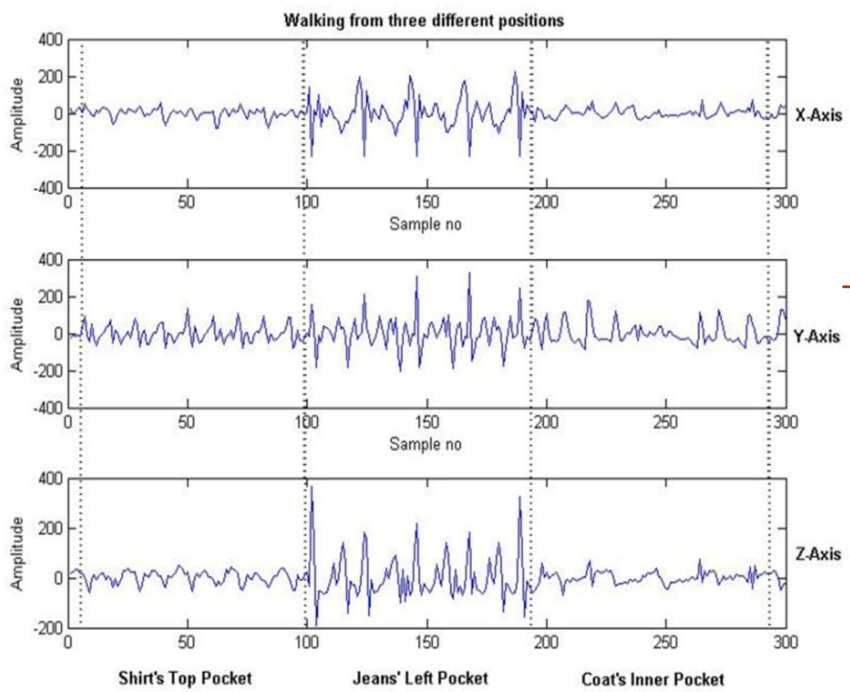
Upper Body	Lower Body
Shirt Top Pocket	Jeans Front Pockets
Coat Inner Pocket	Jeans Rear Pocket



Acceleration signals for walking from different positions

Sensor's Position and Attachment Free Recognition

Results of State-Activity based scheme for the new dataset



Acceleration signals for walking from different positions

State-Activity based Classification

(Fixed Case)

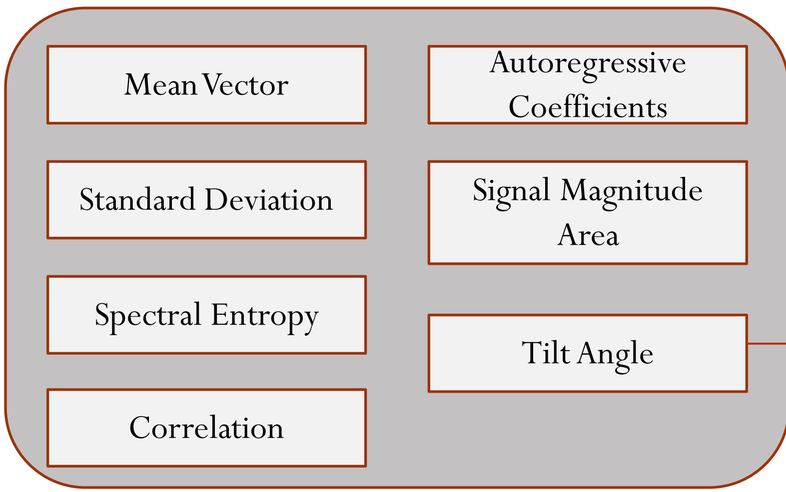
45 % Recognition Accuracy

- High accuracy in the fixed-case, but very low accuracy in position and attachment free case

Sensor's Position and Attachment Free Recognition

Alteration to the feature set

Features and Activities: Fixed Approach



Activities
Lying
Sitting
Standing
Sit-Stand
Stand-Sit
Lie-Stand
Stand-Lie
Walking
Walking-Upstairs
Walking-Downstairs
Running

- Tilt angle played an important role in distinguishing static postures and transitions
- However, its computation requires firm attachment to user's body

Sensor's Position and Attachment Free Recognition

Alteration to the feature set

Features and Activities: Position and Attachment free case

- Mean Vector
- Autoregressive Coefficients
- Standard Deviation
- Signal Magnitude Area
- Spectral Entropy
- Correlation

Activities
Resting (Lying, Sitting, Standing)
Walking
Walking-Upstairs
Walking-Downstairs
Running
Cycling
Vacuuming

- Tilt angle was not used
- Lying , sitting and standing were combined into a single activity "Resting"
- Two new activities were considered "Cycling" and "Vacuuming"

Sensor's Position and Attachment Free Recognition

Problem Statement

Tri-axial Activity Acceleration Signals → Features → Classifier

- Single Sensor
- 7 activities
- 5 different positions
- High within class variance

