Human activity recognition using accelerometer data from wearable sensors

CS 6200 Project Presentation By:

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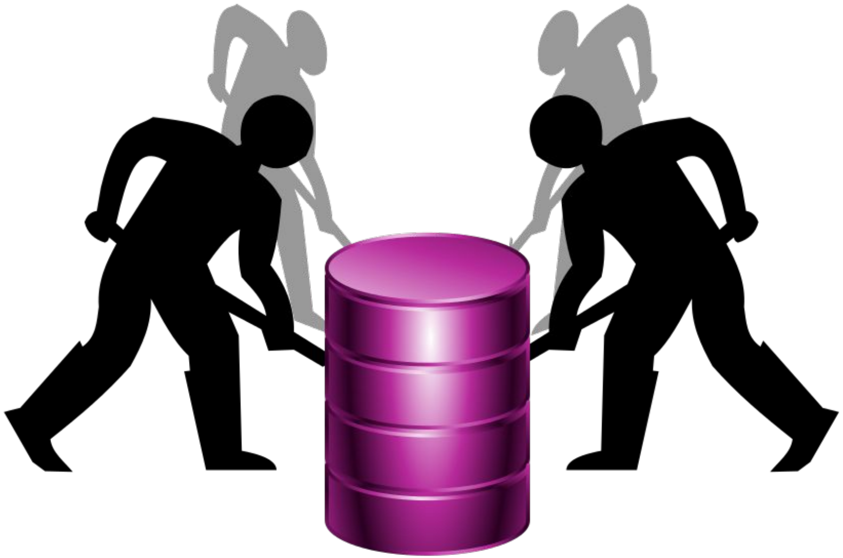
(KClosestNeighbors)

Outline

- Introduction
- Motivation & Goals
- Problem Definition
- Data Mining Steps
- Results and Evaluation
- Conclusion



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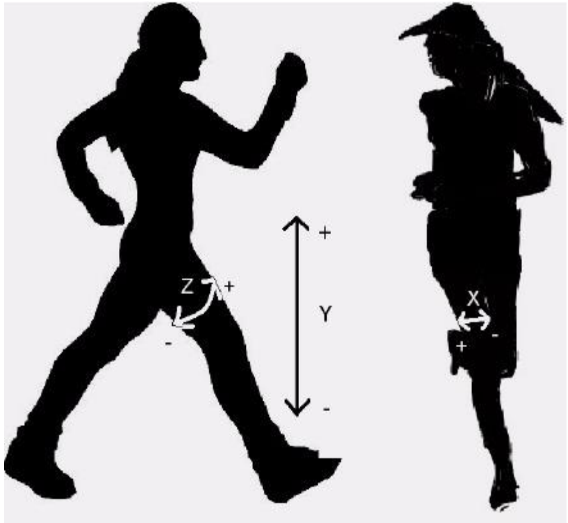
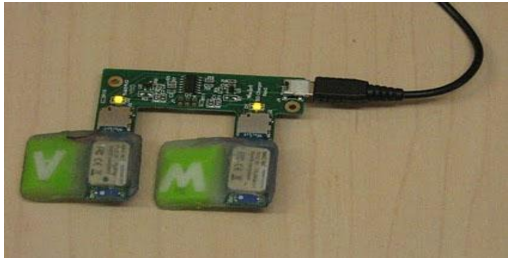
- What is human activity recognition?
  - Recognizing multiple sets of daily human activities under real-world condition.
- What devices are being used to collect data for human activities recognition?
  - Smartphones
  - Wearable devices
- Each of these devices have built in accelerometer (biaxial/triaxial) that keeps track of human body movement in x,y,z axes.
- Device we are using?
  - *Wocket accelerometer (+- 4g, sampling rate=90Hz)*



- Wocket accelerometer contains a triaxial accelerometer, a microprocessor, a Bluetooth transmitter and a rechargeable battery.
- These are sufficiently small and can be comfortably worn on all body locations at the same time.
- Raw accelerometer data is acquired and sent using the bluetooth to a smartphone.

Wocket ready to be placed on body



Wocket connected to a charger

- Analyze and understand the process of commercial wearable devices
  - Commercially available physical activity recognition system like Fitbit, Nike+ FuelBand etc. are widely used but their algorithm has not been validated i.e. it's still a black box system.

  - In this project, we report our efforts to recognize human activities by working on similar raw accelerometer data.
  - By doing so, we gain in-depth understanding of the activity classification system, and provide recommendation based on our findings.

- Applications of these devices in industries such as:[Lockhart et al. 2012]
  - Health: Fitness Tracking, Health monitoring, fall detection
  - Social: Share your fitness activities on social networking sites like Facebook etc.
  - Lifestyle : Context-aware behaviours
  - Targeted Advertising : Advertisement based on user activities.
  - Corporate Management and Accounting.

Goals:

- Classifying user’s daily activities by analyzing and processing raw data from wocket accelerometer.
- Suggest best possible position for sensor placement based on the accuracy.
- Suggest best combination of sensor placement sites to classify activities.

