Activity Classification Using Accelerometers

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Introduction: Motivations and Applications

- Automatic activity classification has been receiving increasing attention in recent years: medical diagnosis, athletic training, physiotherapy, workspace health, behavioral science, neurology, etc.
- In this project, we focus on two tasks: general everyday activities, and workspace activities.
- Our system uses tri-axial accelerometers.

Our system

- User trains the system by performing specified activities
- User uses the system
- Data is uploaded to server and analyzed by software or a third party
- Data yields results and conclusions

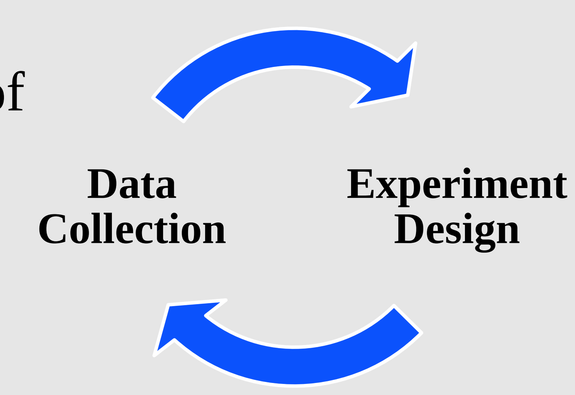
Methodology: Procedure and Design

Data Collection → **Feature Selection** → **Activity Classification**

1.Put sensors on specific body parts according to what kind of data we are collecting

2.Use features that separate the data well.

3.Use the naïve Bayes classifier



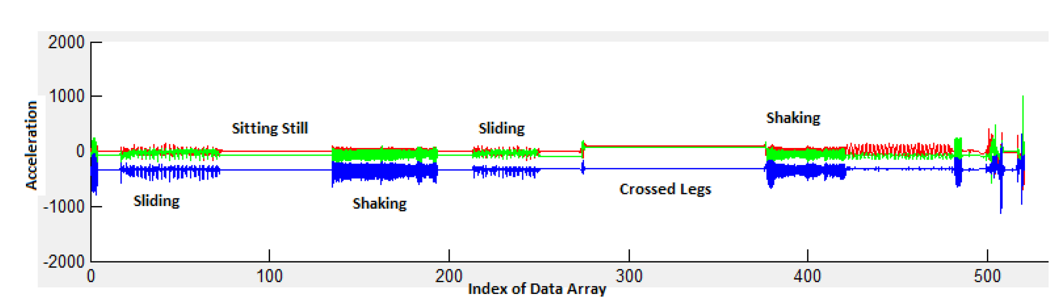
Goals

- **Training**
  - •What is the best training set?
- **•Features**
  - •What are the best features?
  - •How to implement a feature-selection-algorithm?