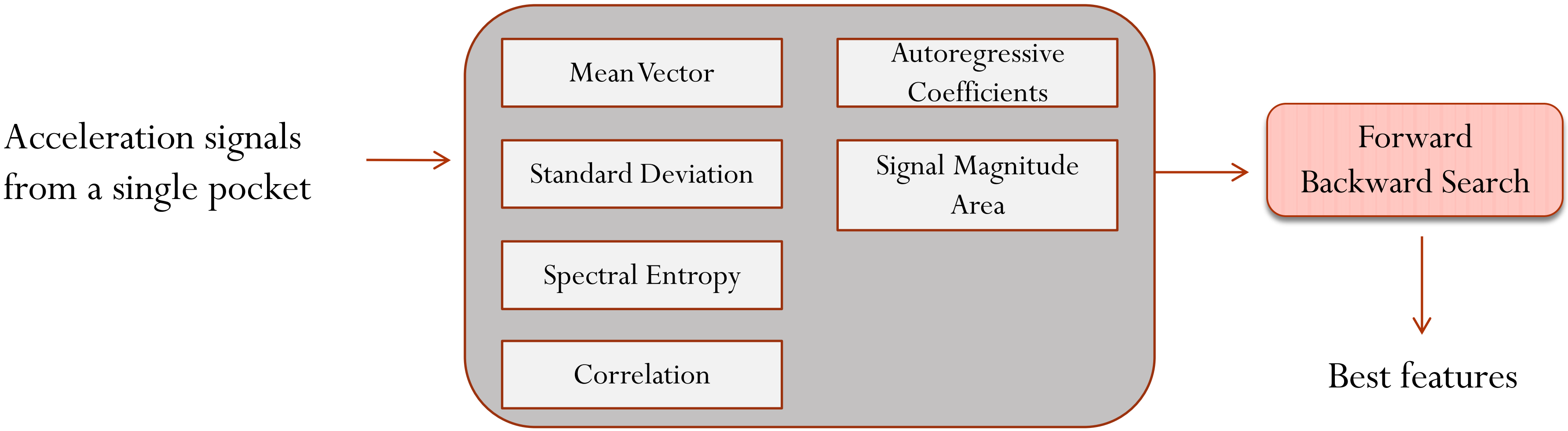
- Statistical features
- Augmented features (No TA)

?

Sensor's Position and Attachment Free Recognition

Just attachment free

- Feature-Selection for single-pocket classification



- Classifier used: ANN
- Process was repeated for all pockets
- Finally, AR+SMA were selected for their better performance, for all positions.

But how to achieve the same accuracy when all positions are considered?