- We are working on this project to recognize few of the most important everyday human activities:
  - Walking
  - Cycling
  - Lying on back
  - Sitting
- Accelerometer are placed at five body locations at the same time.
  - Dominant Upper-Arm
  - Dominant Wrist
  - Dominant Hip
  - Dominant Thigh
  - Dominant Ankle
- These placement sites were selected because of their relevance in exercise monitoring research.[Mannini et al. 2013]

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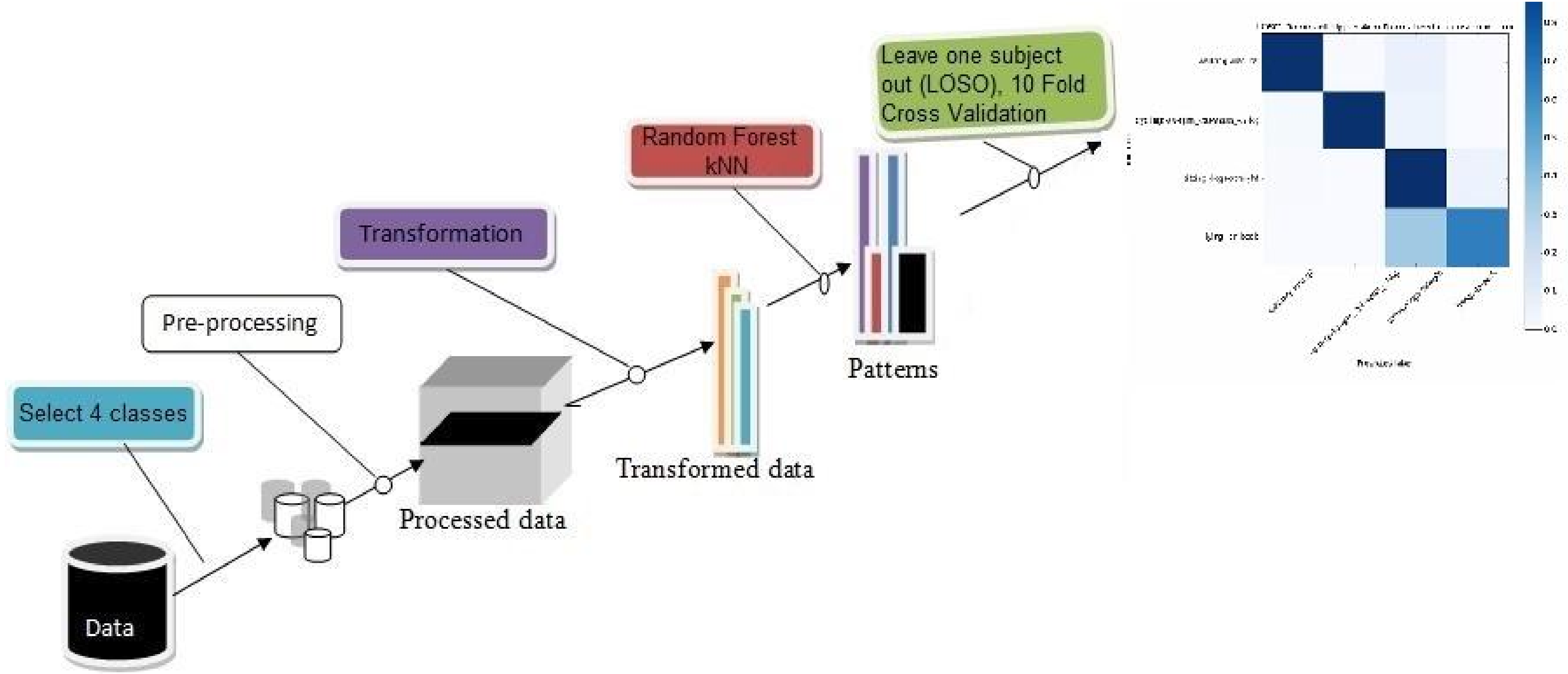