Results and Examination: Examples of Basic and Workspace Activity Data

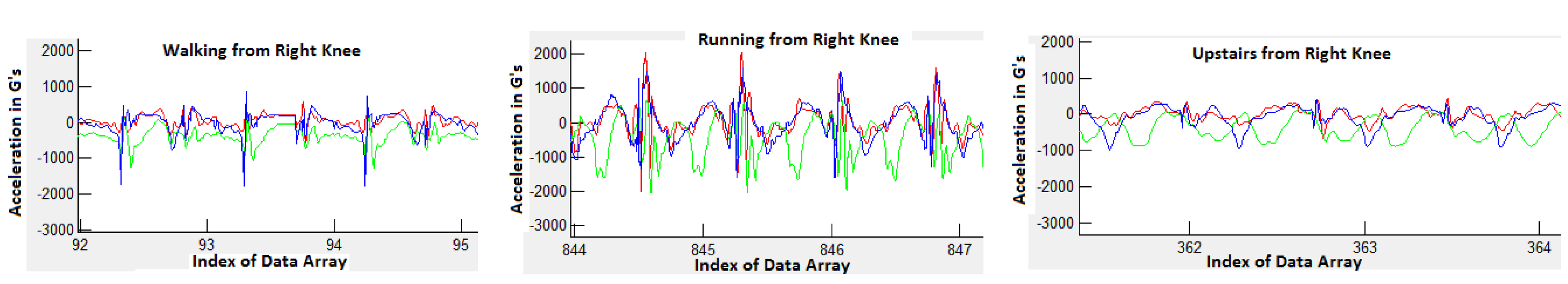
Activity Data

Graphs of **acceleration** in three axes, **x**, **y**, and **z**, for sensors

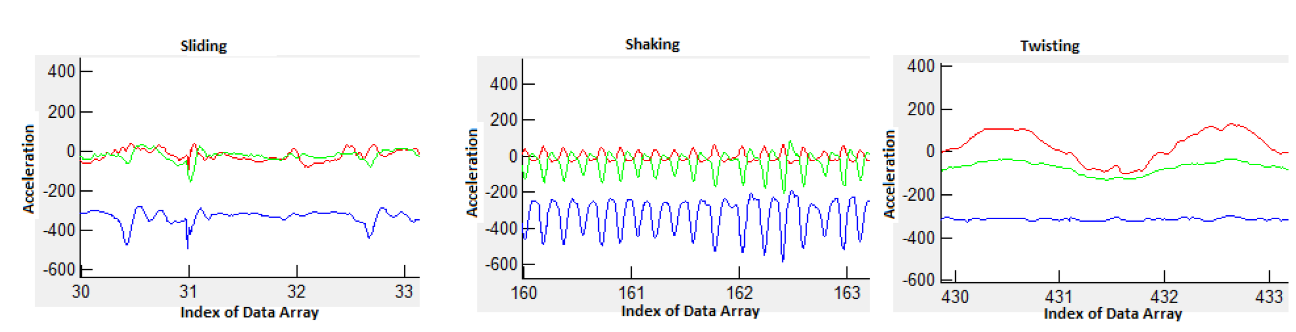


Basic activities from the waist (top) and knee (bottom)

Workplace activities from the knee

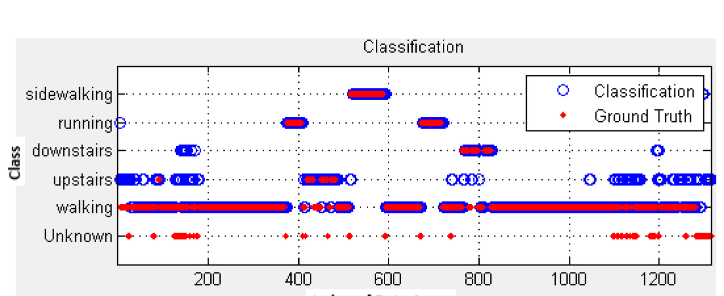


Close ups over a three second window



We have collected 11 data sets for basic physical activities and 21 for workplace.

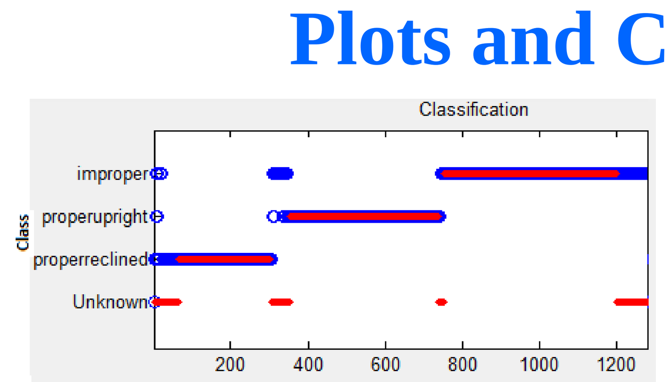
Plots and Confusion Matrices



Sensors: Two on ankles, two on knees, one on waist.
Features: Short-term-energy and max.