Sensor's Position and Attachment Free Recognition

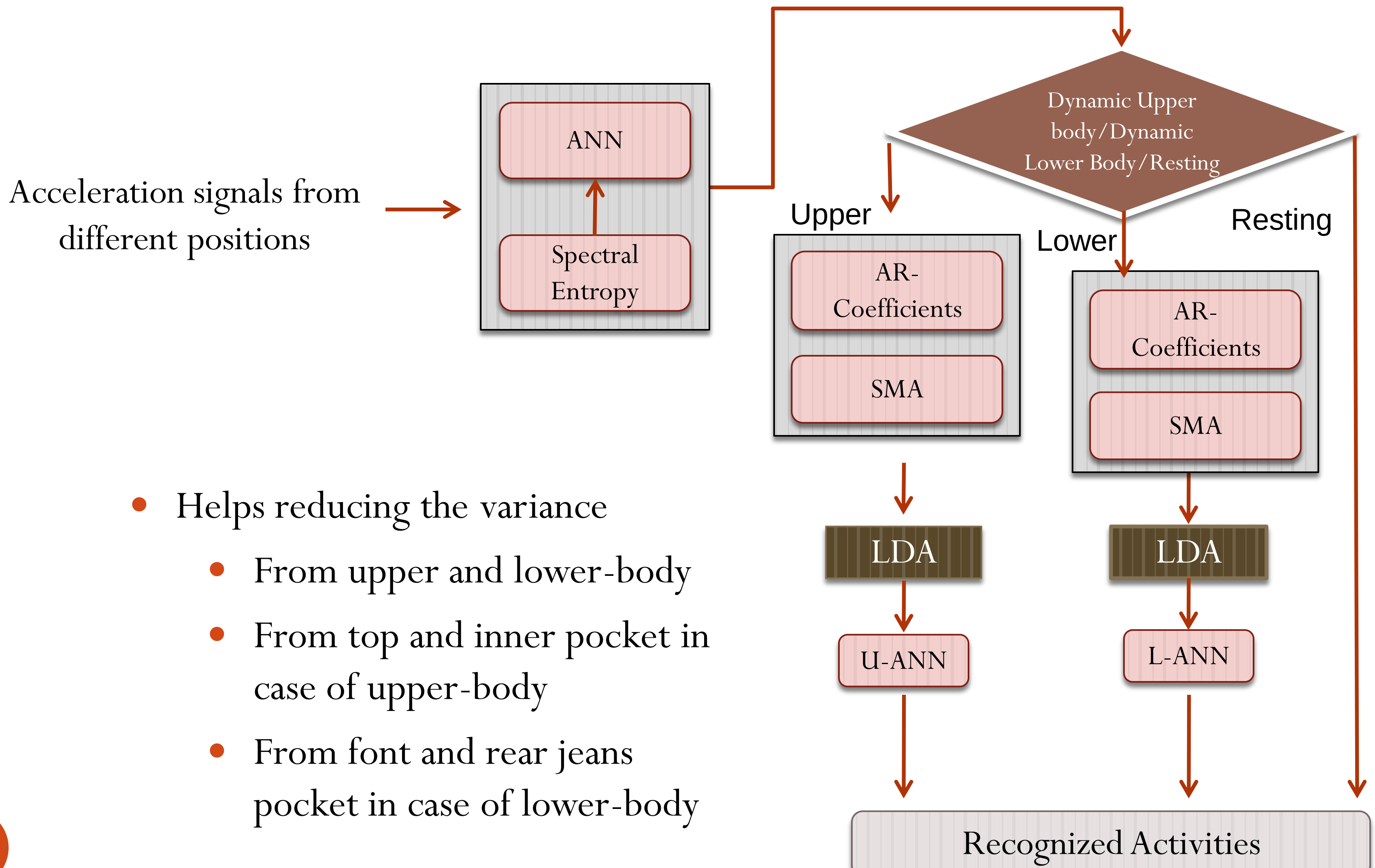
Frequency behavior of bodily activities

- During a dynamic activity, movement that involves legs, higher frequencies occur at the ankle*
- The maximum frequency obtained decreases from ankle to head*
- Thus, greater frequencies are registered at the lower body parts, legs, and lower frequencies are registered at the upper body parts, chest and head
- During resting, the frequencies are almost the same for the whole body

*Low frequency self-generated vibration during ambulation in normal men, *J. Biomech,* 1982

Sensor's Position and Attachment Free Recognition

Hierarchical classification



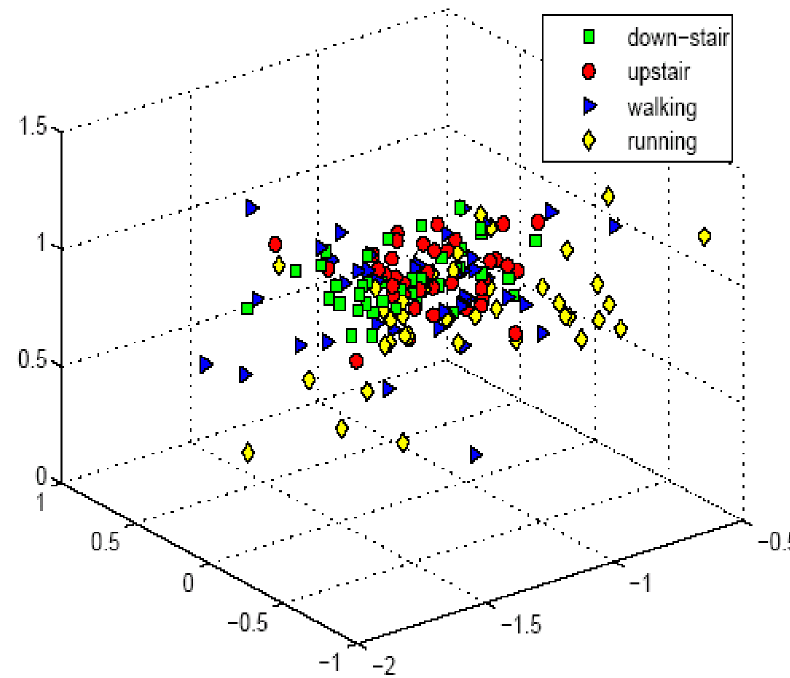
- Helps reducing the variance
  - From upper and lower-body
  - From top and inner pocket in case of upper-body
  - From font and rear jeans pocket in case of lower-body

Sensor's Position and Attachment Free Recognition

Experimental Results: Single-Level using All Features (High within Class Variance)

Activity	Single-Level (S-L)
Resting (Lying/Sitting/Standing)	72
Walking downstairs	42
Walking upstairs	39
Walking	44
Running	52
Cycling	44
Vacuuming	36
Total	47

- Single Feature Vector: AR, SMA, SE
- High within class variance
- Average Accuracy: 47%

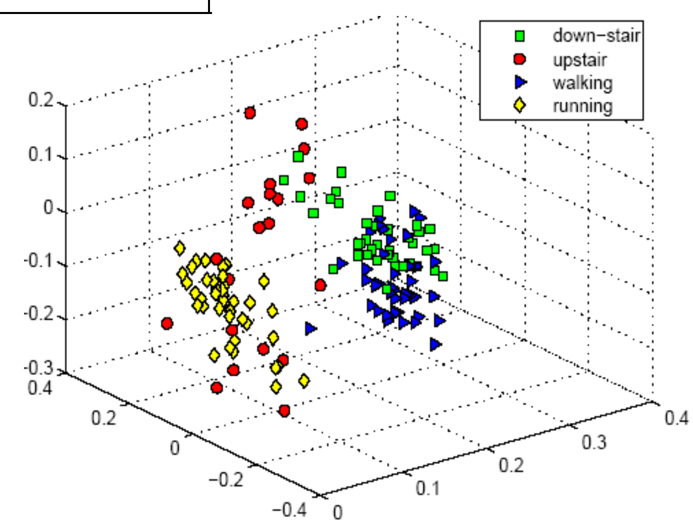


Sensor's Position and Attachment Free Recognition

Experimental Results: Single-Level LDA-based (Improved Class Separation)