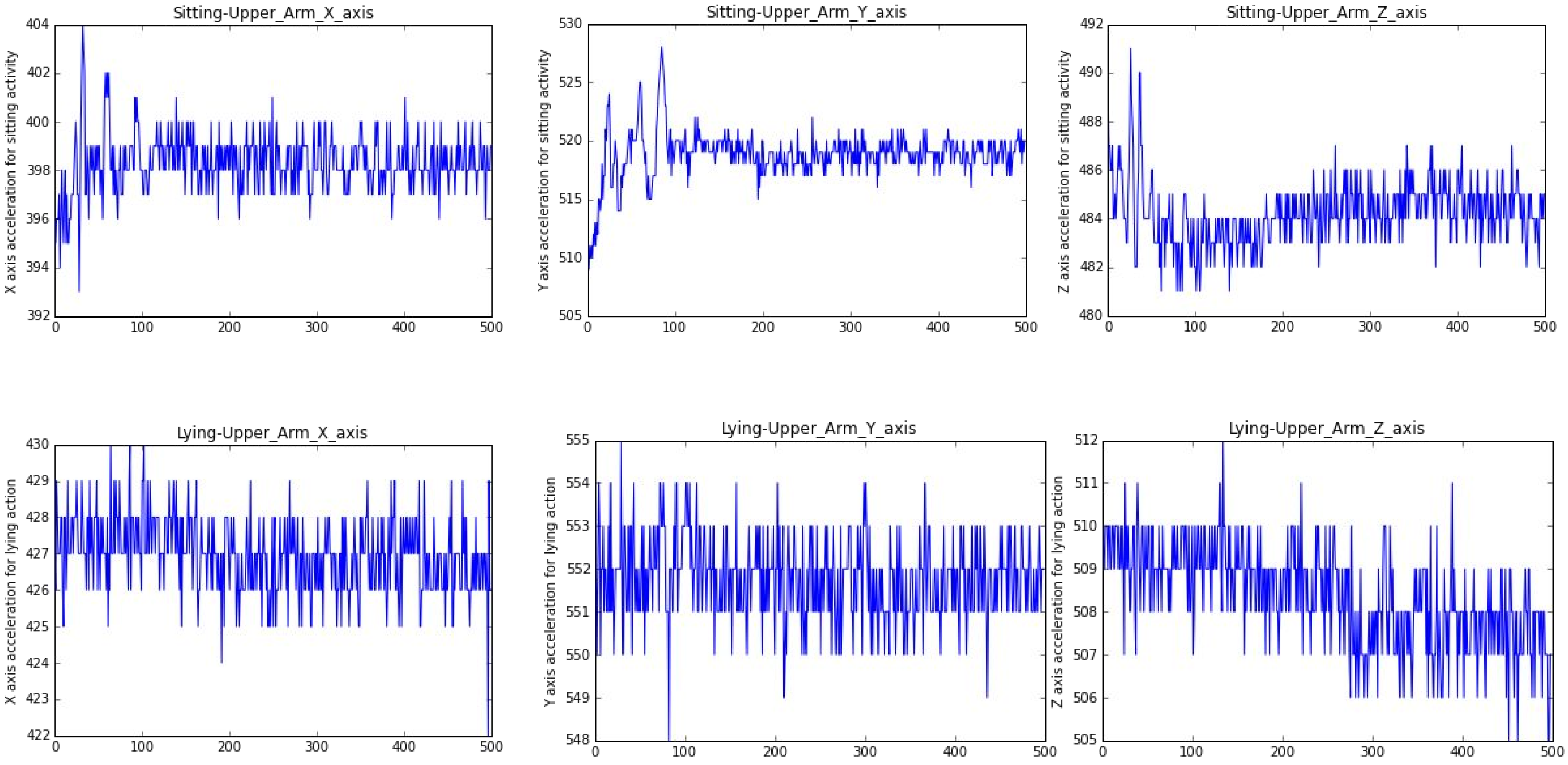
- Dataset : We have raw data set from 33 participants. For each participant we have following files :
  - Annotations.csv
  - Wocket.csv (A total of 5 files for each sensor location)
- Demographics: 33 participants
  - 11 Male, 22 Female, age :18-75, height: 168.5 +/- 9.3cm, weight: 70.0 +/- 15.6 kg

STARTTIME	ENDTIME	activity
12-02-2009 10:38	12-02-2009 10:39	sitting
12-02-2009 10:39	12-02-2009 10:40	cycling:-70-rpm_-50-watts_-.7-kg
12-02-2009 10:40	12-02-2009 10:43	walking:-natural
12-02-2009 10:43	12-02-2009 10:45	lying

Sample Annotations.csv

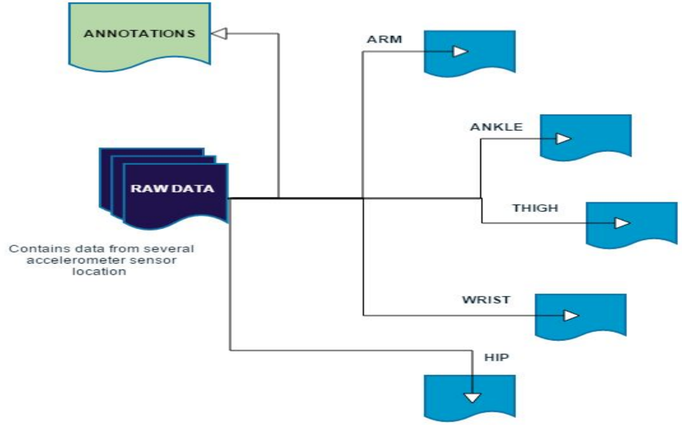
Time Stamp	X	Y	Z
1.25975E+12	427	434	434
1.25975E+12	486	510	420
1.25975E+12	481	477	423
1.25975E+12	475	490	422

Sample Wocket.csv



Plotting x,y,z acceleration values for sitting and lying activities for sensor position at upper-arm

We have data from 33 participants. Let's consider the preprocessing process for one subject



Each of these files have structure as follows:

X	Y	Z	TIMESTAMP

Each of the sensor location files are merged with the annotation file to get a single file

Annotation file have structure as follows:

STARTTIME	ENDTIME	ACTIVITY

We will thus get a file having combined data about the sensor location file with the activity lable

X	Y	Z	TIMESTAMP	SENSOR LOCATION	ACTIVITY

$$SM= \sqrt{acc_x^2 + acc_y^2 + acc_z^2)}$$

Signal magnitude(SM) is calculated using x, y and z for each data point

We divide entire data into 10 s window

SM	TIMESTAMP	SENSOR LOCATION	ACTIVITY

Window 1 (win1)

Window 2 (win2)

Window 3 (win3)

