Physical Activity Recognition from Accelerometer Data Using a Multi-Scale Ensemble Method

Yonglei Zheng, Weng-Keen Wong, Xinze Guan (Oregon State University)

Stewart Trost (University of Queensland)

Introduction

- Goal: accurate, objective and detailed measurement of physical activity
- Why? Many health related reasons…
  - Understand relationship between physical activity and health outcomes
  - Detecting at risk populations
  - Measure effectiveness of intervention strategies

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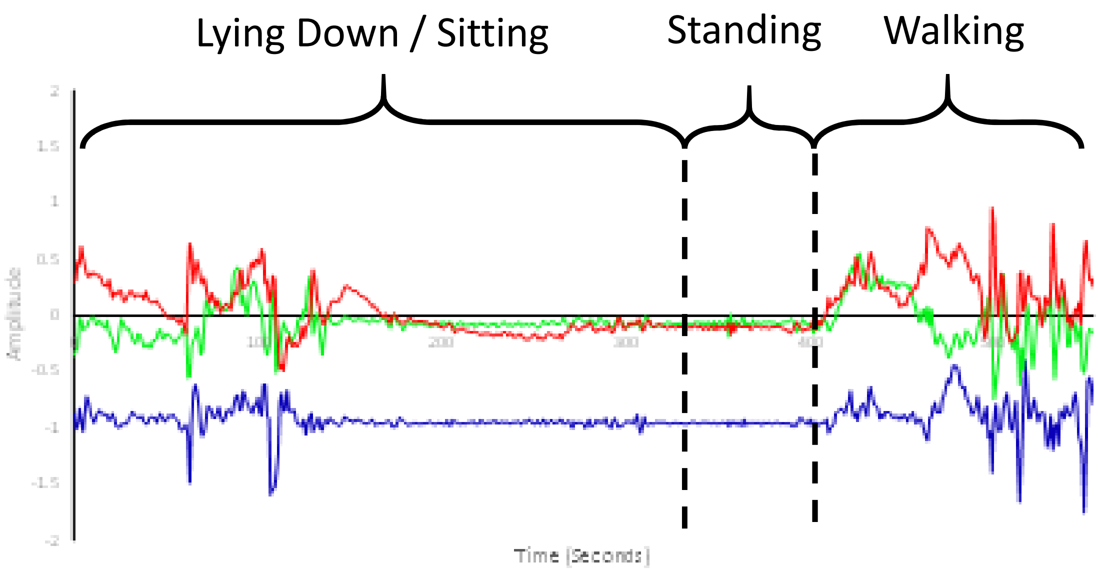
Introduction

- Accelerometers are a cheap, reliable and unobtrusive way to measure physical activity
- Capture acceleration in different planes (typically triaxial)
- Typically attached at the wrist or hip

Actigraph's GT3X+ accelerometer
- Dimensions: 4.6cm x 3.3cm x 1.9cm
- Weight: 19 g

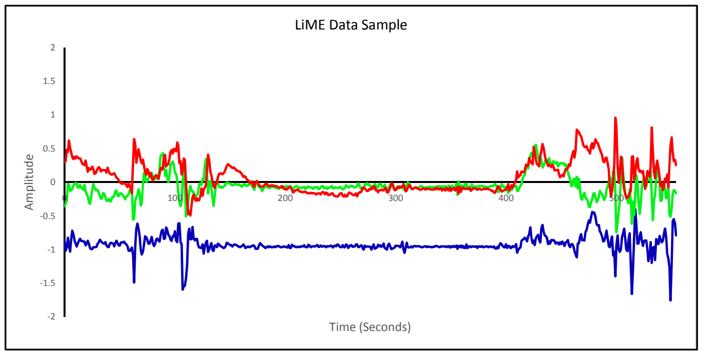
Introduction

- The challenge: interpreting this data



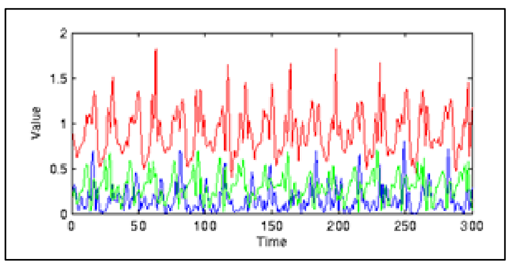
Introduction

Segment and classify free-living data

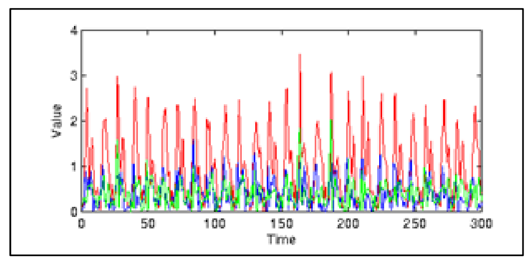


Followup paper (not this talk)