Activity	Single-Level (S-L)	S-L with LDA
Resting (Lying/Sitting/Standing)	72	89
Walking downstairs	42	53
Walking upstairs	39	51
Walking	44	56
Running	52	68
Cycling	44	50
Vacuuming	36	44
Total	47	58.7

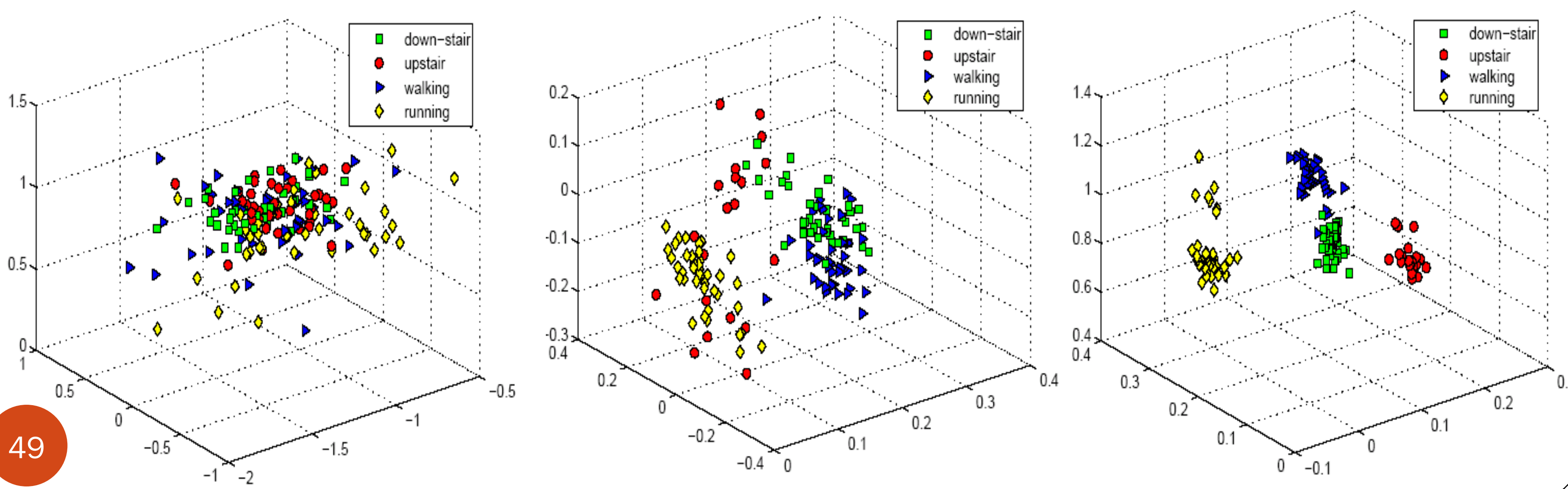
- AR, SMA, SE → LDA
- Improved class separation
- Average Accuracy: 58.7%



Sensor's Position and Attachment Free Recognition

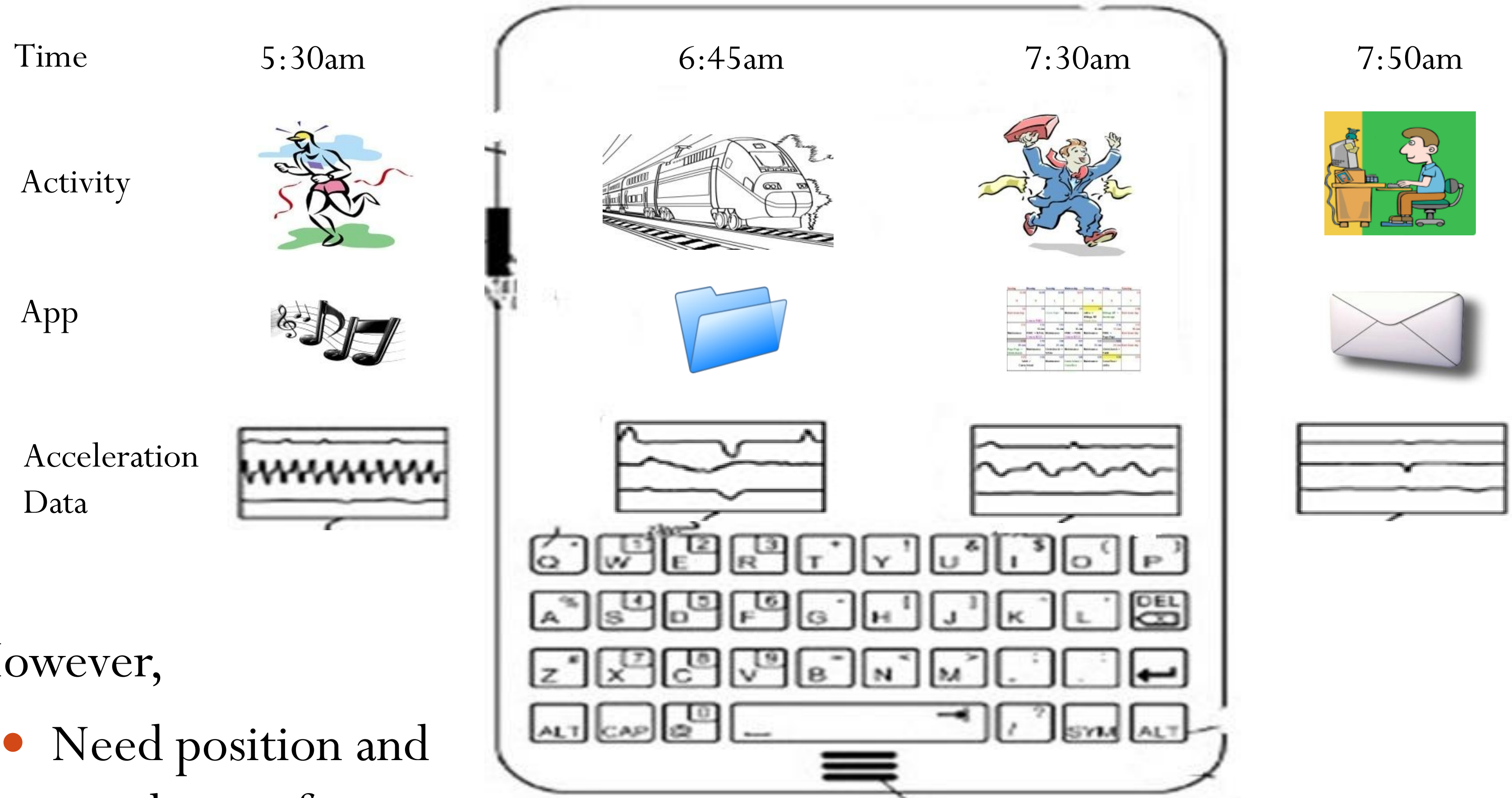
Experimental Results: Proposed Hierarchical Scheme