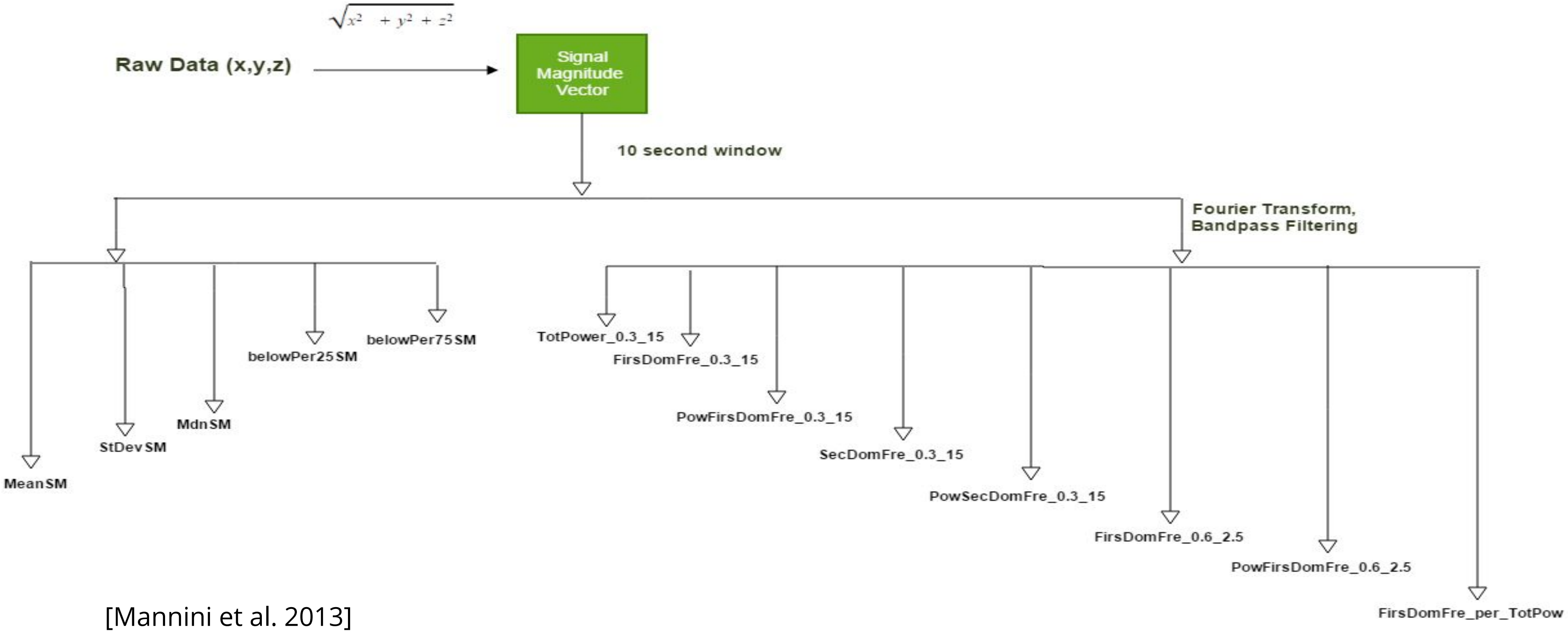
.

Window N (wihN)

All the features are calculated

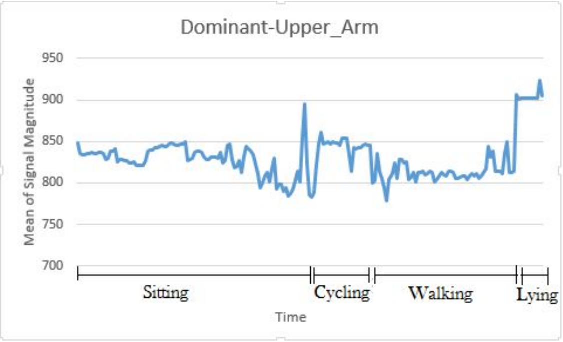
MEAN SM	STANDARD DEVIATION SM	SENSOR LOCATION	belowPer25SM	· · · FirsDomFre_per_ TotPower_0.3_15	Activity
M(win1)	SD(win1)	Upper Arm	12463.062	2.7982709155606251e-09	Walking
M(win2)	SD(win2)	Ankle	12476.897	8.6162771157347734e-09	Cycling
M(win3)	SD(win3)	Thigh	12721.924	2.9776007574470882e-07	Sitting
M(win4)	SD(win4)	Hip	12333.145	5.1579998845580867e-05	Lying
M(winN)	SD(winN)	Wrist	12568.527	3.289271622171694e-07	Cycling

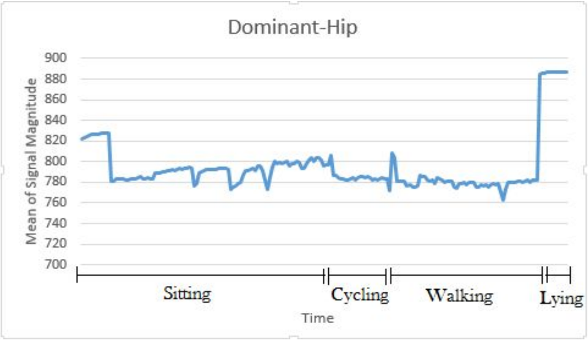
Features Extraction Methodology



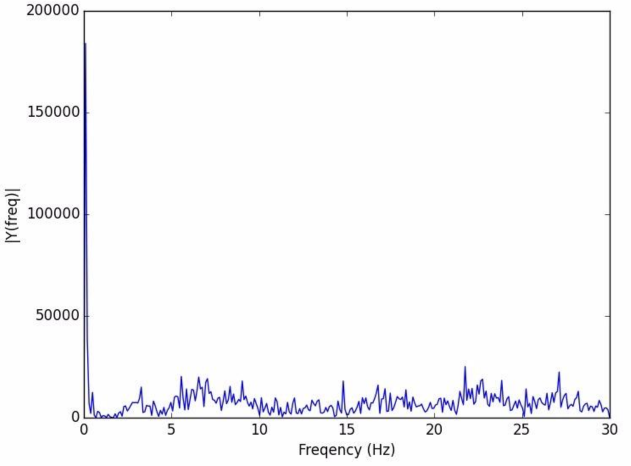
[Mannini et al. 2013]