Classify already segmented data



Walking



Running

This talk

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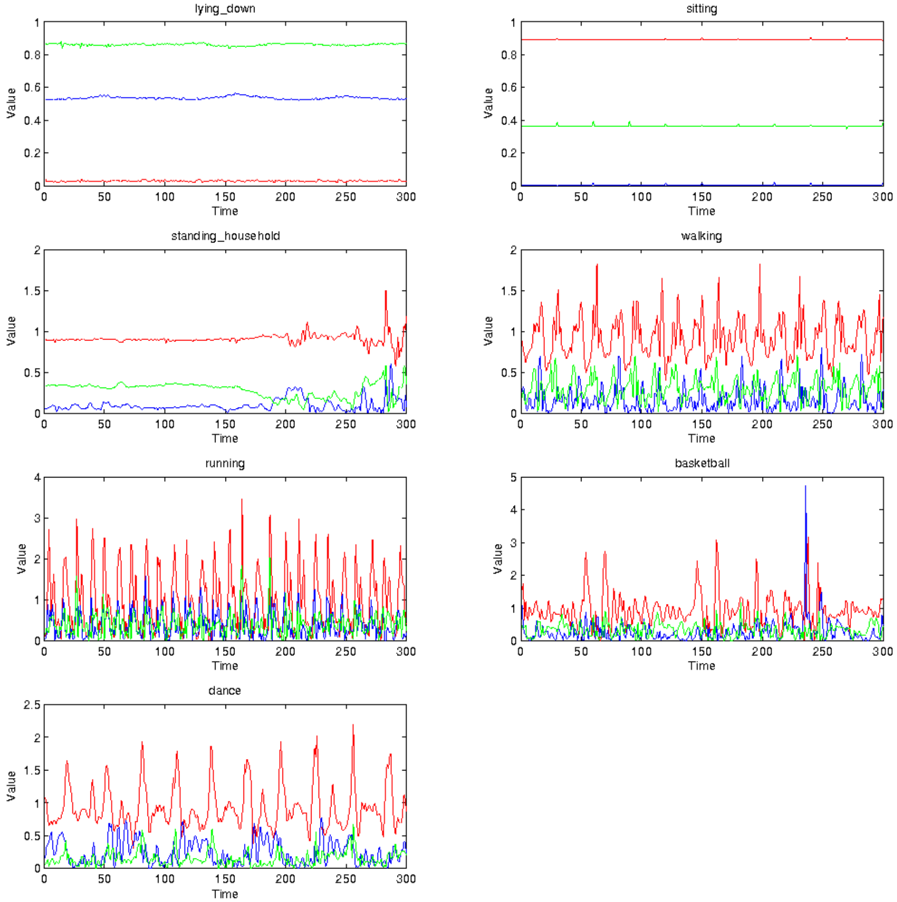
Related Work

1. Time series Classification (see Xing, Pei and Keogh 2010)
    - Nearest neighbor approaches with different distances metrics eg. Euclidean (Keogh and Kasetty 2003), Dynamic time warping (Wang et al. 2010)
    - Supervised Learning eg. decision trees (Bonomi et al. 2009), neural networks (Staudenmayer et al. 2009), support vector regression (Su et al. 2005), ensembles (Ravi et al. 2005)
    - Many different representations used eg. symbolic (Lin et al. 2003), shapelets (Ye and Keogh 2009), etc.
2. Segmentation
    - Hidden Markov Models (Lester et al. 2005, Pober et al. 2006)
    - Conditional Random Fields (van Kasteren et al. 2008, Gu et al. 2009, Wu et al. 2009)