Activity	Single-Level (S-L)	S-L with LDA	Hierarchical Scheme
Resting (Lying/Sitting/Standing)	72	89	98
Walking downstairs	42	53	96
Walking upstairs	39	51	94
Walking	44	56	96
Running	52	68	96
Cycling	44	50	94
Vacuuming	36	44	87
Total	47	58.7	94.4



Recognition of Bodily Activities using an Accelerometer-enabled Smartphone

Activity Aware Smartphone*



An Activity Aware Smartphone

- However,
  - Need position and attachment free recognition

* Activating applications based on accelerometer data, Google, Patent Application US 2009

Position and Attachment Free Recognition using Smartphone

Hierarchical recognition scheme might not be feasible

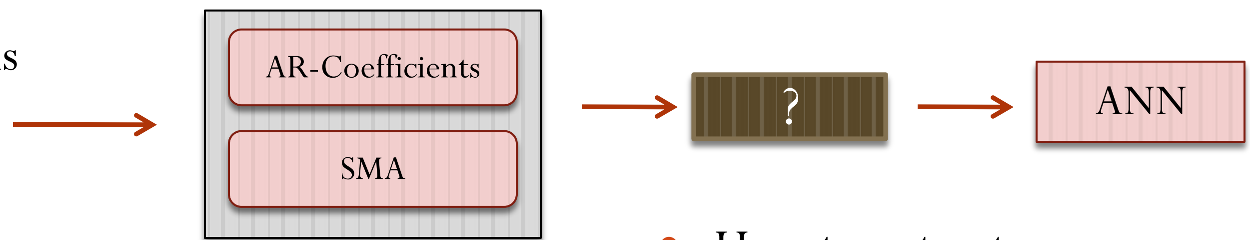
- Time domain features: AR-coefficients, SMA
- Frequency domain features: SE
- Discriminant Analysis: LDA
- Two-Layer classification: 2 ANNs
- Limited memory and computational resources

Position and Attachment Free Recognition using Smartphone

Problem statement

- No spectral entropy
- Only one ANN for recognition

Activity Acceleration signals
from different positions
from a Smartphone

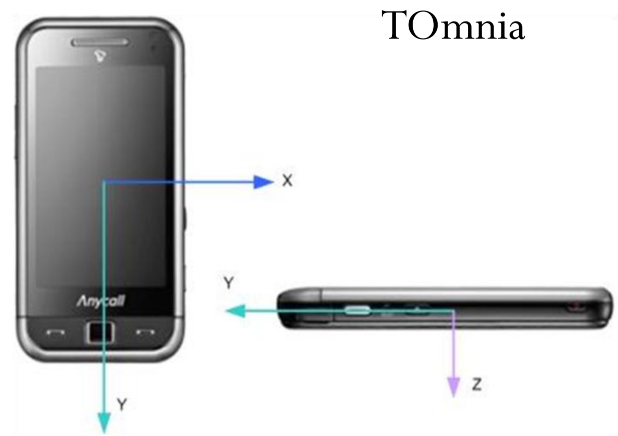


- How to extract discriminating features
  - Minimize the within class and maximize the between class variance

Position and Attachment Free Recognition using Smartphone

Data Collection

- TOmnia: (SCH-M490) Samsung
- Embedded tri-axial accelerometer
- Sampling Freq: 90Hz
- Activities: Same as previous
- 24 hours data