Overall Accuracy: 84%

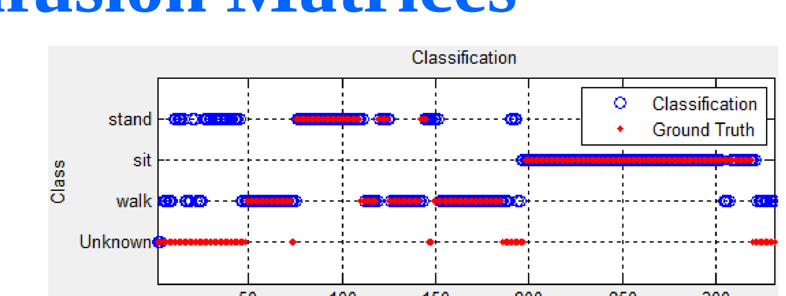
Classification / True Class	Unknown	walking	upstairs	downstairs	running	sidewalking
Unknown	2.4390	43.9024	41.4634	2.4390	2.4390	7.3171
walking	0	82.4841	14.2251	2.3355	0.8493	0.1062
upstairs	0	10.2041	89.7959	0	0	0
downstairs	0	9.0909	11.3636	79.5455	0	0
running	0	4.9383	0	0	95.0617	0
sidewalking	0	0	6.6667	0	0	93.3333



Sensors: Chest
Features: Mean.

Overall Accuracy: 100%

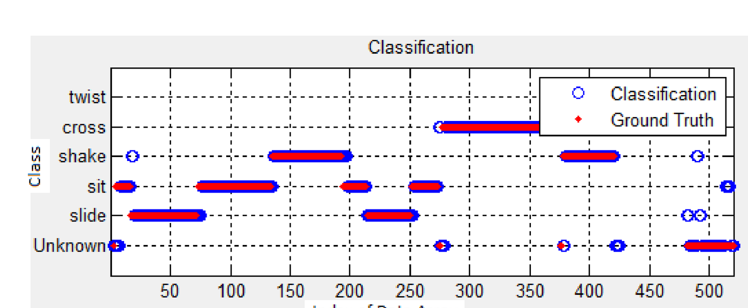
Classification	Unknown	properreclined	properupright	improper
Unknown	2.3490	10.4027	3.3557	83.8926
properreclined	0	100	0	0
properupright	0	0	100	0
improper	0	0	0	100



Sensors: One in the pocket.
Features: Mean and frequency

Overall Accuracy: 94%

Classification / True Class	Unknown	walk	sit	stand
Unknown	3.8961	45.4545	5.1948	45.4545
walk	0	93.1034	0	6.8966
sit	0	3.2787	96.7213	0
stand	0	8.8889	0	91.1111



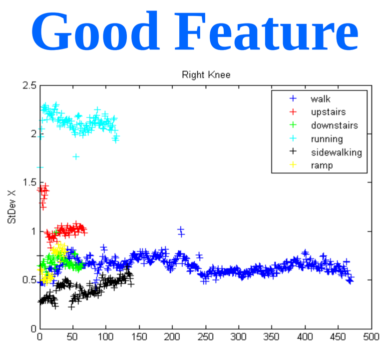
Sensors: One on the knee, one on the arm.
Features: Max, standard deviation, short-term-energy and frequency.

Overall Accuracy: 94%

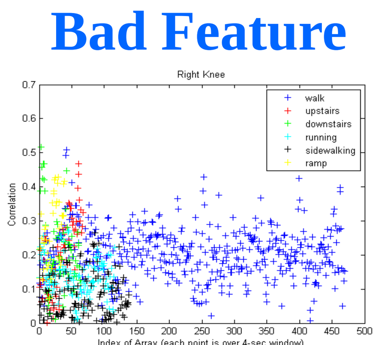
Classification / True Class	Unknown	slide	sit	shake	cross	twist
Unknown	68.7500	8.3333	8.3333	4.1667	8.3333	2.0833
slide	0	96.7742	1.0753	2.1505	0	0
sit	3.3898	5.0847	88.1356	3.3898	0	0
shake	1.9608	0	0.9804	97.0588	0	0
cross	3.0303	0	0	0	96.9697	0
twist	6.6667	0	0	1.6667	0	91.6667

To select good features, we analyzed many plots. We plotted features against time, as well as other features. We also plotted means of features for each activity looking for the ones that were furthest away from each other.

Good Feature



Bad Feature



Observations

•Different shoes and surfaces have a large effect on the data.

•Orientation and position of sensors make a difference.

•The length of the activity in relation to the window size greatly affects the accuracy

Future Work

•**Real time** classification and feedback. Athletes will be able to alter their training, and people, their posture, in real time

•Determine the best **easy** and **reliable** way to collect a training set

•Implement features that **correlate different sensors**