Introduction

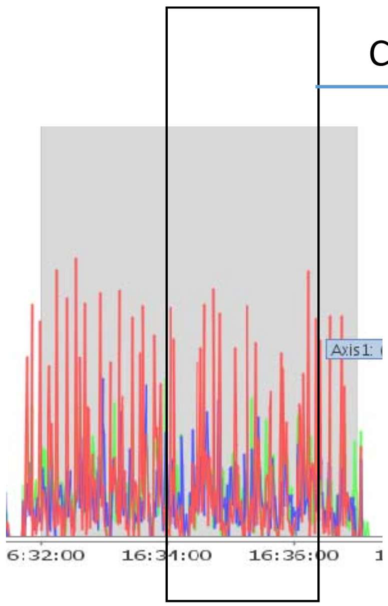
Things to note:

- Each window of data consists of a single activity
- Repetitive pattern
- Discriminative features at different scales
- Supervised learning approach works very well on our data



Methodology

Supervised Learning Approach



Cut time series into non-overlapping windows

Time	Axis 1	Axis 2	Axis 3
16:34:00	191	14	72
16:34:01	36	18	63
16:34:02	6	19	22
16:34:03	21	60	79
…	…	…	…

Feature	Value
X1	0.1
X2	15
X3	2
…	…

Supervised learning approaches

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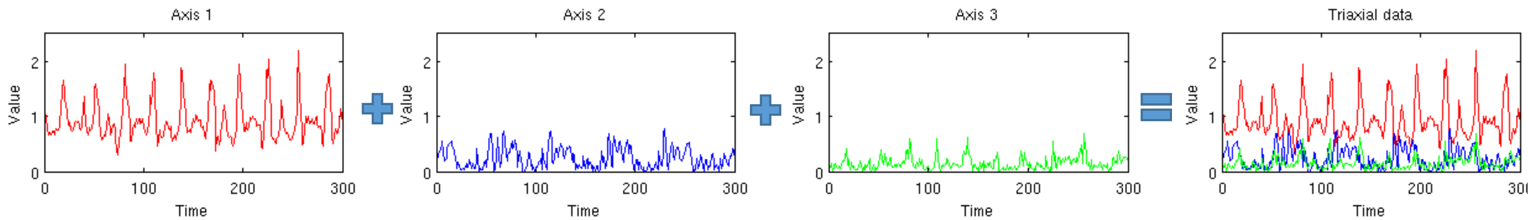
Methodology

Two issues when applying supervised learning to time series data

1. What features to use?
    - Feature extraction ultimately needs to be efficient
    - Bag-of-features + regularization works very well

Features



Axis-1

1. Percentiles: 10^{th},25^{th},50^{th},75^{th},90^{th}
2. Lag-one-autocorrelation
3. Sum
4. Mean
5. Standard deviation
6. Coefficients of variation
7. Peak-to-peak amplitude
8. Interquartile range
9. Skewness
10. Kurtosis
11. Signal power
12. Log-energy
13. Peak intensity
14. Zero crossings

Axis-2

1. Percentiles: 10^{th},25^{th},50^{th},75^{th},90^{th}
2. Lag-one-autocorrelation
3. Sum
4. Mean
5. Standard deviation
6. Coefficients of variation
7. Peak-to-peak amplitude
8. Interquartile range
9. Skewness
10. Kurtosis
11. Signal power
12. Log-energy
13. Peak intensity
14. Zero crossings

Axis-3

1. Percentiles: 10^{th},25^{th},50^{th},75^{th},90^{th}
2. Lag-one-autocorrelation
3. Sum
4. Mean
5. Standard deviation
6. Coefficients of variation
7. Peak-to-peak amplitude
8. Interquartile range
9. Skewness
10. Kurtosis
11. Signal power
12. Log-energy
13. Peak intensity
14. Zero crossings

Between two axes

1. Correlation between axis-1 and axis2
2. Correlation between axis-2 and axis3
3. Correlation between axis-1 and axis3

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Methodology

Two issues when applying supervised learning to time series data

1. What features to use?
2. How big of a window?
   - Too big: features too coarse, high latency of activity recognition
   - Too small: features meaningless
   - Need multi-scale approach