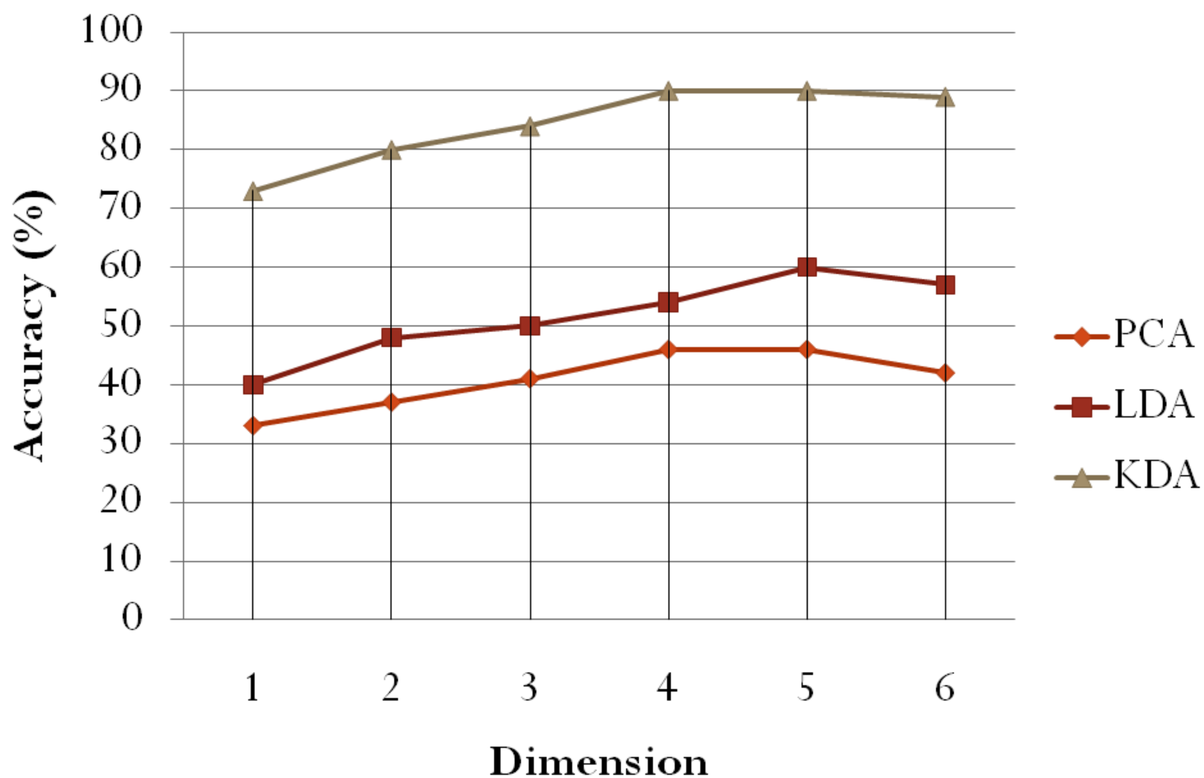
Positions

Upper Body	Lower Body
Shirt Top Pocket	Jeans Front Pockets
Coat Inner Pocket	Jeans Rear Pocket

Position and Attachment Free Recognition using Smartphone

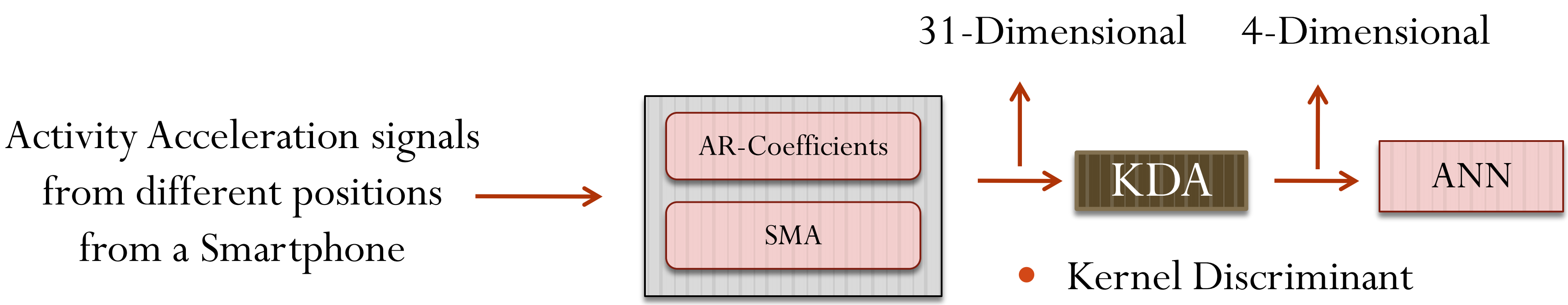
Extraction of discriminating features

- Several techniques exist in machine learning literature
  - PCA, LDA, KDA



Position and Attachment Free Recognition using Smartphone

KDA-based classification



- Kernel Discriminant Analysis
- Non-linear discriminating approach

- Accuracy : 89% (Lower than the hierarchical approach)
- Activities: Lying, sitting, walking, downstairs, upstairs, and running.