Mean Signal Magnitude for each sensor site

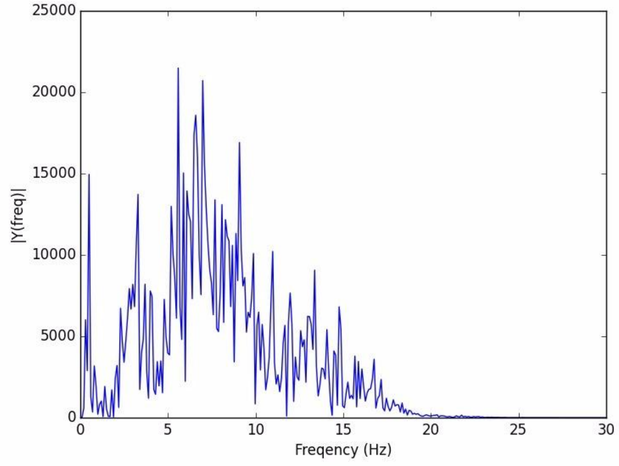




Frequency before filtering



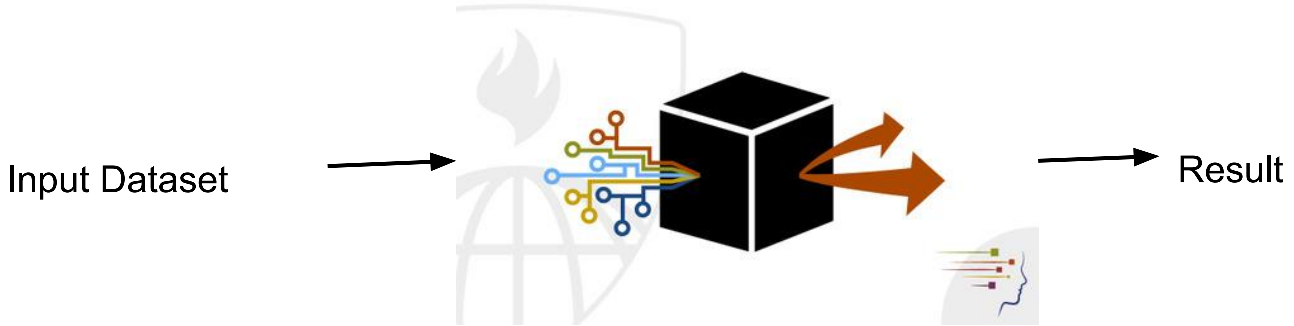
Frequency after filtering



[Mannini et al. 2013]

- As the last step of processing the data, we formed following datasets to meet our goal:
  - Grouped the entire dataset of 33 participants as per the sensor positions.
  - A separate dataset having 33 files, where each file corresponds to a participant.

- Univariate feature selection based on ANOVA : removed features related to SMV percentile



- Algorithms used:
  - Random Forest [Ho. et al. 1995]
    - Random Forests are ensemble learning algorithms for classification that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes.
  - k-Nearest Neighbors (k-NN) [Keller,J.M et al. 1985]
    - The k-NN algorithm is among the simplest of all machine learning algorithms. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its *k* nearest neighbors (*k* is a positive integer, typically small).

- We employed "grid-search" to identify the best parameters suited for above mentioned algorithms.
  - For Random Forest: Number of Trees ranges from numOfTrees(50-200), InfoGain (entropy), all features used
  - For k-NearestNeighbors: Value of k varied from 9 - 11, uniform weight, euclidean distance

Evaluation:

- We used the following methods to evaluate our model
  - 10-Fold Cross Validation
  - Leave-One-Subject-Out (LOSO) : simulating a real-life situation
- Outcome measures included Accuracy, Precision, Recall, and F1-score.