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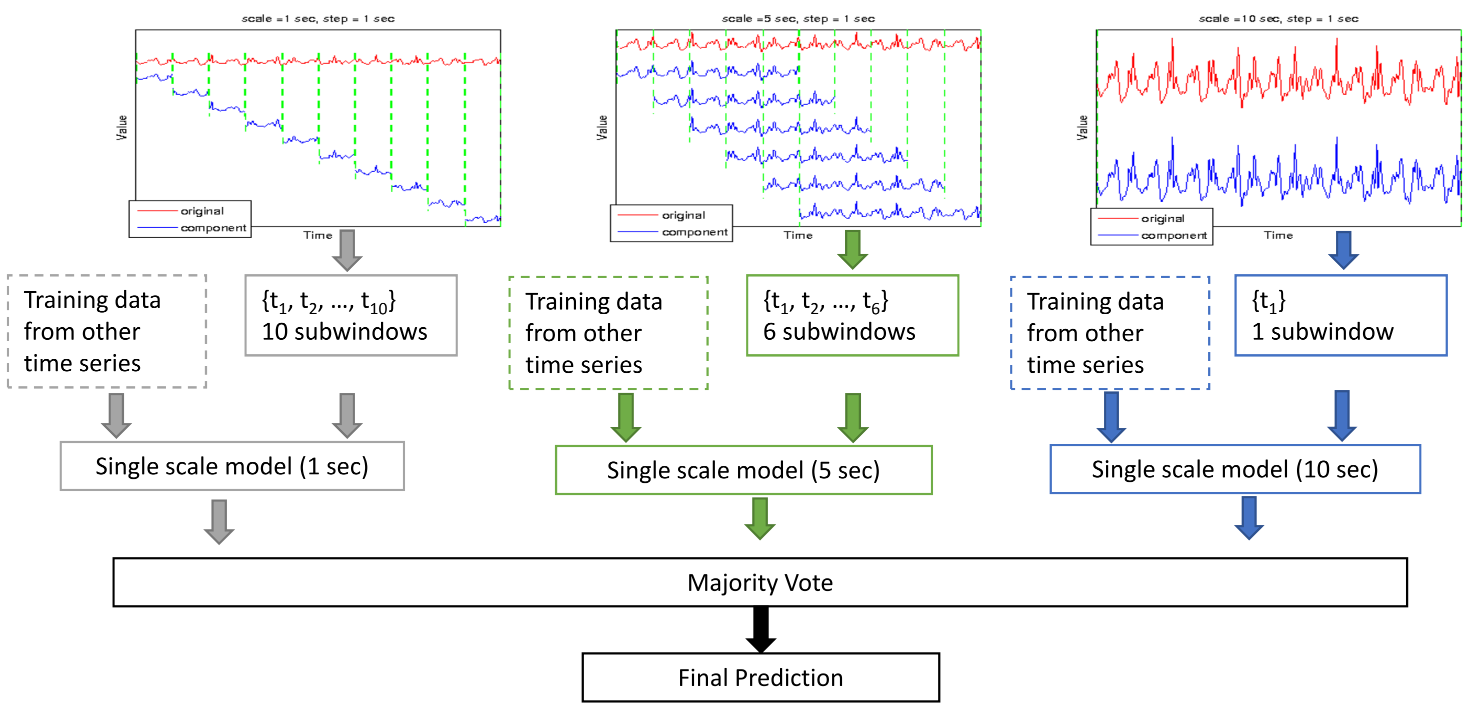
Subwindow Ensemble Model



Experiments

- Datasets
  - Human Activity Sensing Challenge (triaxial, 100 Hz, 7 subjects, 6 classes)
  - OSU Hip (triaxial, 30Hz, 53 subjects, 7 classes)
  - OSU Wrist (triaxial, 30 Hz, 18 subjects, 7 classes)
- Experimental Setup
  - Split by subject into train/validate/test splits
  - Averaged over 30 splits

Experiments

Algorithms

1. 1-NN (Euclidean distance, DTW)
2. (Single scale) Supervised Learning Algorithms (ANN, SVM) with 10 second windows
3. (Multi-scale) SWEM (SVM) with 10 ensemble members

Results

Algorithm	HASC (Macro-F1)	OSU Hip (Macro-F1)	OSU Wrist (Macro-F1)
SWEM (SVM)	**0.820***	**0.942***	**0.896***
SVM (W=10)	0.794	0.937	0.886
ANN (W=10)	0.738	0.919	0.787
1NN (EUC)	0.648	0.572	0.456
1NN (DTW)	0.648	0.561	0.494

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Results

We can also analyze the performance of each ensemble member by itself:

Model	MacroF1	Classification Accuracy of Each Physical Activity						
		lying	sitting	standing	walking	running	basketball	dance
SWEM_SVM	0.9424	0.9806	0.9423	0.9678	0.9541	0.9823	0.9419	0.8041
SWEM_SVM1	0.9090	0.9709	0.9294	**0.9893**	0.9488	**0.9876**	0.7398	0.6931
SWEM_SVM2	0.9339	0.9735	0.9271	0.9836	0.9543	0.9844	0.8931	0.7648
SWEM_SVM3	0.9357	0.9719	0.9365	0.9727	0.9502	0.9870	0.9283	0.7756
SWEM_SVM4	0.9355	0.9800	0.9265	0.9709	0.9533	0.9810	0.9178	0.7861
SWEM_SVM5	0.9345	0.9780	0.9357	0.9564	0.9494	0.9811	**0.9407**	0.7931
SWEM_SVM6	0.9361	0.9787	0.9299	0.9609	0.9572	0.9798	0.9306	0.7911
SWEM_SVM7	**0.9373**	0.9802	0.9353	0.9519	0.9565	0.9798	0.9378	**0.8131**
SWEM_SVM8	0.9371	**0.9819**	0.9296	0.9608	**0.9615**	0.9776	0.9206	0.7991
SWEM_SVM9	0.9383	0.9817	**0.9374**	0.9572	0.9567	0.9789	0.9359	0.8104
SWEM_SVM10	0.9369	0.9772	0.9318	0.9666	0.9599	0.9776	0.9161	0.7978

Conclusion

- Subwindow Ensemble Model able to capture discriminative features at different scales without committing to a single window size
- Outperforms baseline algorithms
- High F1 indicates it is viable for deployment
- Future work: free-living data segmentation, online algorithms

Acknowledgements

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Questions?