Conclusion

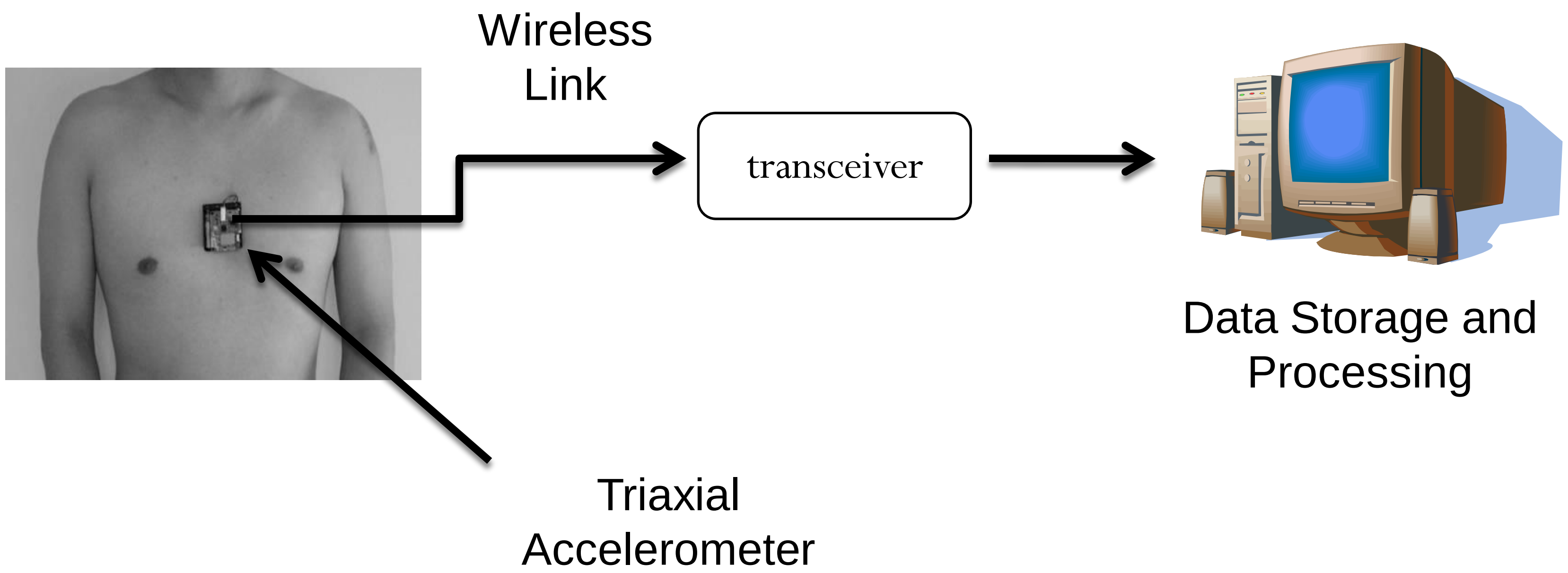
- A single accelerometer-based physical activity recognition framework
  - Capable of recognizing static postures, short-term, and long-term movements with high accuracy
- Sensor's position and attachment free version of the recognition system
  - Allows users to carry sensor in any pocket, without any firm attachment
  - Capable of recognizing a wide variety of movements with an accuracy above 95%
- A prototype of the proposed system for accelerometer enabled smartphones
  - User's don't have to carry any extra device
  - Activities can monitored throughout a longer period of time.

References

1. B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C. J. Bla, and P. Robert "Ambulatory system for human motion analysis using a kinematic sensor: Monitoring of daily physical activity in the elderly," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 6, 2003.
2. M. Sekine, T. Tamura, M. Akay, T. Fujimoto, T. Togawa, and Y. Fukui, "Discrimination of walking patterns using wavelet based fractal analysis," *IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 10, pp. 188–196, 2002.*
3. M. J. Mathie, A. C. F. Coster, N. H. Lovell, and B. G. Celler, "A pilot study of long term monitoring of human movements in the home using accelerometry," *J. Telemed. Telecare, vol. 10,* pp. 144–151, 2004.
4. L. Bao and S. S. Intille, "Activity recognition from userannotated acceleration data," in *Pervasive Computing. Springer* Berlin / Heidelberg, 2004, pp. 158–175.
5. M. Ermes, J. Parkka, J. Mantyjarvi, and I. Korhonen, "Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions," *IEEE Transactions on Information Technology in Biomedicine, vol. 12, p. 2026, 2008*.
6. K. Kiani, C. J. Snijders, and E. S. Gelsema, "Computerized analysis of daily life motor activity for ambulatory monitoring,"Technol. HealthCare, vol. 5, p. 30718, 1997.
7. F. Allen, E. Ambikairajah, N. Lovell, and B. Celler, "Classi- fication of a known sequence of motions and postures from accelerometry data using adapted gaussian mixture models," *Physiol. Meas, vol. 27, p. 935951, 2006.*
8. Preece SJ, Goulermas JY, Kenney LPJ, Howard D, Meijer K, Crompton R (2009) Activity identification using body-mounted sensors–a review of classification techniques. Physiological Measurement 30:R1–R33
9. D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, and B. G. Celler, "Implementation of a real-time human movement classifier using a tri-axial accelerometer for ambulatory monitoring," *IEEE Transactions on Inf Technol Biomed, vol.* 10(1), pp. 156–67, 2006.
10. Scanaill CN, Carew S, Barralon P, Noury N, Lyons D, Lyons GM (2006) A review of approaches to mobility telemonitoring of the elderly in their living environment. Annals of Biomedical Engineering 34:547–563