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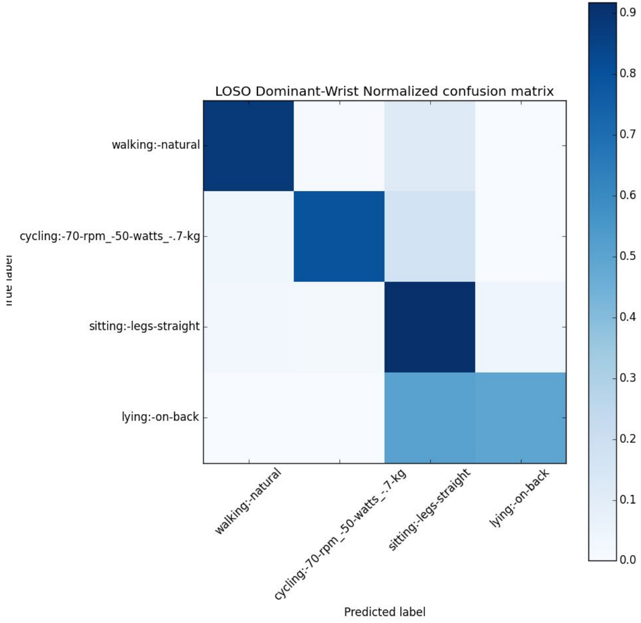
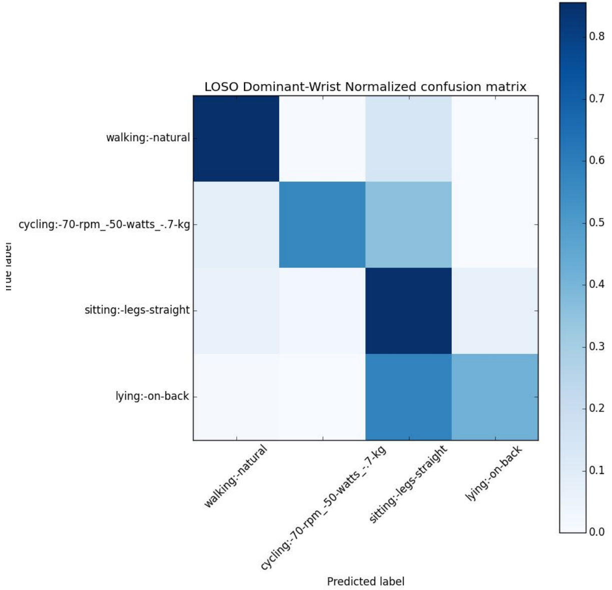
- Confusion matrix after LOSO CV based on Dominant Wrist data:

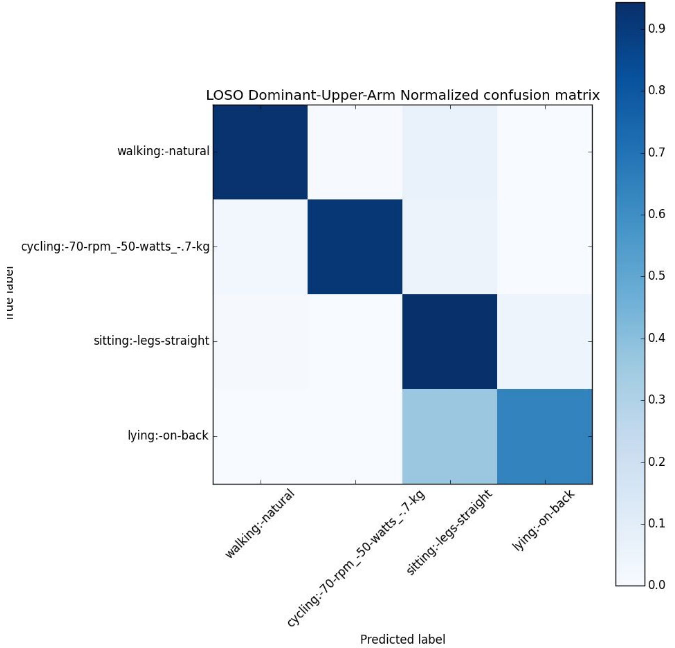


Random Forest

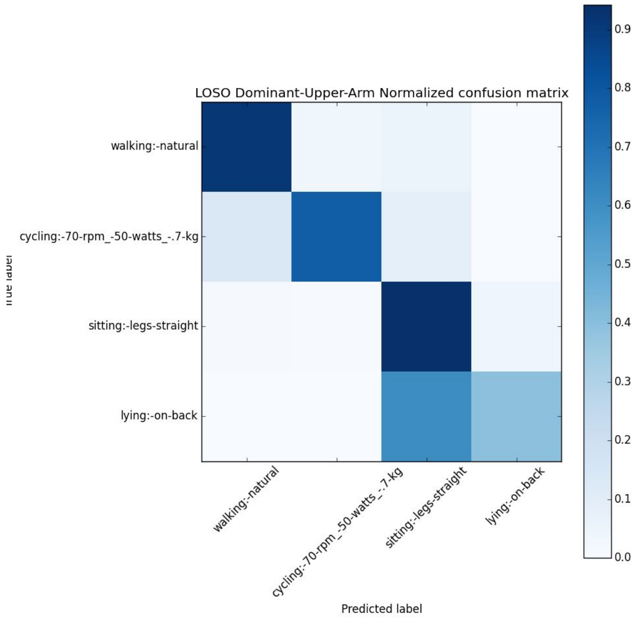


k-NN

- Confusion matrix after LOSO CV based on Dominant Upper arm data:



Random Forest



k-NN

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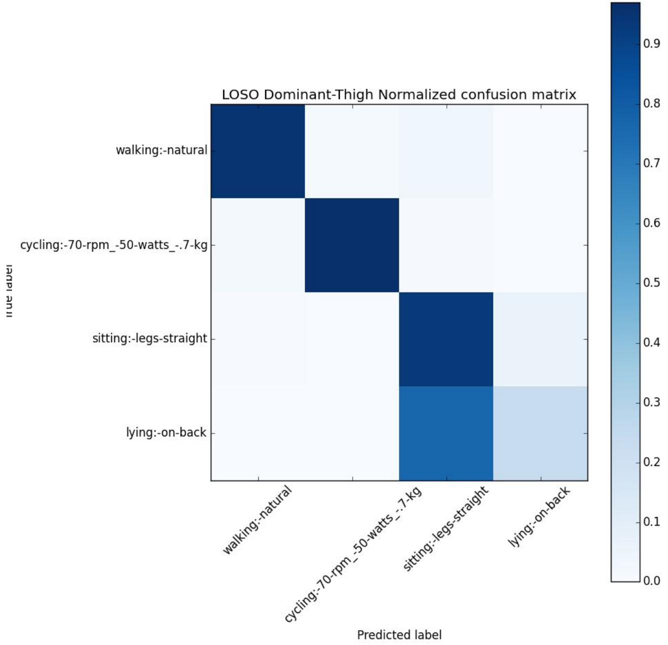
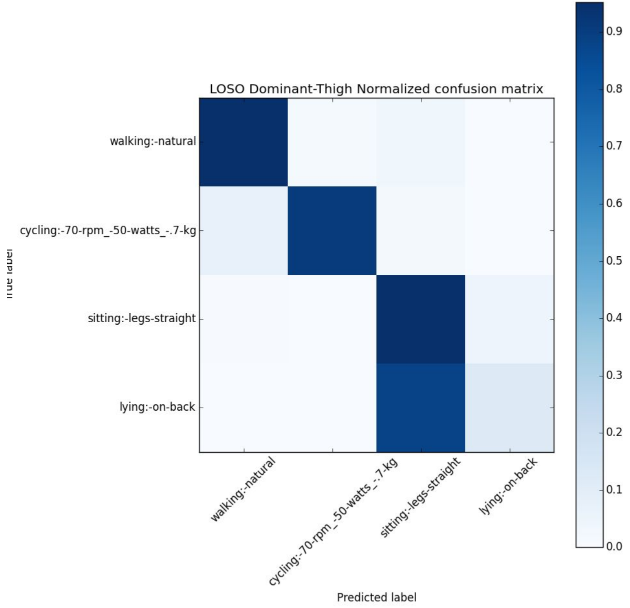
- Confusion matrix after LOSO CV based on Dominant Thigh data:



Random Forest



k-NN

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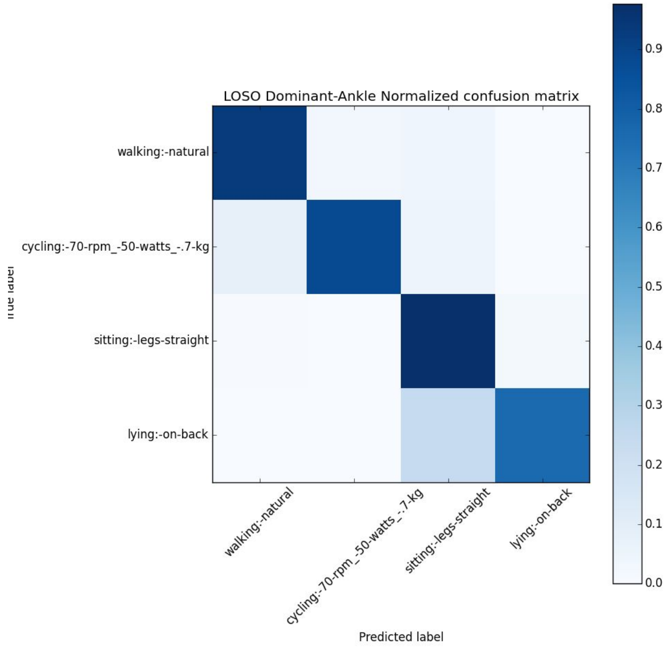
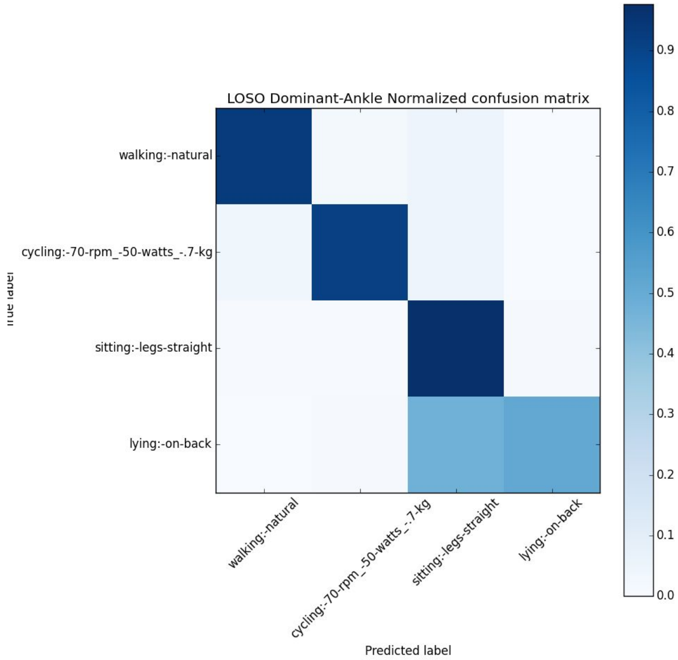
- Confusion matrix after LOSO CV based on Dominant Ankle data:



Random Forest



k-NN

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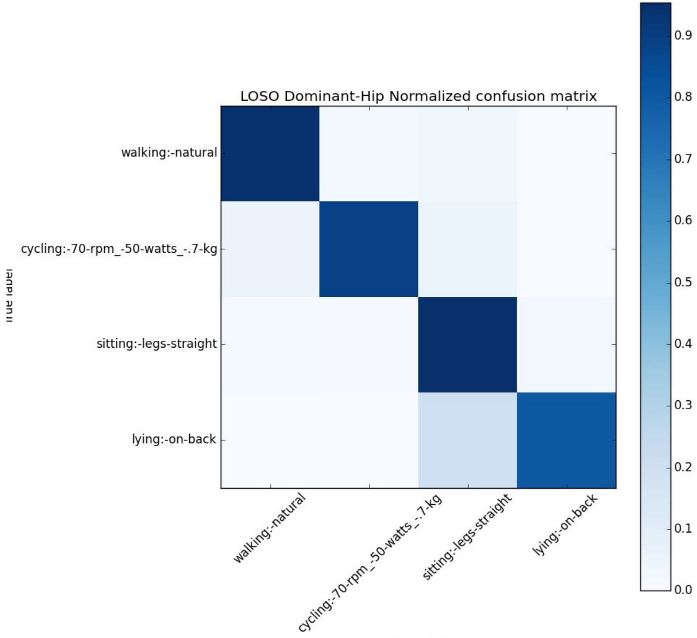
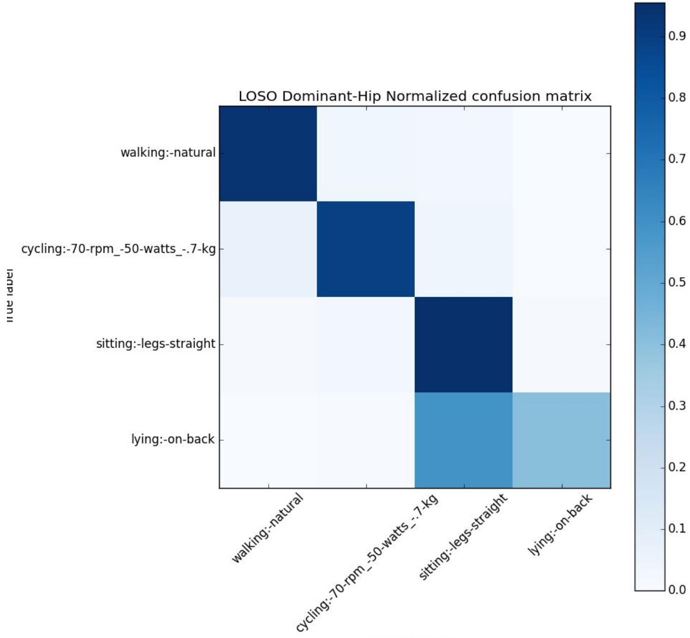
- Confusion matrix after LOSO CV based on Dominant Hip data:



Random Forest



k-NN

Evaluation Results:

Classifier	CV	Sensor Position	Walking	Cycling	Sitting	Lying
Random Forest	LOSO	Dominant-Wrist	88.76%	80.24%	91.89%	50.83%
		Dominant-Hip	93.95%	88.47%	95.47%	80.45%
		Dominant-Thigh	95.52%	96.36%	93.01%	23.93%
		Dominant-Ankle	92.95%	88.86%	97.46%	75.90%
		Dominant-Upper-Arm	92.95%	91.37%	94.29%	65.32%
kNN		Dominant-Wrist	85.58%	56.68%	85.36%	41.12%
		Dominant-Hip	93.69%	89.48%	95.50%	40.29%
		Dominant-Thigh	95.20%	90.84%	94.93%	11.96%
		Dominant-Ankle	93.26%	91.32%	97.67%	51.40%
		Dominant-Upper-Arm	91.37%	77.59%	94.22%	39.05%

Evaluation Results:

Classifier	CV	Sensor Position	Walking	Cycling	Sitting	Lying
Random Forest	10-Fold	Dominant-Wrist	87.93%	78.04%	90.98%	47.73%
		Dominant-Hip	94.97%	91.39%	95.45%	80.46%
		Dominant-Thigh	95.55%	98.19%	91.18%	25.69%
		Dominant-Ankle	95.07%	86.26%	98.07%	75.44%
		Dominant-Upper-Arm	94.14%	94.53%	94.78%	60.73%
kNN		Dominant-Wrist	83.27%	60.44%	83.58%	36.93%
		Dominant-Hip	94.17%	89.87%	95.74%	45.86%
		Dominant-Thigh	95.54%	92.40%	92.54%	16.02%
		Dominant-Ankle	93.85%	90.63%	96.58%	53.65%
		Dominant-Upper-Arm	90.78%	79.52%	92.93%	39.78%

- Combining data from the top two placement sites, Dominant-Hip and Dominant-Ankle

	Walking	Cycling	Sitting	Lying
Precision	0.95429058	0.899217	0.956576	0.879931
Recall	0.9537383	0.887182	0.979197	0.874007
F1	0.95011728	0.887496	0.966129	0.862288
Accuracy	0.953738298	0.887182	0.979197	0.90132

- Thus, we can see in the above table that combining data from Dominant-Hip and Dominant-Ankle improved overall outcome measures.

- Predictive features : Mean, St. deviation, Median, along with Frequency domain features extracted from signal magnitude vector.

- For both LOSO and 10-fold CV, RF performed better than k-NN.

- Data from dominant-hip was the most discriminative in classification, followed by dominant-ankle.

- We recommend combination of both sites for improved classification.

References cited:

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Thank You

Questions?