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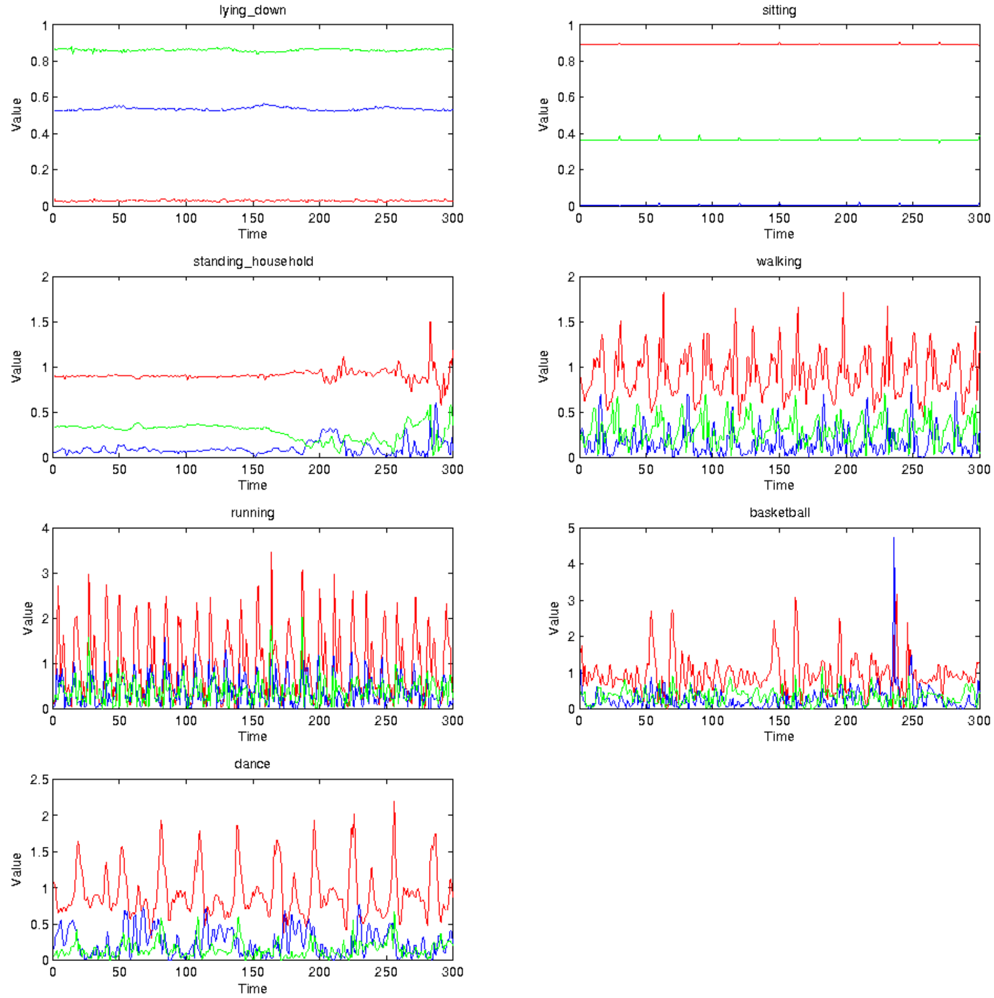
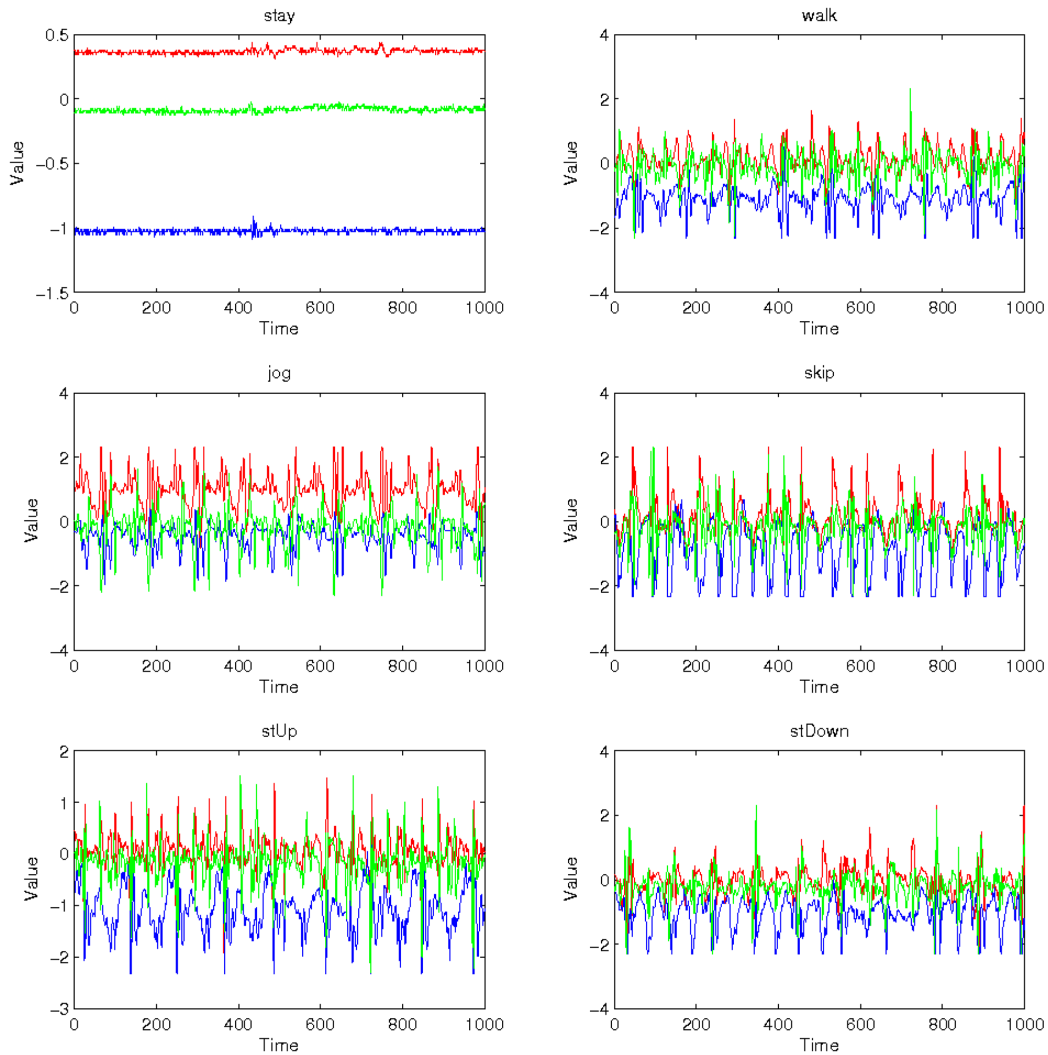
OSU Hip



lying_down
sitting
standing_household
walking
running
basketball
dance
Value
Time

HASC


stay
walk
jog
skip
stUp
stDown
Value
Time
0.5
0
−0.5
−1
−1.5
4
2
−2
−4
1
−3
200
400
600
800
1000