Appendix

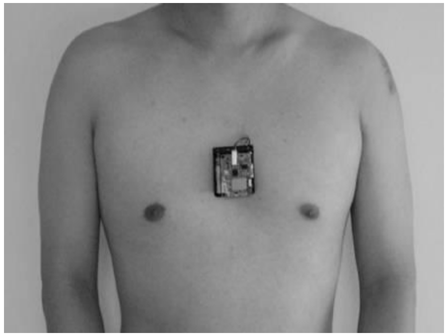
Schematic Diagram of Data Acquisition and Processing



Sensor Attachment

Why Chest

- Sensors are attached to the part whose motions are being studied
- In case of whole body movements
  - A position close to the center of mass is the most appropriate
    - The chest



Noise Reduction

Moving Average Filter

$$y_s(i) = \frac{1}{2N+1}(y(i+N) + y(i+N-1) + \ldots + y(i-N))$$

- Matlab: Curve fitting toolbox
- Function: smooth(data, span)
- data: activity acceleration signal
- span: Number of neighboring values (in this work: 3)
- Removes random noise

AR-Analysis

Calculating parameter/coefficients

- Matlab: Signal Processing Toolbox
- Function: ar (data, n, method)
- data: activity acceleration signal
- n: model order
- method: least square minimization

Separating GA and BA

Filtering

- Band-pass filtering: [0.11-20Hz] to obtain BA by eliminating
  - GA [< 0.1Hz]
  - Noise [> 20Hz]
- Low-pass filtering: cut-off frequency = 1 Hz

Feature Augmentation Experiment

- Four simple activities were chosen
- Classifier: ANN
- Three different training and test sessions

AVERAGE RECOGNITION RESULTS(%) FOR THE FOUR ACTIVITIES FOR THE FEATURE AUGMENTATION TESTS

Activity	[AR]	[AR, SMA]	[AR, SMA, TA]
Lying	59	70	99
Standing	61	71	99
Walking	83	90	99
Running	85	95	99
TOTAL	72	81.5	99

Why Neural Networks

Previously studied classifiers

- HMM, SVM, GMMs, Heuristic Classifiers, Decision trees, Artificial neural nets, etc.
- Most have been used in small-scale studies
- ANNs gave the highest accuracy
  - Also, have been test in both small and large-scale studies
  - Both, controlled and naturalistic datasets

Neural Network Topology

Matlab: Neural Network Toolbox

- One input layer with the same number of neurons as input
- One output layer with the same number of neurons as the number of classes

1. Add a hidden layer with one neuron
2. Train and test the ANN
    - If its not the first layer, analyze the increase in accuracy else step 3
        - If significant increase go to step 3 else terminate
3. Increment the number of hidden neurons by 1
4. Train and test the ANN
    - If significant increase in accuracy repeat 3 else go to step 1

Training Data

Why 40% per subject

- Conducted five experiments
  1. 75%(training) 25% (test): Accuracy (98.2%)
  2. 50%(training) 50% (test): Accuracy (98%)
  3. 25%(training) 75% (test): Accuracy (88.3%)
  4. 35%(training) 25% (test): Accuracy (92.6%)
  5. 40%(training) 60% (test): Accuracy (97%)

Kernel Discriminant Analysis

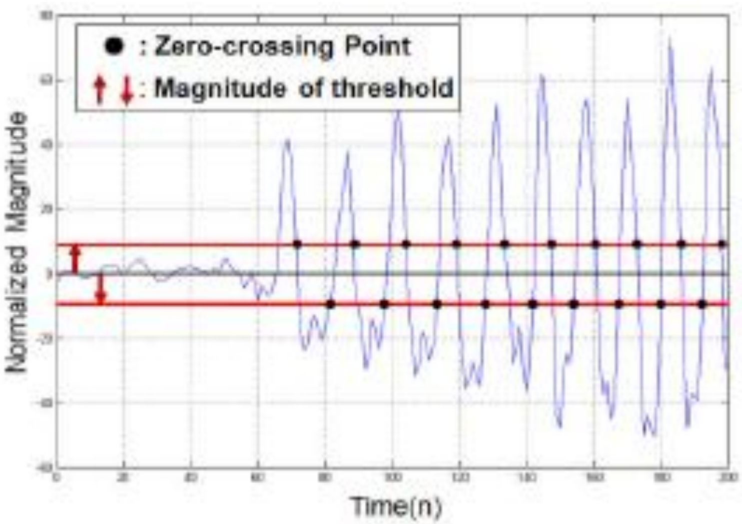
- A non-linear discriminating approach
- Based on kernel techniques
- LDA in a higher dimensional F space induced by a nonlinear mapping

$$\varphi : R^{3p+1} \rightarrow F$$

- Our choice φ of was the radial basis function.
- Have been used for face recognition with large pose variations

Personal Life Log

No of steps = No of zero crossings/2



Stride Length

The Ratio between Stride Length and Height in General Walking Phase of 10-60 Aged Men and Women

Subjects		The Ratio between Stride Length and Height (%)
10-30 Age Group	Male	42.36
	Female	43.56
40-60 Age Group	Male	41.17
	Female	40.55

Distance = Stride Length x Step Counts

Speed = Distance / Duration

Energy Expenditure (kcal) = 1.05 x METS x Duration (hour) x Weight (kg)

$$METS = 0.0272 \times Speed\,(m/\min) + 1.2$$